Fear and the behaviour of virtual flocking animals

Carlos Delgado[1] Mata, Ruth Aylett[2]

carlos@bonaterra.edu.mx, ruth@macs.hw.ac.uk
[1]University of Bonaterra, Aguasclaientes, Mexico; [2]Heriot-Watt University, Riccarton,
Edinburgh EH14 4AS, UK

Abstract. The paper investigates the role of an affective system as part of an ethologically-inspired action-selection mechanism for virtual animals in a 3D interactive graphics environment. It discusses the integration of emotion with flocking and grazing behaviour and a mechanism for communicating emotion between animals; develops a metric for analyzing the collective behaviour of the animals and its complexity and shows that emotion reduces the complexity of behaviour and thus mediates between individual and collective behaviour.

1. Introduction

Minsky [13] was one of the first to emphasise the importance of emotion for Artificial Intelligence. Since then, research in affective systems for embodied autonomous agents, robotic and graphical, has expanded. Approaches divide into low-level, neuro-physiologically inspired accounts, focusing on sub-symbolic behavioural architectures [5,21], and high-level cognitive science-inspired accounts, focusing on symbolic appraisal-driven architectures [9, 16]. This work concentrates on a low-level account, applied to flocking mammals (sheep, deer), and demonstrates the role of fear as a social regulator between individual and group behaviour. We take the 'primitive emotions' namely: anger, fear, disgust, surprise, happiness and sadness, [8] as a plausible set for other mammals than humans, and examine how they can be integrated into an ethologically-based action-selection mechanism.

For affective systems to have developed and remain under the pressure of evolutionary selection, they must play a functional role within the overall architecture of animals. A number of such functions can be identified. One is to modify behaviour: a sheep that experiences an anxiety-inducing stimulus may carry on grazing but bunch up more tightly with the rest of the flock. A second is to switch behaviours: a sheep experiencing a threatening stimulus inside its flight zone will flee. A third is to avoid dithering between competing behaviours by adding weight to one of them [3], and a fourth and related function is to sustain a selected behaviour for an appropriate interval – a fleeing animal can typically no longer perceive the threatening predator, but fear keeps it running, acting like a cheap short-term memory.

Many mammals do not behave merely as individuals, they engage in the collective behaviour known as flocking. Reynolds [17] showed that flocking does not require a complex internal architecture but can be produced by a set of simple rules. In his model of *boids*, every individual (boid) tries to fulfil three conditions: cohesion or flock centring (attempt to stay close to nearby flockmates), alignment or velocity matching (attempt to match velocity with nearby flockmates), and separation or collision avoidance (avoid collisions with nearby flockmates). This approach has produced sufficiently believable behaviour to be used for stampedes in a number of animated films. However, mammals do have a complex internal architecture, unlike social insects, and a wide range of individual behaviours: a motivation for this work was to reconcile the generation of collective behaviour by a small set of rules with the more complex agent architecture required for a mammalian behaviour repertoire.

For ungulates, grazing is a significant behaviour, requiring spatial orientation behaviours. Two are of particular relevance. The first, *kinesis,* can be representeded by a reactive rule of slowing down when encountering favourable conditions and speeding up for unfavourable ones: this can also be related to escape behaviour. However most organisms do not move in an absolutely straight line; when orienting to favourable localities: the effect of kinesis can be improved by increasing the angle of the random deviations from the straight line, in any case inherent to locomotion. By these means, the organism is kept in the desirable environment longer and is made to exploit an increased part of its area, especially relevant to grazing. This second enhanced mechanism is termed *klinokinesis* and it is found in grazing mammals, as well as in swimming protozoa and higher crustacea. This represents an important example of individually-oriented behaviour which conflicts with the rule-set for flocking.

2 An ethologically inspired action-selection mechanism

The work discussed here has been implemented with graphically-embodied flocking animals (sheep, deer) in a 3D interactive virtual environment. In order to test the hypothesis that an affective system can act as a regulating mechanism between individual and social behaviour, an ethologically-motivated architecture was developed for the virtual animals.

The basic task of a virtual animal brain has often been split into the three sub-tasks of perception (sensing the environment and interpreting the sensory signals to provide a high-level description of the environment), action selection (using the perceptual and emotional inputs to decide which of the animal's repertoire of actions is most suitable at that moment) and motor control (transforming the chosen action into a pattern of "physical" actions to produce the animation of the animal). To this we add a fourth subtask: generating emotions (affecting the behaviour of the animals, exemplified by the conspecifics flight-flocking), Figure 1 shows a detailed diagram of the designed architecture developed as a result, and the next sections describe its components.

While not claiming neurophysiological accuracy, the architecture splits its overall functionality across biologically-plausible subsystems. Thus the module *hypothalamus* is used to store the drives (for example, hunger), the *sensorial cortex* stores sensor data, the *amygdala* contains the emotional systems such as Fear, Joy and Anger, and *Basal Ganglia* contains the hierarchical mechanism for selecting actions, similar to those described by ethologists. Each of the listed modules is defined in

XML giving the name of each of the system/variables, the inputs associated to them, a weight, and a function (acting as a filter, in most cases a sigmoid) which in turn generated a feed-forward hierarchy like the one described by Tyrrell [20].

Taking the position that emotion partly functions as a communication mechanism, a novel feature of this work is that the perceptual component has been designed to support the communication of emotion among conspecifics. In the real world, emotional transmission is almost certainly multi-modal, with certain modes such as the perception of motion being particularly difficult to model. Thus we have limited ourselves for now to a single mode, and the one we have chosen is pheromones, perceived by a virtual olfaction sensor.
Recent experiments [10] have shown that mammals, including humans, emit pheromones through apocrine glands as an emotional response, and as means to communicate that state to conspecifics, who can adapt their behaviour accordingly; research has found that odours produce a range of emotion responses in animals, including humans [12]. This is adaptively advantageous because olfaction is part of the old smell-brain which can generate fast emotional responses, that is without the need of cognitive processes. Grammer [10] argues that every living creature has a distinctive molecular signature that can be carried in the wind, variously showing it to be nutritious, poisonous, sexual partner, predator or prey. Neary [15] points out that sheep, particularly range sheep, will usually move more readily into the wind than with the wind, allowing them to utilise their sense of smell.

Our architecture models the exteroceptors used by real animals to detect the presence of chemicals in the external environment as a virtual nose. An environmental simulator has been developed: its tasks include changing the temperature and other environmental variables depending on the time of day and on the season, using statistical historical data. An alarmed animal sends virtual pheromones to the

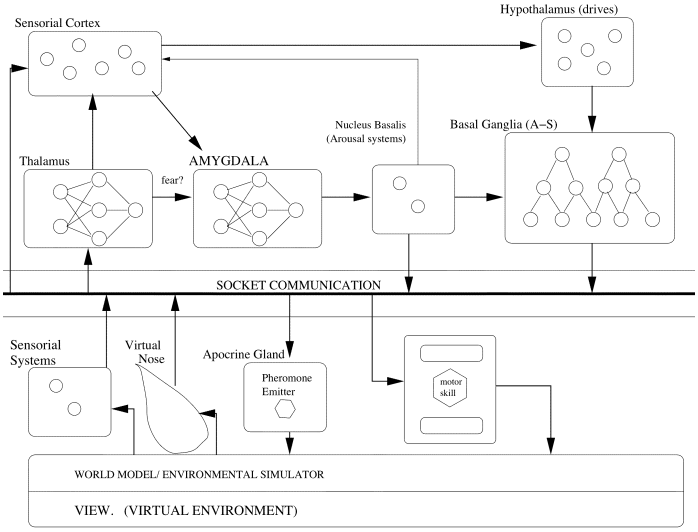


Fig. 1. The complete architecture

environmental simulator and they are simulated using the free expansion gas formula in which the volume depends on the temperature and altitude (both simulated environmental variables). The expansion of the pheromone cloud at timestep=9 can be seen in a graphical environment in Figure 5 below. To compute the distribution of the pheromones a set of particles has been simulated using the Boltzmann distribution formula:

$$n(y) = n_o e^{\frac{mgy}{k_b} T}$$

Here m is the pheromone mass; g is the gravity; y is the altitude; k_b is the Boltzmann number; T is the temperature; n_0 is N/V where N is the number of molecules exuded from the apocrine gland (related to the intensity of the emotion) and V is the volume. The virtual nose detects pheromones from a threshold of 200.10^{-16} reflecting values taken from the relevant literature.

The problem of action selection is that of choosing at each moment in time the most appropriate action out of a repertoire of possible actions. The process of making this decision takes into account many stimuli, including in this case the animal's emotional state. Action selection algorithms have been proposed by both ethologists and computer scientists. Models suggested by the former are usually at a conceptual level, while those of the latter (with some exceptions – as [3,20]) generally do not take into account classical ethological theories. Dawkins [6] suggests that a hierarchical structure represents an essential organising principle of complex behaviours: a view shared by many ethologists [2,19]].

Recent research has found that the Basal Ganglia plays an important role in mammalian action selection [14] and our mechanism is implemented in the *Basal Ganglia* module in Figure 1 as a three-level tree. To avoid sensory congestion, each of Top, Intermediate and Bottom nodes receives sensor data directly as well as data from a higher-level node. Actions are selected by Bottom nodes, dispatching them via a UDP socket to the Animation engine located in the *Body* module of Figure 1.

This mechanism is based on [20] who in turn developed Rosenblatt and Payton's original idea [18] of a connectionist, hierarchical, feed-forward network, to which temporal and uncertainty penalties were added, and for which a more specific rule for combination of preferences was produced. Note that among other stimuli, our action selection mechanism takes the emotional states (outputs of the emotional devices) of the virtual animal. Klinokinesis was modelled as a Finite State Acceptor [1], augmented with transitions based on probability, as seen in Table 1.

Table 1. Finite State Acceptor for klinokinesis

State	**Input**	**Resulting state**	**State**	**Input**	**Resulting state**
start	go-default	stand-still	walking	P(0.7)	walking
stand-still	P(0.3)	walking	rotating-left	P(0.9)	stand-still
stand-still	P(0.3)	starting-to-eat	rotating-left	P(0.1)	rotating-left
stand-still	P(0.2)	rotating-left	rotating-right	P(0.9)	stand-still
stand-still	P(0.2)	rotating-right	rotating-right	P(0.1)	rotating-right
stand-still	in-fear	end	starting-to-eat	head-down	eating
stand-still	do-nothing	stand-still	eating	P(0.6)	eating
walking	P(0.3)	stand-still	eating	P(0.4)	finishing-eating
			finishing-eating	head-up	stand-still

The basic Reynolds rules of cohesion, alignment and separation have been extended with an additional rule (escape) in which the virtual animal moves away from potential danger (essentially, predators) in its vicinity. More importantly, the flocking behaviour itself is parameterised by the emotional devices output, that is, by the values of the emotions the virtual animals feel. Therefore, in our model each virtual animal moves itself along a vector, which is the resultant of four component vectors, one for each of the behavioural rules.

The calculation of the resultant vector, V(elocity), for a virtual animal A is as follows:

$$V_A=(Cf \cdot C_ef \cdot Cv)+(Af \cdot A_ef \cdot Av)+(Sf \cdot S_ef \cdot Sv)+(Ef \cdot E_ef \cdot Ev) \tag{2}$$

$$Velocity_A=limit(V_A, (MV_ef \cdot MaxVelocity)) \tag{3}$$

where Cv, Av, Sv and Ev are the component vectors corresponding to the cohesion, alignment, separation and escape rules respectively. Cf, Af, Sf and Ef are factors representing the importance of the component vectors Cv, Av, Sv and Ev and allow weighting of each component vector independently. In our current implementation they can be varied, in real time, from a user interface. C_ef, A_ef, S_ef and E_ef are factors representing the importance of the respective component vectors given the current emotional state of the virtual animal. Each of these factors is a function that takes the current values of the animal's emotions and generates a weight for its related component vector. MaxVelocity is the maximum velocity allowed to the animal. In the current implementation it can be varied from a user interface. MV_ef is a factor whose value is calculated as a function of the current values of the animal's emotions. It allows the increase and decrease the animal's MaxVelocity depending on its emotional state as shown in Figure 2. limit is a function whose value is equal to the greater of its two parameters.

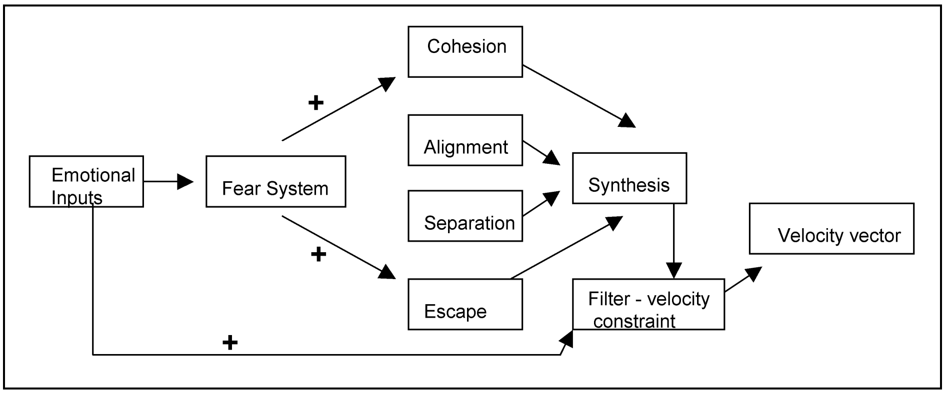


Fig. 2. Influence of Fear on Flocking

The emotional factors (C_ef, A_ef, S_ef, E_ef, and MV_ef) reflect ethological heuristic rules. For example, the greater the fear an animal feels, the greater the weight of both its cohesion vector (it tries to stay closer to nearby flockmates) and its escape vector (it tries to stay farther from the potential danger). The resultant vector obtained by adding the four basic vectors is then scaled so as not to exceed the maximum speed.

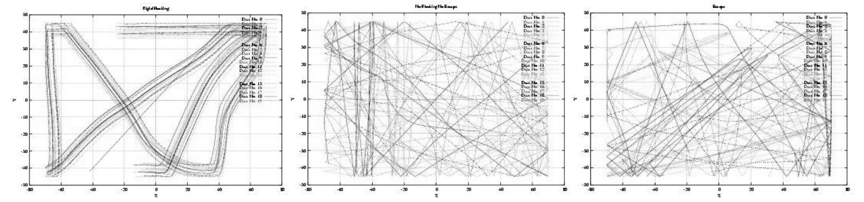
Note that maximum velocity is also parameterised by fear: the greater the fear an animal feels, the greater the speed it is able to reach.

3. Evaluating the emergent behaviour

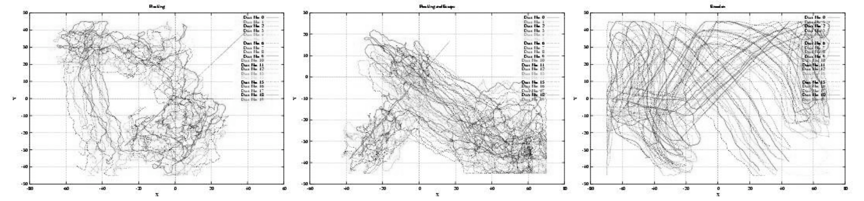
Our hypothesis that fear can serve as a regulator between individual and social behaviour was evaluated through an experiment in which 5,10, 15 and 20 animals were plotted over 600 timesteps for the following six conditions:

1. *Rigid Flocking*. The herd of animals was tightly packed (maximum10 centimetres distance between each) and animals were all facing the same direction at all times. This is the baseline condition for optimum coordination.
2. *No Flocking No Escape*. Each animal moved on its own with no knowledge (perception) of other animals or predators. This is the baseline condition for individual behaviour.
3. *Escape*. Similar to the previous scenario except that animals perceive predators and individually move to avoid them.
4. *Standard flocking*. Animals perceive each other, try to avoid collisions between each other and try to stay close to the herd.
5. *Standard flocking with Escape.* As the previous case but animals perceive predators, and move to avoid them.
6. *Escape with emotion*. Emotion (fear) is elicited and communicated amongst animals via artificial pheromones when predators are perceived.

Figure 3 shows the trajectories plotted for the 20 animals case, and it is intuitively clear to the eye even at this very low resolution that very different patterns of behaviour are being produced. What is required is a way of assessing the complexity of the emergent behaviour in each case. We follow the approach of [22] who presented a method for characterising the pattern of emergent behaviour and its



Plots of 1.Rigid Flocking; 2.No Flocking/No Escape; 3.Escape



Plots of 4.Standard Flocking; 5.Standard Flocking/Escape; 6.Emotion/Escape

Fig. 3. Plots of 6 cases, 600 timesteps, 20 animals

complexity using singular values and entropy. In the matrix A below, M = 600 (number of samples) and N = 4 (degrees of freedom: position x,y and velocity x,y):

$$A = \begin{pmatrix} {x_1}^1 & {y_1}^1 & \dot{x}_1^1 & \dot{y}_1^1 & \cdots & {x_1}^N & {y_1}^N & \dot{x}_1^N & \dot{y}_1^N \\ & & & & \vdots & & & & \\ {x_M}^1 & {y_M}^1 & \dot{x}_M^1 & \dot{y}_M^1 & \cdots & {x_M}^N & {y_M}^N & \dot{x}_M^N & \dot{y}_M^N \end{pmatrix}$$

To compute the singular values, the following equation from linear algebra is used:

$$A = USV^T$$

The singular values $\sigma_i = S_i$ are all non-negative and generally are presented in a decreasing sequence $\sigma_1 >= \sigma_2 >= \ldots >= \sigma_N >= 0$; singular values can be used as an approximation of the matrix. We do not have space to display the singular values for 5,10,15,20 animals for all six cases here, but if they are represented in bar chart form they show that each flocking case has its own distinctive shape.

The next step is to compute the entropy from the N singular values which are normalised, because by definition $\Sigma_i P_i = 1$ [4]: in our case P_i is σ_i. The following equation is used to calculate entropy:

$$E_s = -\sum_{i=1}^{N} \sigma_i' \log_2 \sigma_i'$$

where σ'_i. is the normalised singular value. And since entropy can be seen as a $\log_2$ count of the number of states in a system [4], the effective number of states and thus the complexity is given by the expression:

$$\Omega = 2^{E_s}$$

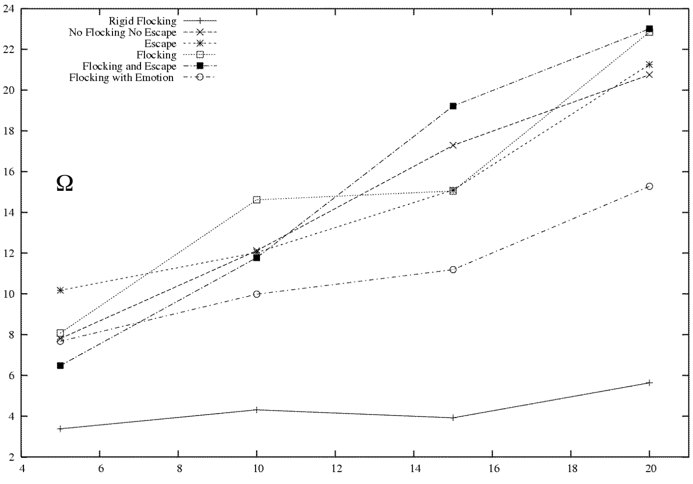


Fig. 4 Plot of complexity (Ω) against animal numbers for 6 cases

Figure 4 shows a plot of the complexities for different types of flocking with different number of animals. It can be seen that rigid flocking (bottom line) shows the least complexity, intuitively supported by looking at Figure 3, top left. Flocking; flocking with escape; no flocking, no escape; and escape behaviours (top four lines) are more complex than rigid flocking, but they are also almost always more complex than flocking with emotion (second line up). The exception is the 5-animal case where flocking with emotion, is more complex than flocking with escape. This can be explained by a further set of experiments carried out in which it is shown that at least nine animals are needed to maintain flocking behaviour. With fewer than this, when the animals escape from a predator, some separate from the flock and do not regroup at all during the 600 time-steps.

Thus we conclude that the introduction of an emotional system into action-selection, where emotion can be transmitted between animals, mediates between the complexity of individual behaviour and the rigidity of collective behaviour. It allows a dynamic trade-off between spreading widely, advantageous in seeking new grass to graze - inherent in klinokinesis - and staying together, advantageous in the case of attack by predators. Emotion in this case acts as a social regulator for flocking animals, demonstrating that it has an important social function in addition to its already-understood role in regulating individual behaviour.

In addition to the 2D-tracking of trajectory just described, the virtual animals have also been implemented in a real-time 3D graphical world, which can be run in a 4-sided immersive display system (or CAVE). The implementation consists of nearly 28,000 lines of C++ code of which 10,949 implement the brain. Figure 5 shows a screen-shot of a sheep in a graphical world illustrating the spread of the pheromone cloud at timestep = 9. A further objective of the work discussed elsewhere [7] is to examine how far the presence of emotionally-driven autonomous animals can increase the feeling of immersion experienced by a human user in such environments.

4. Conclusions and further work

We have presented an ethologically-inspired virtual animal architecture in which primitive emotions have been incorporated into action-selection and a method for communicating emotion between animals using virtual pheromones has been included, allowing the extension of the classic approach to flocking to incorporate emotion. We have shown that the effect of adding the emotional input to flocking together with the communication mechanism is to reduce the complexity of individual behaviour without requiring rigid lock-stepping. This substantiates the hypothesis that emotion mediates social behaviour, underlining the functional role of affect in action-selection.

Extensions to this work might include individual variation in animals, both across characteristics like fearfulness, and across gender: there is evidence that ewes spend more time grazing and rams significantly longer lying. The presence of lambs would also introduce an interesting element of social heterogeneity, while animals with other behavioural responses to predators – musk ox for example form an outward facing ring – could be explored.

The use of 3D space in this implementation is limited to the pheromone propagation algorithm: both perception and locomotion were implemented as 2D mechanisms. Given mammals have significantly less mobility in 3D than the classic

Fig 5: Pheromone cloud visualised at timestep = 9

examples of fish or birds, a more realistic application of manoeuvrability constraints would not only look more natural but might also have practical implementations for flock fragmentation in the face of predators. A classic predator strategy is to peel off an individual flock member, and including one or more intelligent predators would allow predator-prey interaction to be investigated.

Finally, although the architecture developed targetted animals such as sheep and deer rather than humans, the extension of the approach into emotionally-driven human crowds would open up a much larger field of investigation.

References

[1] Ronald C Arkin. Behavior-Based Robotics. MIT Press, Cambridge,Massachusetts, 1999

[2] G. P. Baerends, "The functional organization of behaviour," *Animal Behaviour*, no. 24, pp. 726–738, 1976.

[3] Bruce Blumberg, Action-selection in hamsterdam: Lessons from ethology, Proc 3rd Int Conf. on Simulation of Adaptive Behavior SAB 94, 1994

[4] Eric Bonabeau, Marco Dorigo, and Guy Theraulaz. Swarm Intelligence: From Natural to Artificial Systems. Oxford University Press, USA, 1999.

[5] Canamero, D. Modeling Motivations and Emotions as a Basis for Intelligent Behaviour, Proc1st Int. Conf. on Autonomous Agents. ACM Press pp148—155, 1998

[6] Richard Dawkins, Hierarchical organisation: A candidate principle for ethology, Growing Points in Ethology (Bateson & Hinde, ed.), Cambridge University Press, 1976.

[7] Delgado-Mata, C; Ibanez, J and Aylett, R.S. Let's run for it: conspecific emotional flocking triggered by virtual pheromones. Proc. Smart Graphics 2003, LNCS 2733, Springer-Verlag 2003

[8] Ekman, P. Emotions on the Human Face. Cambridge University Press

[9] Gratch, J; Rickel, J; & Marsalla, S. Tears and Fears, *5Th Int. Conf. on Autonomous Agents*, ACM Press, pp113-118 2001

[10] Karl Grammer, 5-alpha-androst-16en-3alpha-one: a male pheromone ?, *Ethology and Sociobiology* 14 (1993), no. 3, 201–207.

[11] Ibanez, J, Delgado, C, Aylett, R.S. & Ruiz, R. (2004) Don't you escape. I'll tell you my story. *Proceedings, MICAI 2004,* Mexico City, April 2004 Springer Verlag LNAI 2972 pp49-58

[12] Carol~E Izard, Four systems for emotion activation: Cognitive and noncognitive processes, *Psychological Review* (1993), no.1, 68--90.

[13] Marvin Minsky, The society of mind, Simon & Schuster, New York, USA, 1985

[14] Fernando M Montes-Gonzalez. An action Selection Mechanism based on Vertebrate Basal Ganglia. PhD thesis, Psychology Department, University of Sheffield, Sheffield, UK, 2001.

[15] M.Neary, Sheep sense, *The Working Border Collie* www.working-border-collie.com/article3.html

[16] Ortony, A; Clore, G. L. and Collins, A. The Cognitive Structure of Emotions, Cambridge University Press 1988

[17] Craig W.Reynolds, Flocks, herds, and schools: A distributed behavioral model, *Computer Graphics* 21 (1987), no. 4, 25–34

[18] J.K. Rosenblatt and D.W. Payton, A fine-grained alternative to the subsumption architecture for mobile robot control, *Proc. IEEE/INNS IJCNN* (Washington DC), v 2, June 1989, pp. 317– 324.

[19] Nikolaas Tinbergen, The study of instinct, Oxford University Press, United Kingdom, 1969.

[20] Toby Tyrrell, Computational mechanisms for action selection, Ph.D. thesis, University of Edinburgh, Edinburgh, Scotland, 1993

[21] Juan Valasquez Modeling emotions and other motivations in synthetic agents. *Proc 14th Nat Conf on AI, AAAI 1997,* MIT/AAAI Press 1997

[22] W A Wright, R E Smith, M Danek, and P Greenway. A generalisable measure of self-organisation and emergence. In G. Dorner, H. Bischof, and K. Hornik (eds) *Artificial Neural Networks – ICANN 2001*, LNCS 2130, pp 857-864. Springer-Verlag, 2001