Emotion and Action Selection: Regulating the Collective Behaviour of Agents in **Virtual Environments**

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1. Introduction

This paper presents an ethologically inspired actionselection mechanism, part of a larger architecture for selfanimated artificial animals (agents) that communicate emotions to each other, influencing each other's behaviour. 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.

Action selection algorithms have been proposed by both ethologists and computer scientists. Models suggested by ethologists are usually at a conceptual level, while those of computer scientists (with some exceptions [3]) generally do not take into account classical ethology theories. According several ethologists [2], a hierarchical structure represents an essential organising principle of complex behaviours. We have chosen to add emotion to a hierarchical action selection mechanism so that behaviour shows persistence (emotion acting as a short term memory [2]) and to avoid dithering between competing behaviours, namely the herding group behaviour, and the individual behaviour of grazing.

2. Architecture

The four sub-tasks in our system are: 1. Perception (sensing and interpretation to provide a high-level description of the environment) 2. Emotions (which affect the behaviour of the animals, e.g. the conspecifics flight-flocking). 3. Action selection (using the perceptual and emotional inputs to decide which of the animal's repertoire of actions is most suitable at that moment) 4. Motor control (transforming the chosen action into a pattern of "physical" actions to produce the animation of the animal).

Figure 1 shows a more detailed diagram of the design. Note that our action selection mechanism adds the emotional states (outputs of the emotional devices) of the virtual animal to incoming stimuli.

Grazing mammals spend most of their time grazing: an experiment showed that gazing and ruminating made up



Figure 1. Detailed architecture

80% of the animals day-time activity. To model this, klinokinesis is simulated through a Finite State Acceptor [2] and has been augmented with transitions based on probability. The architecture described in the previous section has been implemented and it has been tested in a virtual environment [2]. The architecture described is three layered. Namely the creatures' brain, the world model and the virtual environment. As seen in figure 1 the agent's brain is composed of processes that run independently (on a Linux workstation) and each of the agents' brains receives the sensor data via network sockets; similarly they send the selected action to the world model which contains agents' bodies and the environmental simulation.

On the one hand, it is evolutionarily advantageous for animals in a herd to flock close to each other to have more chance of surviving the threat posed by predators. On the other hand, grazing mammals spend most of the time grazing so it would be expected that scattering widely into grassy areas would be beneficial. Somehow a compromise must be reached between collective and individual behaviour.

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3. Results

Some plots of the trajectories followed by the animals, over 600 time steps were produced, like those shown in figures 2(a)-2(b). It is intuitively clear that different flocking choices produce different plots. For example:

- **Rigid Flocking.** The herd was tightly (maximum 10 centimetres distance between members of the herd) packed and the animals were all facing at the same direction at all times. Baseline condition for optimum coordination.
- No Flocking No Escape. Each animal moves on its own with no knowledge (perception) of other animals or predators. Baseline condition for individual behaviour.
- Emotion. In this scenario emotion (fear) is elicited in the animals and communicated amongst them. To achieve this artificial pheromones are exuded when fear is 'felt' as they perceive the danger presented by the predators[2], this 'feeling' affects the behaviour of the animals as they try to stay close as a herd and their velocity is affected as well.

A matrix was composed out of 600 samples taken for the animals' movements, so for 20 boids as seen in figure 2, and with N degrees of freedom that is 20 (4) (20 animals times position x,y and velocity x,y.

Out of the singular values an entropy can be computed from N values. The singular values are normalised, because by definition $\sum_i P_i = 1$ [1], in our case P_i is σ_i . The formula for entropy is:

$$E_{s} = -\sum_{i=1}^{N} \sigma_{i}^{'} \log_{2} \sigma_{i}^{'}$$
(1)

To compute complexity a tool was developed, firstly to receive data from the virtual environment, secondly to produce plots of different types of flocking (shown in this section), thirdly to compute complexity ($\Omega = 2^{E_s}$) and lastly to



produce a plot out of the complexities with different types of flocking and with different number of creatures. In figure 3 it can be seen that the plot of the rigid flocking is the one that shows the least complexity, intuitively supported by looking at figure 2(a). Flocking, flocking with escape, and no flocking, no escape, and the escape behaviour are more complex than rigid flocking, and they are almost always more complex than flocking with emotion. The exception is the five boids case where flocking with emotion, according to the result obtained and shown in the plot, is more complex than flocking with escape. This can be explained as follows: a separate test has shown that in order to show flocking behaviour at least 9 animals should be in a herd. With fewer animals escaping from a predator, they separate from the flock and they do not regroup at all during the duration of the test [2].

4. Conclusions

The results have shown that emotion can be used to mediate between group behaviour (flocking) and individual behaviour (grazing). 1

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