Characterising Emotion Signalling and Affected Group Behaviour in Virtual Mammals.

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Abstract. This paper investigates how emotions, in this case fear, affect behaviour. We consider deer and sheep as exemplary flocking mammals. The paper also describes and applies a mechanism to measure different types of flocking, using singular values and entropy to compute complexity. Results show that emotion can be used to regulate two competing and vital behaviours inherent in herding animals: the group behaviour (herding) and the individual behaviour (grazing), thus demonstrating that emotion is a functional organiser of group behaviour.

1 Introduction

Current Virtual Environment technology is capable of recreating virtual scenes with an impressive degree of realism. However users often lose their interest rapidly in these types of environment because they tend to be empty and static, lacking "life". One way to address this is to add virtual creatures (artificial animals) to the virtual world. But this is very challenging as they have to give the "illusion of life". To achieve this, animals must have convincing behaviour. This is to be autonomous, each animal requires an action-selection mechanism allowing their behaviour to be generated in real-time.

This paper presents an ethologically inspired signalling technique, part of a larger architecture for self-animated artificial animals (agents) that communicate emotions amongst each other, influencing each other's behaviour.

We have chosen to add emotion to the action selection mechanism so that behaviours show persistence (emotion acting as a short term memory [1]) and to avoid dithering between competing behaviours, namely the herding group behaviour, like Reynold's flocking [2], and the individual behaviour of grazing.

1.1 Emotions

Until recently the field of Artificial Intelligence (AI) had largely ignored the use of emotion and intuition to guide reasoning and decision-making. Minsky [3] was one of the first to emphasise the importance of emotion for Artificial Intelligence. Other models of emotion have been proposed; Picard focuses on recognising emotions [4]; Velásquez [5] synthesised emotions and some of their influences on behaviour and learning, using a similar approach to the one proposed in this work, that is a model based on Izard's Four Types of Emotion Elicitors [6]. Neural Processes, sensorimotor processes, affective processes and cognitive processes.

Based on the description given above we decided to define emotions as reflective autonomic responses. That is primary emotions [7], triggered by particular stimuli. An extended review is provided in [8].

1.2 Emotion Signalling

Animals signal conspecifics to communicate different messages. In this study pheromones were chosen as they have been acknowledged very important in animal signalling [9]. Pheromones are widely used in animals to achieve different goals such as signal conspecifics of danger, create a bond between a mother and her son. To signal oestrus in females is thought to play an important role in mating, the so-called "chemistry".

The mechanism for signalling used in the architecture is shown in figure 1. This mechanism is three layered:

- The Body.
- The World Model and
- the Virtual Environment.

The route of an emotional signal follows this pattern. When a creature 'feels' an emotion (fear) it excites a gland in the body that exudes a pheromone to the ambient simulator, a component of the world model, the ambient simulator keeps a list of all the exuded pheromones which are modelled as particles in a free expansion gas, described in [1] [10]. The current states of the simulated particles are read in the Virtual Environment Simulation and they are rendered by the Simulated Particles Geometry if the user wishes to visualise the Particle Set.

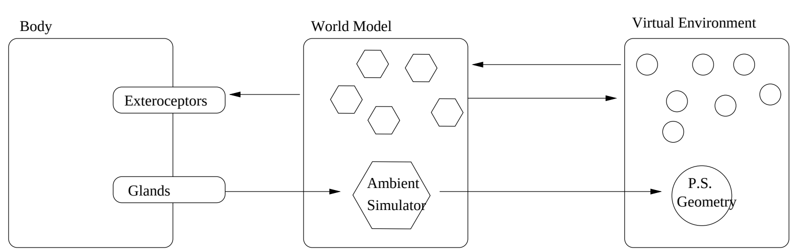
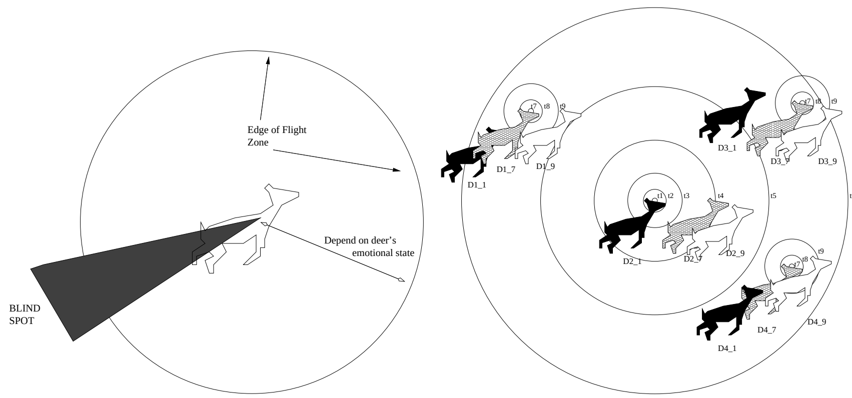


Fig. 1. Overview of the animals signalling in a Virtual Environment

To signal emotions two main sensors are used an artificial nose, described in [8] [10] and a flight zone sensor. The flight zone sensor, see figure 2(b), is part of the creature's body. The body sends the data to the brain at constant intervals (defined in a configuration file) and the brain, this may elicit an emotion. Diagram 2(b) represents mammals signalling through pheromones. The diagrams represent four animals that communicate an emotion, for example fear through pheromones exuded through glands [9]. The different shaded colours represent the animals' position at three different times, with the darkest the oldest t_1 and the white the last time-step of the simulation. Pheromones are represented through the concentric circumferences, taken at 9 different time steps.



(a) Flight Zone (b) Emotion Signalling

Fig. 2. Signalling emotions through a Flight Zone

2 Agents in a Virtual Environment

The architecture described in the previous section has been implemented and tested in a virtual environment [8]. The architecture described is three layered. Namely, the creatures' brains, the world model and the virtual environment. The agent's brain is composed of processes that run independently (on a Linux workstation). Each of the agents' brains receives the sensor data via network sockets. Similarly, they propagate the selected action to the world model which contains agents' bodies and the environmental simulation. The changes made to the model are reflected on each frame in the virtual environment which was developed using IRIS OpenGL Performer. This mechanism allows modularity and extensibility to add/modify the behaviour of the artificial animals. Figure 3 shows the system running a virtual environment with artificial sheep.

Tests have been carried out in the system and they have shown that the users are significantly more engaged when artificial animals [10] like sheep populate the virtual environment and perform what they perceive to be "intelligent" behaviour than when there are no animals at all or where the sheep are just standing in static poses. However, we also hypothesised that emotion plays an important role in regulating flocking behaviour amongst herding mammals.

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 them widely into grassy areas would be beneficial. Somehow a compromise must be reached between collective and individual behaviour. As previously described, emotion and the communication of it amongst conspecifics is used to enhance action selection mechanisms. A test was designed to test the hypothesis, in which a rigid flocking would serve as a baseline for organised group behaviour and a purely individual behaviour of animals would be tested as the other end of the scale. In between would lie flocking and emotional flocking.

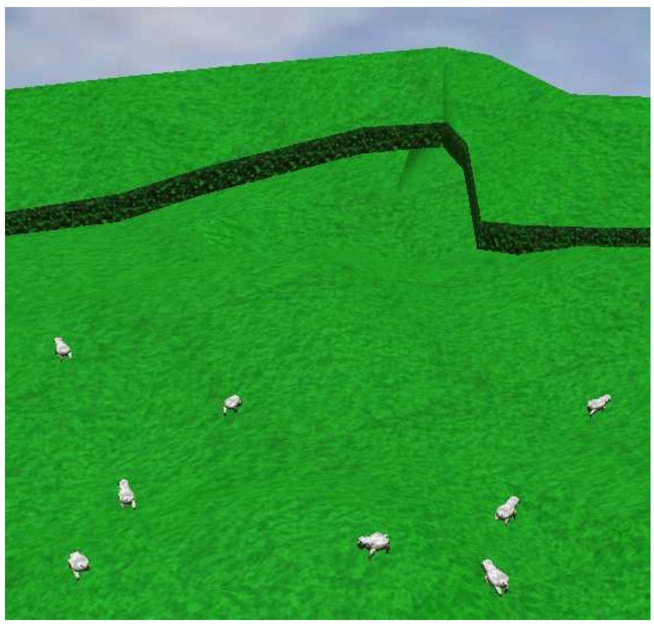


Fig. 3. Artificial sheep grazing in a Virtual Environment

3 Experiments and Results

Some plots of the trajectories followed by the animals were produced, as seen in figures 4(a)–4(f). Several positional plots (X, Y) were carried out where 600 time steps were obtained and the trajectories are shown. It is clear from these diagrams that different flocking choices produce different plots. This resulted from the tests described next.

- **Rigid Flocking.** To produce rigid flocking, the herd of animals was tightly packed (maximum 10 centimetres distance between members of the herd) and all animals were facing the same direction at all times. This was the baseline condition for optimum coordination.
- **No Flocking No Escape.** In this scenario the animals were not moving as a herd, but each one was moving on its own with no knowledge (perception) of other animals or predators. Baseline condition for individual behaviour.
- **Escape.** This scenario is similar to the previous one except that the animals perceive the danger presented by the predators and move to avoid them.
- **Flocking.** In this scenario the animals perceive each other, try to avoid collisions between each other and try to stay close to the herd.
- **Flocking and Escape.** This scenario is similar to flocking with the addition that the animals perceive the danger presented by the predators, and move to avoid them.
- **Emotion.** In this scenario emotion (fear) is elicited in the animals when a predator enter its flight zone and communicated amongst them. To achieve this artificial pheromones are exuded when fear is 'felt' as they perceive the danger presented by the predators[1][10], this 'feeling' affects the behaviour of the animals as they try to stay close as a herd and their velocity is affected as well.

As is shown in figure 4; in the trajectories described when an emotion is elicited, the movement is more organised than with normal flocking but not as inflexible as in the rigid flocking. A method of measuring different types of flocking is described next.

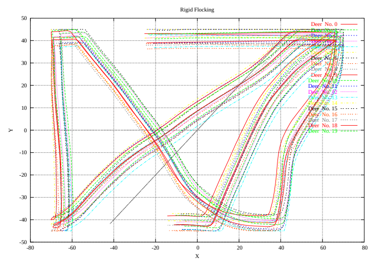
3.1 Complexity measurement

In emergence something more complex arises from simpler rules. In this case flocking emerges from the interactions between the agents and the agents and its environment, so it is difficult to characterise emergence. Taking this into account a useful approach is described in [11]

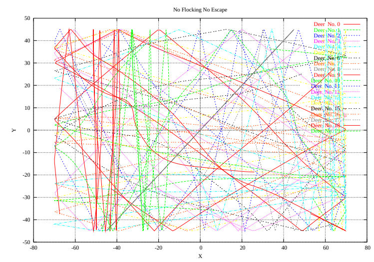
First we will describe the measurement system used. Then the results using the system are presented. In [11] a system to measure emergence and complexity was presented. We have used a similar approach to test the different flocking mechanisms.

As previously stated, 600 samples (M) were taken for the animals, so for 20 boids as seen in figure 4, and with N degrees of freedom that is 20 (4) (20 animals times position x,y and velocity x,y), which give a matrix A was composed.

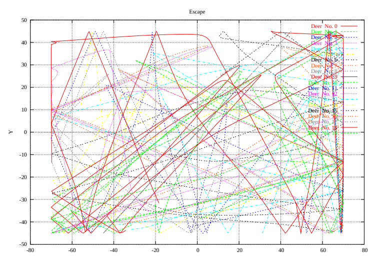
$$A = \begin{pmatrix} {x_1}^1 & {y_1}^1 & \dot{x}_1^1 & \dot{y}_1^1 & \cdots & {x_1}^N & {y_1}^N & \dot{x}_1^N & \dot{y}_1^N \\ & & & & \vdots & & & & \\ {x_M}^1 & {y_M}^1 & \dot{x}_M^1 & \dot{y}_M^1 & \cdots & {x_M}^N & {y_M}^N & \dot{x}_M^N & \dot{y}_M^N \end{pmatrix}$$



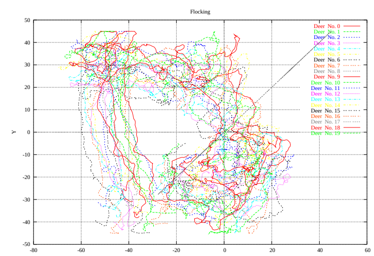
(a) Rigid Flocking



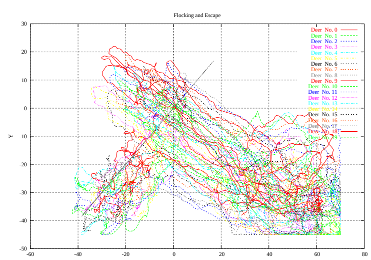
(b) No Flocking No Escape



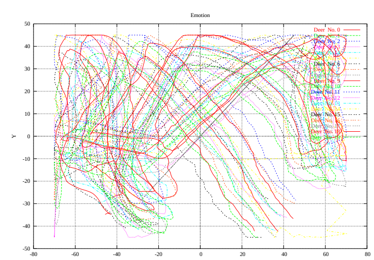
(c) Escape



(d) Flocking



(e) Flocking Escape



(f) Emotion

Fig. 4. Flocking with 20 animals plots

To compute the singular values, from linear algebra, the equation 1 was used.

$$A = USV^T \tag{1}$$

The singular values $\sigma_i = S_i$ are all non-negative and generally are presented in a decreasing sequence $\sigma_1 >= \sigma_2 >= \cdots >= \sigma_N >= 0$. Singular values can be used as an approximation of the matrix, because of space constraint the reader is referred to [10] to see plots of the singular values. In these plots it can be seen that each type of flocking has a distinctive shape. Thus, out of the singular values an entropy can be computed from N values. The singular values are normalised, because by definition $\sum_i P_i = 1$ [12], in our case P_i is σ_i. The formula for entropy that was used is:

$$E_s = -\sum_{i=1}^{N} {\sigma_i}' \log_2 {\sigma_i}' \tag{2}$$

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

$$\Omega = 2^{E_s} \tag{3}$$

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 as defined in formula 3 and lastly to produce a plot out of the complexities with different types of flocking and with different number of creatures. In figure 5 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 4(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 boid 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. When there are fewer animals than this, the animals escape from a predator. They separate from the flock and they do not regroup at all during the duration of the test [10]. The results from this section have shown that emotion can be used to mediate between group behaviour (flocking) and individual behaviour (grazing).

4 Conclusions and future work

An ethologically imbued action-selection mechanism for self-animated artificial animals that communicate emotions amongst each other to influence their behaviour was presented here. The mechanism is hierarchical which is consistent

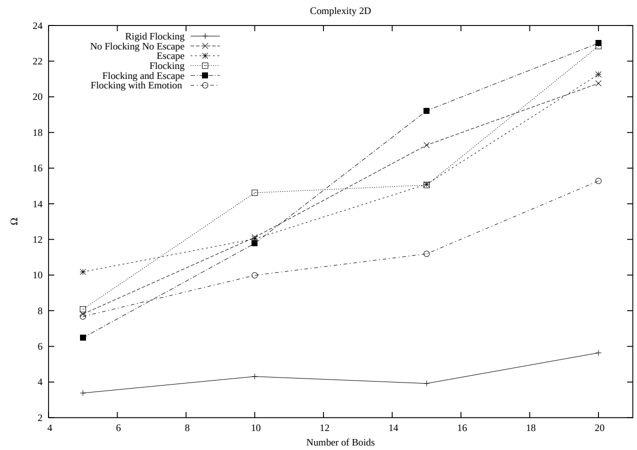


Fig. 5. Complexity plot

with what ethology researchers have found when observing the behaviour of real animals. Finite State Acceptors were added to simulate grazing behaviour. Further results have shown that grazing behaviour when coupled together with emotional group communication [1] adds to the sense of presence in virtual environments. The Action Selection Mechanism that was used here is described in detail in [10]. A mechanism for measuring the characteristics of flocking was explored and the results are consistent with the hypothesis that emotion plays an important role in action selection, having been tested in a framework of different flocking algorithms. It was shown that complexity per se does not make a better flocking algorithm, but when complexity (flocking) is directed by emotion a more believable behaviour is obtained.

A further development of the architecture might incorporate evolution, using genetic programming. It would then be possible for this architecture to evolve different personalities which could be coded in genes which would define the connections between different parts of the brain. For example different animals could have contrasting personalities like fearful or aggressive depending on the weight and connections of the emotional system in turn affecting the action selection of the creature. Also it would be interesting to to differentiate the behaviour of males and females, for example in [13] the result of observing sheep behaviour shows that ewes spend more time grazing that males and rams spend significantly longer lying.

5 Acknowledgements

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References

1. Delgado-Mata, C., Ibanez, J., Aylett, R.: Let's run for it: Conspecific emotional flocking triggered via virtual pheromones. In Butz, A., Krüger, A., Oliver, P., eds.: LNCS Smart Graphics 2003, Heidelberg, Germany, Springer-Verlag (2003) 131–140
2. Reynolds, C.W.: Flocks, herds, and schools: A distributed behavioral model. Computer Graphics **21** (1987) 25–34
3. Minsky, M.: The Society of Mind. Simon & Schuster, New York, USA (1985)
4. Picard, R.: Affective Computing. MIT Press, Cambridge, MA, USA (1997)
5. Velásquez, J.: Modeling emotions and other motivations in synthetic agents. In: Proceedings of the Fourteenth National Conference on Artificial Intelligence (AAAI-97), Providence, RI, MIT/AAAI Press (1997)
6. Izard, C.E.: Four systems for emotion activation: Cognitive and noncognitive processes. Psychological Review **100** (1993) 68–90
7. Damasio, A.: Descartes' Error:Emotion, Reason and the Human Brain. Papermac, Oxford, United Kingdom (1996)
8. Delgado-Mata, C., Ruiz-Rodarte, R., Aylett, R.S., Perez-Cisneros, M.A., Cook, P.A.: Illusion of life in palenque: Communicating emotions inside a virtual environment for maya cultural heritage. In Prendinger, H., ed.: PRICAI: Seventh Pacific Rim International Conference on Artificial Intelligence, Tokyo, Japan, PRICAI (2002)
9. Wyatt, T.D.: Pheromones and Animal Behaviour. Cambridge University Press, Cambrigde, U.K. (2003)
10. Delgado-Mata, C.: A Mechanism for Emotion Signalling in Multiple Intelligent Virtual Agents. PhD thesis, University of Salford, Salford, United Kingdom (2004) In preparation.
11. Wright, W.A., Smith, R.E., Danek, M., Greenway, P.: A generalisable measure of self-organisation and emergence. In Dorffner, G., Bischof, H., Hornik, K., eds.: Artificial Neural Networks - ICANN 2001. Number 2130 in LNCS, Springer-Verlag (2001) 857–864
12. Bonabeau, E., Dorigo, M., Theraulaz, G.: Swarm Intelligence: From Natural to Artificial Systems. Oxford University Press Inc, USA (1999)
13. Ruckstuhl, K.E.: Foraging behaviour and sexual segregation in bighorn sheep. Animal Behaviour **56** (1998) 99–106