Evaluating the Models and Behaviour of 3D Intelligent Virtual Animals in a Predator-Prey Relationship

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ABSTRACT

This paper presents the intelligent virtual animals that inhabit Omosa, a virtual learning environment to help secondary school students learn how to conduct scientific inquiry and gain concepts from biology. Omosa supports multiple agents, including animals, plants, and human hunters, which live in groups of varying sizes and in a predator-prey relationship with other agent types (species). In this paper we present our generic agent architecture and the algorithms that drive all animals. We concentrate on two of our animals to present how different parameter values affect their movements and inter/intra-group interactions. Two evaluations studies are included: one to demonstrate the effect of different components of our architecture; another to provide domain expert validation of the animal behavior.

Categories and Subject Descriptors

I.2 ARTIFICIAL INTELLIGENCE;I.6 SIMULATION AND MODELING, I.6.3[**Applications**] I.6.7 [**Simulation Support Systems**] *Environments*

General Terms

Algorithms, Measurement, Design, Experimentation.

Keywords

Agents, artificial life, boids, educational virtual worlds, biology education, science inquiry.

1. INTRODUCTION

Understanding the nature of and processes involved in scientific inquiry is an important skill that is difficult for most school students to acquire. This is an important challenge as inquiry figures pivotally in many national science plans. Key inquiry skills include a wide range of activities involved in scientific research such as hypothesis formation, experimental design, data collection and analysis, evaluation and reflection on the quality of evidence for hypotheses. Yet despite the aspirations for curriculum reform expressed in science policy documents, the practice of science education does not generally provide significant opportunity for students, especially at primary/middle school and secondary school, to experience genuine scientific inquiry [1].

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The goal of our overall program of research is to develop innovative learning technologies that consist of 3D virtual worlds with embedded agent architectures. These educational "VWorlds" provide "virtually" authentic contexts for students to engage in scientific inquiry practices as they learn about biological systems, such as problem-identification, making observations and drawing inferences, interviewing characters, and collecting and analyzing data. Our project involves multidisciplinary collaboration with researchers in computer science and graphics, learning and cognitive sciences, and biology, as well as classroom science teachers. In this paper, we focus on the agent architecture we are developing by describing the artificial animals that inhabit our VWorld. We begin with consideration of related research.

2. RELATED RESEARCH

There is considerable interest in the use of computational modeling in modern biological research [15]. In particular, agent-based modeling (ABM) techniques (sometimes referred to as "individual-based models" in the literature) have been used to model a variety types of biological phenomena, such as flocking behaviors of birds and fish [8], synchronous firefly flashing [14], and the dynamics of predator-prey interactions in ecosystems [6]. Topping et al. [13] use ABMs to model an entire ecosystems in the animal, landscape and man simulation system (ALMaSS) that allows policy decisions to be made and includes many vegetated and non-vegetated areas, a range of crops with multiple growth models and multiple animals. Interactions between species are minimal in their ABM. Siebert, Ciarletta and Chevrier [10] are also interested in modeling complex systems. However, rather than creating a multi-agent system (MAS), they simulate a co-evolution where each agent type (sheep, grass and wolves) is a separate model/system connected via a coupling artifact.

In the intelligent virtual agent/virtual world research space, foundational work was done by [3]. More recent and specific to intelligent animals concerns deer with an artificial nose that detects the emotions of other conspecifics [2] and gray wolves that begin as pups and overtime develop certain social behaviours through learning to express age appropriate emotional states involving context-specific emotional memories [12]. Unlike our virtual world, these studies only concerned one type of animal.

In terms of the overall learning technology environment we are developing, research exploring the nature of learning with multi-user virtual worlds and 3D game environments has documented interesting educationally relevant outcomes, such as their motivational power and the opportunity to help develop important skills (e.g., collaboration [11]). The learning design features of our VWorld build upon earlier agent-augmented multi-user virtual environments research [5] that were found to deliver significant benefits in science secondary classrooms.

3. OUR VIRTUAL WORLD - OMOSA

Omosa is a fictitious world that allows students to gain science inquiry skills and explore scientific concepts about biological systems. We chose not to model a specific place, flora, or fauna as we did not want the concepts learned to be restricted to the context we provided. To create Omosa, we needed to balance the level of detail in our environment with the complexity of our animals and human agents in a virtual environment with real-time graphics. We are using multi-platform game development software called Unity3D (http://unity3d.com/), which contains in-built features to reduce complexity while maintaining appearance such as lightmapping and occlusion culling.

We put several locations on Omosa (see Figure 1) where students can collect information and complete learning activities. These areas are: the village (where the indigenous Omosans live); the hunting ground (where our animals are located); the research lab (where students can collect information on ecological research and speak to an ecologist); and the weather lab (where students can collect information on climate research and speak to the climatologist). Artefacts can be collected in each location.

Figure 1. Our virtual world, Omosa

We modeled all our structures using Blender (http://www.blender.org/) to keep the polygon count as low as possible. We used Mixamo (http://www.mixamo.com/) to design and purchase low polygon human models. From TurboSquid (http://turbosquid.com/) we purchased three extinct animals (Andrewsarchus, Bluebuck, and Indricotherium) and an Iberian Lynx. In this paper we focus on two of our animals: the Bluebuck and Andrewsarchus, which we call a Yernt (one is laying on the ground in Figure 2) and a Tooru (three are feeding on a Yernt in Figure 2); the Yernt is the prey and the Tooru its predator.

Figure 2. Tooru (Predator) and Yernt (prey)

4. ARCHITECTURE

Our animals are agents who are embodied and situated in the Omosan environment. Each animal has its own state but shares its behaviour and population parameters with other animals of the same species (i.e. flockmates or conspecifics). As well as knowledge of its own state, each animal has access to lists of its predators, prey and flockmates. Each agent acts autonomously seeking to satisfy the goals determined by a combination of parameters introduced in this section.

In this section we present our model parameters and agent states and describe how the agents reason to decide what action to perform (e.g. chase, flee, eat) and the direction to move in.

4.1 Flocking - Tweaking the Boids algorithm

Reynolds [8] suggested that the seemingly complex group behavior seen in flocking can be modeled when individuals (boids) are driven using a small number of simple rules. A basic Boid algorithm includes: separation (or collision avoidance with nearby flockmates), alignment (or velocity matching with nearby flockmates), and cohesion (or centring by staying close to nearby flockmates).

The SeparationVector is a direction vector that is calculated and achieved at the individual boid level. If any other boid is too close then the SeparationVector will steer the boid away. Given a desired spacing, the distance to all other boids is measured. If *distance* < *spacing* then a vector can be calculated such that *boid1_position* – *boid2_position* = *SeparationVector*. This SeparationVector is a *xyz* direction that the current boid now intends to travel in order to maintain a distance from other boids. If multiple boids fall within the desired spacing then the resulting SeparationVectors can be summed together.

The AlignmentVector is a direction vector that is calculated at the entire boids group level. It is the average direction that the entire group of boids is travelling in.

The CohesionVector is a direction vector that is calculated at an individual level. It points from the current boid towards the average position of all other boids.

These three vectors can be summed to produce an output vector, the direction the boid will finally move, that represents the intentions of the boid. To represent the unpredictability of individuals (1) includes a RandomVector, as follows:

$$OutputVector = SeparationVector + AlignmentVector + CohesionVector + RandomVector \quad (1)$$

This random value could be replaced by a probability if a suitable stochastic model was identified for that animal type (i.e. species, gender, age, etc). Also, greater or lesser importance can be applied to any of the input vectors by multiplying them by a weight. For example in (2) we increase the importance of grouping together with:

*OutputVector = SeparationVector + AlignmentVector + (CohesionVector * 1.5) + RandomVector* (2)

The individual boid will now move in the OutputVector direction from its current location. To avoid collisions (3) builds upon this algorithm as follows:

OutputVector = SeparationVector + AlignmentVector + CohesionVector + RandomVector + ObstacleVector (3)

Where ObstacleVector points away from a tree or a rock that an individual boid is getting too close to and would prefer to not crash into.

Finally, in Omosa we do not want the entire population for each animal to behave as a single group. For each type of agent our model allows us to specify the size of subgroups within a population. In our implementation, herding is achieved by modifying both the AlignmentVector + CohesionVector to only consider the nearest HerdSize boids. In this way we have sub groups of boids that will dynamically readjust itself to only use the nearest boids. Different size herds can be seen in Figure 3.

Figure 3. Yernt and Tooru Boids

4.2 Beyond Boids – Predator/Prey agents

The animals in Omosa, as in real ecosystems, do more than move around; they exhibit behaviours such as growing, dying, hunting, eating, etc. Here we focus on the predator-prey relationship which drives many of the group and individual behaviours. To achieve this we have developed a predator model and a prey model. Figure 4 depicts how these models influence the boids.

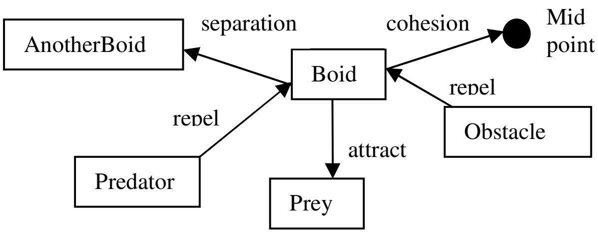

Figure 4. Simple model of factors influencing the individual boid.

Prey Model –This model produces a vector (4) calculated at an individual level that points towards prey animals. In order to indicate urgency some prey animals will be given greater importance, or weight, for a number of reasons:

- The closer the prey the greater the weight. This simulates the predator singling out a target as it bears down on it.
- The more fatigued the prey the greater its weight. The predator attacks the weak.
- The more injured the prey the greater the weight. The predator attacks the weak.

PreyDistance, PreyFatigue, and *PreyHealth* are all values between 0.0 and 1.0.

*PreyVector = PreyDirection * (1.0 – PreyDistance) * PreyFatigue * (1.0 – PreyHealth)* (4)

Predator Model – In contrast to the Prey model, this model produces a vector (5) calculated at an individual level that points away from predator animals. In order to indicate urgency some predators are given greater importance for the following reasons:

- The closer the predator the greater the weight. This simulates the prey fleeing for its life.
- The more threatening the prey the greater the weight. This simulates some animals or even human hunters being more dangerous than others, and the prey reacting accordingly.

PredatorDistance and *PredatorThreat* are values between 0 & 1.

*PredatorVector = PredatorDirection * (1.0 – PredatorDistance) * PredatorThreat* (5)

Figure 5 shows how each of the components in our architecture fit together. We can see a pipes and filters like structure between the Flocking, Predator and Prey components which allow the agent to achieve its decision making goal about which direction to go in. This decision is influenced by FollowVector, a vector that behaves much like a leash. Depending on whether they are hunting or resting we can adjust FollowVector to migrate the entire group from one location on the map to another. We can also adjust the weight of this leash to ensure the group does not go running off into the ocean or another area we want them to avoid. In the future, this vector could be replaced with a subsystem that intelligently determines locations of herds both for initial spawning and migration purposes.

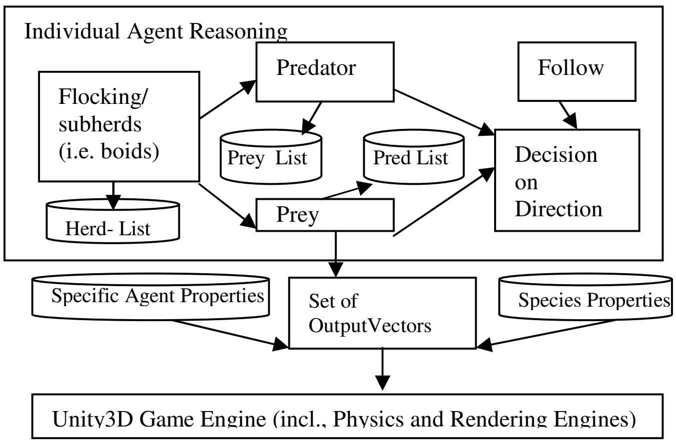

Figure 5. Omosa Architecture and Agent Reasoning.

The Individual Agent Reasoning System is used to determine the direction that the individual agent intends to go. However, our agents have additional restrictions that will define the eventual *OutputPosition*. These other factors are seen as being beyond the control of the agent and not part of their reasoning. For example, the physics engine will slow agents down as they attempt to ascend hills and accelerate agents as they descend.

Another factor applied after the agent has made their own decision regarding their intended direction is maximum speed, a value defined by the type of animal represented, which is further limited by the agent's health, fatigue, stamina and age. This models the fact that animals, including humans, are externally limited by these factors, in addition to their internal influence on the individual decision making as described in the prey model presented. To provide a more natural model of klinokenesis (change in direction) in our animals we have developed a smoothing algorithm that allows the animal to adjust speed and angle to provide a more rounded trajectory rather than a 180 degree turnaround which can result in strange behaviours in conjunction with the physics engine. For the same reason, we also adjust the animals speed to slow down when approaching another agent/object. A summary of individual and group parameters, states and behaviours is given in Table 1.

Table 1. Agent parameters, states and behaviours

Intra-agent (conspecific) parameters	**Inter-agent (different species) parameters**
Cohesion – individual	Separation – individual
Alignment – group	Obstacle - individual
Follow – group	Prey – individual
Obstacle - individual	Predator - individual
Individual States	**Group/Species States**
Health, Stamina, Life Stage (i.e. birth, mature, dying which affects size & colour), Urgency, Threat level, Location	Population/Herd size, Life Expectancy, Stage duration, Spacing, Perceptual Distance, Speed, Health Regeneration
Individual Behaviours	**Group Behaviours**
Roaming, Hunting, Standing, Feeding, Fleeing, Dying, Birth	Hunting/Stalking

As a group the animals work together to hunt down prey and avoid obstacles and predators, while as individual agents they maintain their own goals and states. While some of the group behaviours are very efficient, as the individual characteristics became more complex and specific, it has been necessary to find ways to maintain performance. For example, not all behaviours need to be refreshed every cycle to create believability. Performance is discussed again in the conclusion section.

5. EVALUATION STUDIES

At stated in our introduction, the goal of our project is to provide experience in conducting scientific inquiry and improve knowledge of biological concepts in secondary schools. In this section we present condensed results from two evaluation studies. The first study seeks to verify our models, algorithms and architecture as presented in the previous section. The second study seeks to validate our approach through an interview with an expert ethologist who has not been involved in the project.

5.1 Study 1 – Model Verification

In the first study we have collected data which evaluates the components in our Individual Agent Reasoning System. The design is presented next, followed by results and discussion.

5.1.1 Design

To evaluate the effect of the flocking, predator and prey components on the behavior of our animal, we have collected data about our predator and prey populations over a 20 minute period using different combinations of components in our architecture. Each run/simulation used identical population parameter settings. The parameters used were the default settings for each population identified by the biologist on our team as most appropriate for our predator and prey population. For each run, we collected the total population, number of births and deaths for both prey and predators as well as the number of predator kills and prey deaths from old age. The six runs reported in this paper include:

1. Default/Complete: Flocking/herding, Predator/Prey awareness.
2. No flocking/herding (1 minus Boids model)
3. No predator awareness (1 minus Predator model)
4. No prey awareness (1 minus Prey model)
5. No prey or predator awareness (1 minus Prey and Predator)
6. No subherds (1 minus herds, i.e. influenced by entire flock not just neighbours/herd members).

5.1.2 Results and Discussion

The results of data analysis are shown in Figures 6-11. The comments below are based on review of those figures as well as observations of agent behavior on the screen during each run. We are particularly interested in the kill rates, as the domain expert (see next subsection) equated success with natural/low kill rates.

The data in Figure 6 is based on the complete model presented in the previous section and includes flocking, predator / prey awareness and herding. We observe normal agent behavior and a fairly balanced system. The birth rate maintains the prey population. The predator made 13 kills over 20 minutes.

In Figure 7 the flocking component was turned off, although obstacle avoidance is included to avoid collisions with each other. Without any flocking enabled the agents still functioned surprisingly well. Prey were able to escape predators on most occasions. The level of realism seemed to be reduced, the prey behaved somewhat like water trickling between the predators, but definitely not as a group. Prey population fluctuated but was near maximum after 20 minutes. Predator made 12 kills in 20 minutes.

In Figure 8, when there is no predator awareness (i.e. prey does not respond to predator), we see that the prey were wiped out in less than 2 minutes. Prey did not attempt to evade the predator. We observed that the predator had some difficulty getting to all of the prey because there were too many prey carcasses in the way. Prey were unable to reproduce and maintain population. Predators made 80 kills over 2 minutes. Note that this simulation is not realistic: there would be an upper limit on how many prey a predator seek to kill; the predator population will die out when the food source is gone.

In Figure 9 there is no prey awareness (i.e. predators do not respond to prey); the predator completely fails to function. The prey was aware of the predators when they moved to the hunting area, but just moved to a safe distance. Prey population fluctuates due to life span, birth rate is able to maintain maximum population. Predator made 0 kills in 20 minutes.

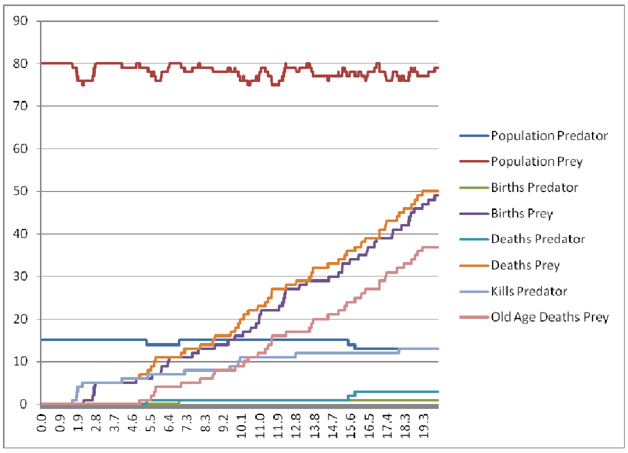

Figure 6. Default Settings (Flocking, Predator / Prey Awareness, Herding) Normal behaviour.

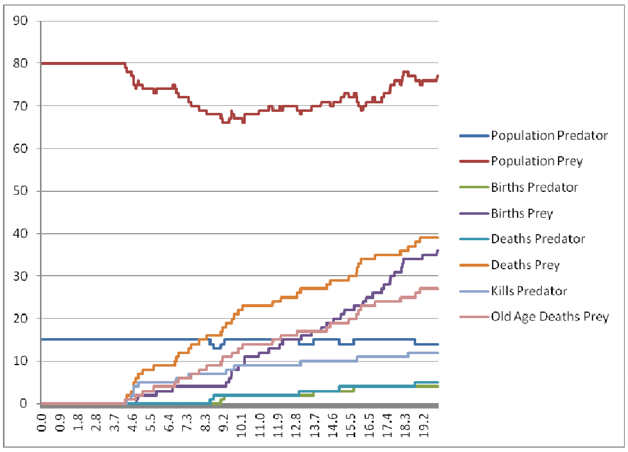

Figure 7. No Flocking (Boids still avoid collisions with each other).

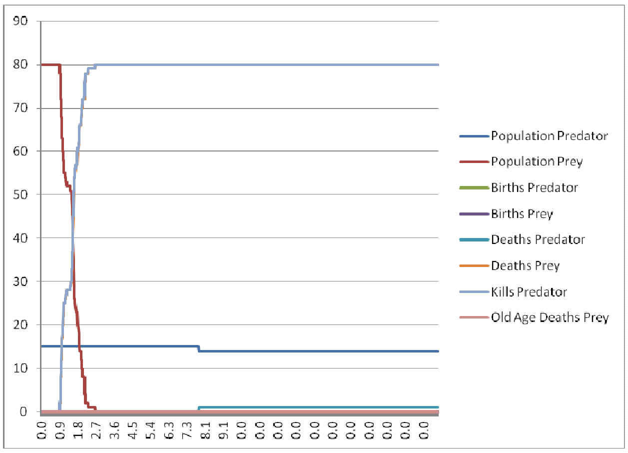

Figure 8. No Predator Awareness (Prey does not respond to predator)

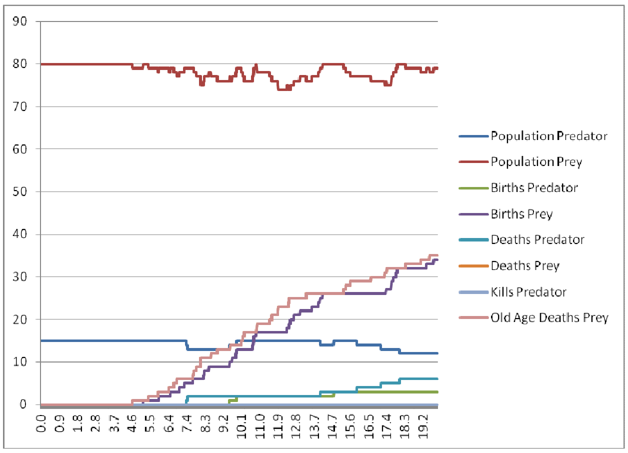

Figure 9. No Prey Awareness (Predator does not respond to prey)

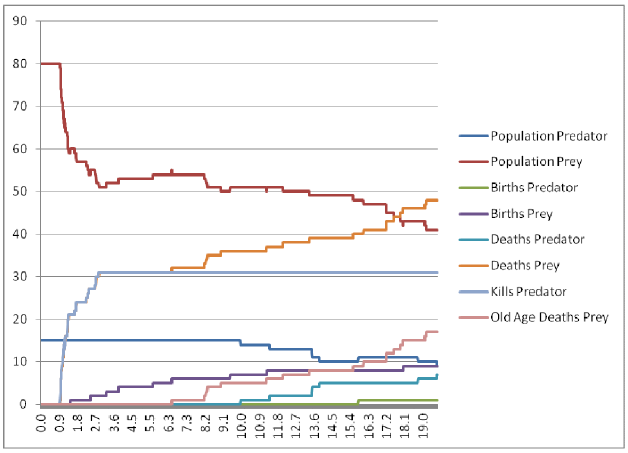

Figure 10. No Predator Vector and No Prey Vector (Both predator and prey don't respond to other).

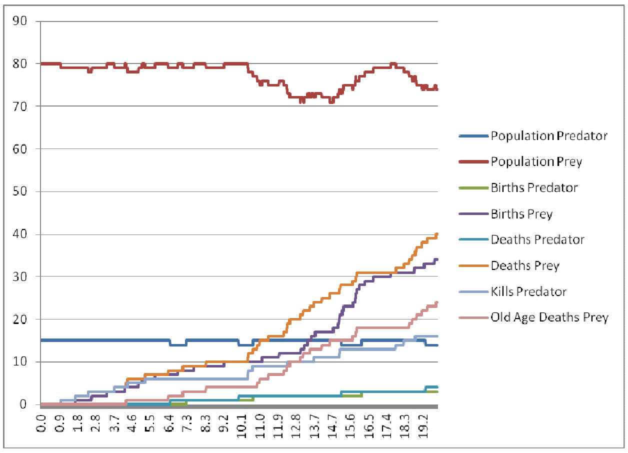

Figure 11. No Sub Herds (Flocking is enabled, boids are influenced by all of their own type, not just those nearby)

In Figure 10 the predator and prey models are both switched off. (Both predator and prey don't respond to other). Predators perform badly as in the previous condition. However at approximately one minute the predator herd happens to walk right into the prey herd, which in turn doesn't respond and takes a lot of losses. After that the predator never came close to the prey again, instead spending most of the time splashing around on the beach. Predator made 31 kills over 20 minutes.

Finally in Figure 11 we evaluate turning off the herding feature so that no subherds exist within a population. Flocking is still active but boids are influenced by all of their own type, not just those nearby). Both predator and prey function well. Predators seemed to benefit from this setting, showing more cohesion, while the prey may have been hampered from too much influence from others of their species (instead of just relevant ones nearby). Prey population fluctuated but was maintained. Predators made 16 kill.

We conclude that the predator and prey models are essential to model natural success/kill rates. Though success rates are mostly unaffected by flocking/herding they are necessary to provide a realistic 3D simulation of animals which live and act in groups.

5.2 Expert Validation

In addition to having access to a number of advisers, one of the investigators in this research project is a biologist. However, to provide independent evaluation of our animal behaviours we approached an expert in the field of animal communication and conservation, whose particular area of expertise and interest was ungulates, with a focus on elk and bison. We conducted a one (1) hour interview involving demonstration of our system and a series of structured questions. The steps we followed and questions posed, together with responses are described below.

5.2.1 Step 1: First Impressions

In order to put our animals in their current environmental context and to gain first general impressions, we began with a tour of the village including a conversation with an Omosan hunter and then we used the game/site map (Figure 1) to locate animals that we then introduced up close, as in Figure 2. We then took a bird's eye view of a part of Omosa containing herds of both animal types. Our first question was simply "What are your first impressions?"

We were unaware of the expectations of our expert, and she was unaware of what she would see. Thus, as a first response she commented that [real] animals are predictable but ours are unpredictable. She mentioned the *many eyes hypothesis* where the animals would stay in groups, always with some animals watching while others fed/grazed. The expert's response regarding unpredictability occurred after a relatively lengthy initial period where the two populations had been grazing independently and then appeared to become aware of one another. This time delay can be seen in Figure 12. Figure 12 shows a plot of the agent movements over time. The red (left side) path shows predators. The green (right side) show prey. We can see over time that the separate populations begin to interact and that the two populations are moving regularly with predators following prey and prey tending to flee from predators as shown more clearly in the pathways at the bottom of the figure.

As the behaviours became more interesting, including predators circling a wounded or dead prey, which our expert said is like wolf pack behavior, the expert became more engaged and excited, sometimes intrigued by the behaviours observed. When students use the world, the animals will have potentially been through numerous life cycles and it is unlikely they will be at the initial and less interesting reset/spawning stage.

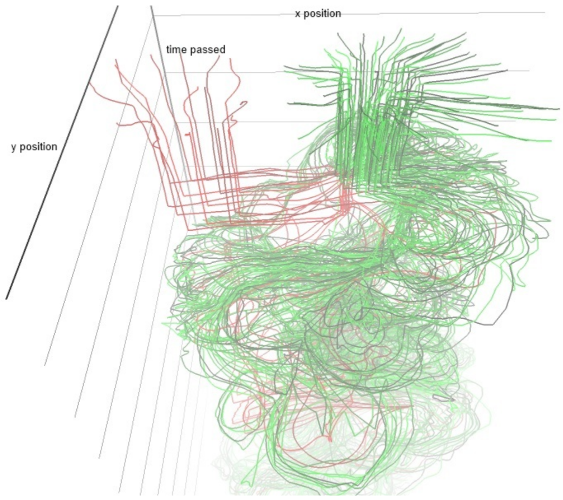

Figure 12. 3D Model of animal paths showing agent position over time(red/left=predator, green/right=prey

5.2.2 Step 2: Parameter Testing

To allow model adjustment and assist learning, we allow the group level parameters (see Table 1) to be adjusted via sliders. We asked the expert to select up to 3 parameters that they would like to change, though only one a time. We asked her to make a prediction for each parameter before any changes were made. Our expert was only interested in changing two parameters: speed and perceptual distance and stated that prey can move faster and have further perceptual distance than predators. The other parameters, such as stamina, were perceived to be secondary. The expert stated that there should be at least two or three times as many prey than predators and was happy with our relative herd sizes of 3 for predators and 15 for prey. In terms of population sizes of 80 for prey and 15 for predator, the biologist was also satisfied.

Speed was changed first by increasing the speed of the prey and reducing the speed of the predator. The prediction was there would be less kills/success and the animal behaviours would be more lifelike. In accordance with the prediction, there were considerably less kills. Surprisingly we also observed that the predators seemed to be moving as one towards the prey rather than in herd sizes of 3 towards selected prey and this inefficient behavior would have affected success rates. The expert added that a kill success rate of 10% was normal for natural populations but that speed should be slightly unnatural resulting in greater numbers of kills so that the simulation is not too boring.

The second parameter to be changed was perceptual distance. In line with natural differences, the predator value was decreased to 20 and prey value was increased to 35. Again the prediction was that the behavior would be more natural and would result in less kills/predator success. Indeed less kills were observed. What was not predicted and was quite surprising was the opposite behavior to our change relating to speed. Even though we left the speed settings to those specified by our expert, this time rather than predators appearing to act as a whole population moving slowly towards the prey, the majority of Tooru continued to ignore the Yernt. Only individuals at the edge of the predator group closest to the prey group appeared to notice the prey and run off in that direction, leaving their herd (the other two) behind. It appears that the individual had come within the perceptual distance allowing them to recognize the prey, and was quite hungry by that time pulling them more strongly towards the prey than their mates. The mates who had not been able themselves to see the prey, were still close enough to other conspecific herds and thus they joined the new herd to satisfy that need. The increased perceptual vision of the prey in detecting the predator resulted in the flock of prey moving away from the predator herds/population, making it increasingly difficult for the predator to spot them.

5.2.3 Step 3: Rating of Environment

We chose to use the questions from [2] to "establish the contribution of behaviours to the perceived realism of the animals within the environments and the contribution to the overall experience" (p.155). However, we sought to validate our complete architecture, system and the emergent behaviors with a domain expert rather than test alternative models/combinations of system components to subjects (e.g. no-flocking, no flight, no fear/emotion, etc) with immersive technology students. Thus we did not use Likert scale responses but allowed the expert to use their own term. Table 2 shows the questions and brief answers.

Table 2. Parameters defining our three current conspecifics

Question	Response
1. How realistic was the graphical representation of the animals in the environment?	Good
2. How much did the environment engage you generally?	Very
3. How much did the animals add to the realism of the environment?	Very
4. Did the animals seem alive in the environment?	Yes
5. Did the animals appear to be behaving in an intelligent manner?	Depends
6. How realistic was the behaviour of the animals?	Good
7. How quickly did you adjust to the virtual environment experience?	Immediate
8. To what extent did the animals seem to be reacting to their environment?	Good
9. To what extent did the animals appear to be reacting with one another?	Good
10. To what degree did the animals appear to make an emotional reaction?	Motivation observed

Regarding whether the animals were perceived as alive, (Q4) the expert added that "movement is critical, it brings the animal to life and the animals bring the virtual world to life". Regarding whether the animals appeared to be behaving in an intelligent manner (Q5) the answer was qualified by saying that it depends on what parameters are used. The expert was "bothered by lack of group cohesion within the pack" which was not always evident. However, the circling of a pack around prey and chasing after the same prey could be observed at times. We asked the question "How compelling was your sense of moving around inside the virtual environment?" but it was not answered due to lack of relevance as the expert did not control the initial tour of the world and watching the behaviours did not involve interaction with the animals.

Regarding questions 8 and 9, the expert commented that the flocking indicated awareness of conspecifics; prey were aware of predators and reacted by fleeing when they were chased. Chasing was evidence of predators being aware of prey and reacting to them. The fact that at times both animal agent types grazed and showed no interest in the other animal type indicated that there were also other factors affecting their interest in and desire to hunt or flee. However, for some settings a lack of cohesion on the part of predator was observed. At these times it seemed that predators were not reacting to one another even though prey did react to one another.

Though our model does not explicitly include emotion (fleeing could be triggered by fear), we included the question from [20] regarding emotion to test and provide opportunity for discussion whether the ethologist had endowed our animals with emotional behavior or believed that emotional factors should be modeled. The expert stated outright that they were uncomfortable with the word "emotion" when considering the behavior of animals. They preferred the term and concept of motivation. The expert observed that the prey were motivated to avoid the predators, which could be seen as due to fear, but they did not feel it necessary or appropriate to attribute emotion as the cause.

5.2.4 Step 4: Usefulness for Education

The goal of our intelligent animals is to allow students to observe animals in a natural setting to see how they may behave, allow them to set various hypotheses about the animals and phenomena occurring in Omosa and to teach them about complex systems. It was not our goal to provide ecologically sound and complete animal models which would allow us or others to make decisions and predications about these populations in the real world. Thus, we asked "Do you believe the world would be useful for educational purposes?' They responded "Definitely, it would get the students engaged".

When asked if the world would be useful at the tertiary level, perhaps in some of their own teaching context, they were more hesitant and remarked with respect to the animals that it could be useful if more parameters could be made available (though none were specifically suggested) and students would need to be able to change them. The expert suggested that Omosa 2.0 would be needed for tertiary biology students. When asked what would be in 2.0, they suggested multiple prey types and predator switching between prey depending on factors such as availability.

5.2.5 Step 5: Additional Features and Directions

Throughout the interview a number of behaviours were suggested for possible inclusion, as follows:

- Reproduction rates influenced by success rates,
- Targeted kills, e.g instead of attacking many/closest prey, predators would intelligently pick one or two, e.g. smallest. (we already factor in health).
- Complementary/coordinated group behaviours, e.g. some prey-flockmates would come back and defend, some pack members may not join in.
- After killing predators go back to foraging (which we do).
- Might need to change life span.

These features and others are considered as further extensions to our agents in the next section.

6. CONCLUSIONS & FUTURE WORK

Animals have provided agent researchers with so called biologically-inspired solutions to issues such as coalition formation (e.g. [4]) and other social dilemmas involving communication, coordination and cooperation to solve problems such as load balancing, message congestion and bandwidth allocation. Similarly, we anticipate that software/network agent research related to the handling of social interactions, decision making, self-interested agents and cooperation (e.g. [9]) could potentially offer some insights and extensions to our animal agents. As demonstrated, behaviours which simulate group communication and coordination exist in our model, however, to produce more lifelike animals we may want to extend our models with natural communication methods involving gestures and sound, similar to the use of the scents and an artificial nose [2]. MAS-based group decision-making may be a feature that our animal or human agents will need as in the study by [16]. Inclusion of updating schemes which allow the evolution of our models is also potentially attractive.

Currently, we simulate different life stages through size of the animal and intend to use changes in colour as a feature to indicate age. Also, while we have different values for traits for different species we do not currently have separate traits for different species or differentiate between behavior in males and females as in ALMaSS [13]. We would like to include stochastic elements into our models to potentially provide more authentic behaviours in determining initial locations to spawn animals and affecting whether a kill is successful or not. At this stage, we do not believe that explicit modeling of emotions is appropriate or necessary for our animals. We will conduct further studies using our models and more of our animals, as suggested by the expert, involving multiple predators and alternative prey.

Scalability is an issue facing both graphics researchers and agent researchers involved in building complex cognitive architectures and multi-agent platforms [7]. On the graphics side we have paid close attention to polygon counts. For example, using MeshLab (http://meshlab.sourceforge.net/) we were able to reduce the number of polygons in purchased animal models from around 6000 to no more than 1800 each. To support both the processing requirements of our agent reasoning approach with the processing requirements of the graphics, we have increased the number of frames between each animal in the herd updating its behavior. While this slightly decreases the realism of the animals' behavior, it significantly improves the overall game performance. As the complexity of the models and agents in Omosa increase, we will have to consider more strategies for maintaining the balance between processing speed and environment complexity.

Initial trials with teachers and a Science special interest group were enthusiastically received and led to modifications to Omosa involving the dialogue engine, interaction controls and smoothing of animal movement transitions. In November 2011 we began testing our workbooks and lessons in the classroom over 4 lessons. We are currently processing student data including measurements of learning gains and changes in levels of interest in science inquiry. Results will appear in a future publication.

7. ACKNOWLEDGMENTS

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