Investigating the Impact of AI Techniques on Inter-Flock Dynamics

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ABSTRACT

Context: Artificial intelligence is a rapidly expanding field, there is a clear useful context in their use in Flocking Techniques.
Aim: Investigate the impact of AI techniques on the dynamic interaction of flocks with each other to see if this has a beneficial effect in comparison to regular flocking algorithms.
Method: Using an application that models flocking behavior developed by the author, observe and compare AI flocking strategies to those of regular flocking algorithms. This will be developed using the AI techniques found to be most likely to produce viable intelligent flocking behaviours.
Results: The analysis of the effectiveness of strategies that the AI come up with in their interactions with other flocks, with contrast and comparison to the behaviour of standard flocking algorithms.
Conclusion: This project will display the flocking strategies that emerge from their interactions with other flocks and conclude on their effectiveness in relation to other strategies and flock type. This will demonstrate the impact the AI techniques have on this kind flocking interaction.

KEYWORDS

Artificial Intelligence, Flocking, Boids, Collective Knowledge, Artificial Life, Multiple Flocks.

1. INTRODUCTION

Flocking is a behaviour in which all social organisms engage; it is the common movement of organisms guided by both social and environmental pressures. These flocks of organisms can be found interacting with other flocks in nature, and the way they interact is as varied as it is interesting.

Producing flocking behavior that recreates those found in nature is an endeavor already undertaken and in constant update. The field, taking off in 1987 with Craig Reynolds' influential paper (Reynolds, 1987), shows how realistic flocking behaviour can already be achieved by applying 3 simple rules to each boid ('boid' as coined in the prior paper, this is essentially an agent) in regard to its neighbours: Cohesion, movement toward the average position; Alignment, movement toward the average direction; and Separation, movement to avoid collision.

Since then, the original flocking algorithm has been extended in various ways, with communication techniques, mathematical models for how leadership arises in the flock, as well as models for how consensus is made in a flock.

Learning behaviours have also been added. The behaviour and strategies flocks produce are patterns. This means if a flock can learn and understand those patterns it has a significant advantage over that other flock – an interesting example would be a group of honey hunters and smoke; bees flee the nest if they think there is a fire, the first warning sign to this is smoke, as a group (or flock) they take advantage of this by releasing smoke into the hive. The bees evacuate the nest, they get honey.

This dissemination of new knowledge, either through behaviour or communication is interesting because it can increase the complexity of the reactions the flock has to a given situation. This added complexity may lead to new behaviours that may not have been easily predicted or thought of as something a flock could produce.

Imagine the kinds of complex behaviours that might arise out of interactions of different types of flock with these added behaviours in an RTS (Real-Time Strategy) game. Not only would you have to focus on resource management, but on the counter play that each of the flocks would come up with against each other. Maybe a flock has a certain area advantage so moves to that area nearby, or is less in numbers in comparison so has to adapt its strategy to deal with that (possibly by making it seem like its more numerous than it is, forcing that other flock to adapt).
This is purely speculative, however much like science fiction is to science, it's sometimes good to think about what might be possible first, and then think of a path to get there.

1.1 Aim

To investigate the impact of AI techniques on the dynamic interaction of flocks with each other to see if this has a beneficial effect in comparison to regular flocking algorithms.

1.2 Objectives

- To research and evaluate AI techniques, studying their relevance and potential for further development in applying them to flocking algorithms, with particular focus on artificial life techniques.
- To produce an application that models flocking behaviour, and allows the observation and comparison of AI flocking strategies to regular flocking algorithms. This will be developed using the prior identified AI techniques most likely to produce viable flocking behaviours.
- To analyse the effectiveness of strategies that the AI come up with in their interactions with other flocks, comparing and contrasting that to the behavior of standard flocking algorithms.

1.3 Research Question

What impact do AI techniques have on the dynamic interaction of flocks with each other in comparison to that of regular flocking techniques?

2. BACKGROUND

Flocking, since its initial algorithmic conception and discussion in academics (Reynolds, 1987), is a field of study that has been expanded on in various ways.
What should be understood is that flocking behavior is an emergent property of boids acting on the influences of their surrounding environment. Viewing flocking algorithms through this lens makes it easier to see why implementation decisions have been made that might not be intuitive at first glance.

2.1 Artificial Life (Alife)

Flocking has always been inherently related to Alife in its modelling of behaviours in the natural world. Developments since have adapted the algorithms to produce the group behaviour of many different species; it has also expanded to include further communication between boids, for example ants may use pheromones to find shortest paths (Dorigo & Gamberdella, 1997) – this is a whole extra field of research, known aptly as Ant Algorithms, modelling the ants' eusocial behavior.

How a flock makes a decision is interesting, considering its decentralized approach. The specifics can depend on species; however the two types of decision making can be seen as consensus and leadership. An interesting look at this can be found in a study of flocking behavior in pigeons (Jorge & Marques, 2012) where it was found that younger pigeons emerged as initial leaders in a flight but as they went on older members of the flock led the group, and the paper goes on to discuss how social versus personal information affects the group behavior.
What this displays though, is how the extra experience of older members of the flock is taken advantage of in determining leadership and therefore the actions they take as a flock, in this way they build consensus on their leadership though the choices individual flock members make in the group. This is further evidentially confirmed in the paper '*Misinformed leaders lose influence over pigeon flocks*' (Watts, et al., 2016).

An interesting way of producing leadership in an artificial flock can be found in a paper titled *'Autonomous Boids'* (Hartman & Benes, 2006). Here they propose the use of an 'Eccentricity' variable to determine leadership in the group in order to make decisions based on the boids proximity to the front of the flock, the closer it is, the higher a chance of 'escape' or leading the flock. This mimics the way some species of bird, such as starlings, decide on leadership of the group.

Consensus building has also been modelled, in this case in swarms (Shang & Bouffanais, 2014). They consider the interaction between individuals and how that ripples out to form a consensus within the flock. In the paper they look at a hybridisation of two types of models that cover this behaviour, one based on metric distance, and the other on topological distance; both of these models have a lot of research behind them.
This shows how communication can work in a flock to produce decisions, and if expanded could be used to disseminate more complex information throughout the group.

What can be seen throughout this research is there are many ways in which a flock can make decisions, and how a flock makes decisions in its environment can determine its behaviour in a more dynamic way. This makes the emergence of decision making in a flock important to note, as there are different answers for many different types of group behaviour.

2.2 Collective Knowledge

Flocks in nature have a collective knowledge. They can avoid obstacles, detect and evade prey; they can learn from the environment and encounters they experience.

A common way in which to learn is through curiosity, investigation. The groundwork for this can be seen in the "Social Force" model described by Helbing & Molnár (1995). This paper introduces a similar forces concept to Reynolds on a basis of motivation and adapting them as such. They also introduce a new attractive force fed by the same motivation mechanic. This new attractive force will make them move toward objects or other pedestrians.
This algorithm however, only models them in a way that replicates pedestrian behaviour, a pedestrian boid here doesn't discover anything about the things they are attracted to, and won't develop an understanding of its world.

A model that does take learning into account is published by Saunders & Gero (2004). This builds off of the aforementioned social force model and several other sources, creating in their paper a "Curious Agent Architecture". This introduces three new parameters: Interestingness, Novelty and Curiosity. This all lays the framework for how a boid can learn through the experience it gains from its surrounding environment.

2.3 Multiple Flocks

The focus so far has been to evaluate and find ways in which flocking has been expanded upon in ways that allow flocks to learn and process their environment, understand ways in which they can make collective decisions, and how the flock disseminates knowledge throughout the group (taking advantage of more experience flock members).
The interaction between multiple flocks is the other main pillar of focus to the research question in hand. The research specifically on the interaction of different types of flock is limited.

In the paper *'Simulating Species Interactions and Complex Emergence in Multiple Flocks of Boids with GPUs'* (Husselmann & Hawick, 2011), multiple flocks, each a different type of boid, are run in a closed environment to see what aspects of species interaction could be reproduced. This paper is important as it covers how the authors created their different types of flocks and what sort of parameters they used when differing them. They also offer an interesting way of getting results; "histogramming in 3D-space" as the authors put it, describing it by writing: "the 3D space is discretised and then each boid's position is mapped to a discrete cube in 3D space". This is used in order to view the patterns of behaviour more clearly, and may come of use in discussing and testing the patterns produced by flocks in the application to be built.

The main limitation of the paper is the simplicity of the boids in question, and while it's noted in the paper that they wish to address this, further research into the authors' papers since show no further research into the interactions of multiple flocks.

For this project, taking into account the research that has been outlined above, including features that expand the original flocking algorithm's ability to learn, communicate, and make decisions is crucial to making smart flocking algorithms that can adapt to the behaviours of other flocks in simulation.

In this background section what should be clear now is that in the combination of these adaptations to the flocking algorithm lies the groundwork for making smart artificially intelligent flocking behaviour that can learn and adapt to its surroundings. This is what the author hopes to achieve.

3. METHOD

3.1 Application Development

The application will be developed in C++, utilizing a direct3D11 framework provided in past by a university lecturer (which is in turn based on the RasterTek tutorials). This framework will be used to provide the visual component to the application; this will allow for the study of flocking behaviours.

The application will start as a simple box area, which will be the area to be populated with boids.
This may be evolved to have varied landscapes if found suitable or beneficial to the project and therefore will be tested at a later stage to see if this is the case. A beneficial example of this may be to balance the available strategies the flocks have and to provide more variation in behaviour.

3.2 The Basic Flocking Algorithm

The initial implementation of the flocking algorithms will start with the key ideas from the original implementation described by Craig Reynolds (1987).
This involves creating a set of boids, each of which will have three controlling parameters: Cohesion, Alignment and Separation. Tweaking these three parameters should give a nice basic flocking result for each type of boid.
The boids will also have a basic awareness of their environment, having a specified field of view (this could be the natural field of view of an animal, for example), and have an area of awareness (i.e. how far in the distance this field of view applies).
The flocks produced will also be written to take advantage of the techniques developed for producing multiple flocks (Husselmann & Hawick, 2011); they will also take inspiration from different naturally occuring flock in that respect too.

3.3 Building AI Flocking Behaviour

For this research to work the boids have to be capable of learning. The first focus of this has to be Pattern Recognition. A boid, and therefore a flock, can learn the patterns behind the behaviour of nearby flocks.

This is where the flocking algorithm is built upon, based on the background research conducted.
The first addition to be made will be the addition of communication capabilities. Based off of the knowledge gained by observing the implementation described by Shang & Bouffanais (2014) a hybridisation of communication based off of the metric and topological distance techniques. This may be simplified as it comes to implementation, as the main focus is that these boids will be able to communicate messages to each other within a certain distance. This may also be expanded to include vocal calls which deliver messages over a wider area.

Communication also falls into the learning that the group makes. Building on techniques developed in the article written by Saunders & Gero (2004) on curious agents. Their curiosity will lend them to be more outreaching to learn about new things in their environment, which will be for these purposes other flocks.
The boids in this learning state will then make determinations based off of the information they obtain. They will then adjust their internal biases accordingly.

There will also be testing of genetic algorithms and similar strands of AI in order to increase the complexity of decision making and what can be learned.
It could also be interesting to see how the application could benefit from applying fuzzy logic to the learned biases of the individual boids and how that might be communicated between flock members. This is something that could be added later on in the project to add more variability to flock behaviour.

3.5 General Purpose GPU (GPGPU)

The GPU is an excellent way to improve the performance of highly parallelizable tasks, therefore exceedingly useful in the real-time modelling of the behaviour of flocks.

There were multiple considerations for what could have been used here. The CUDA API for example, shows potential. Already used in research (Husselmann & Hawick, 2011), the API is great as the process can be imporved using this API by directly rendering from the CUDA "kernel", which skips copying agent data back to the GPU (to paraphrase the authors of the aforementioned paper).
The issue however, is that the API only works with CUDA-enabled GPUs; this limits the harware on which this platform can work on, which would limit the time in which to develop the application.

FLAME (Flexible Large-scale Agent Modelling Environment) GPU was another considered API, built specifically for this type of task. The main issue when it came to this is that to program in this platform it has to be in XML, it also has a lot of functionality to make developing flocks a lot easier; while these may be positives in other situations, this isn't felt as appropriate to demonstrate the skills the author has learned over the course.

The last consideration, and the one that shall be used in the application is the well-documented DirectCompute API. This is due to its ability to send commands normally sent to the CPU to the GPU via Compute Shaders. Due to the similar release time as direct3D11, and the fact they are both produced by the same developer (Microsoft), makes using both of these in conjunction in an application an ideal match.

3.6 Testing Criteria and Method

The testing criteria for the how successful a flock is will be easier to define later as the application is developed.

Potential candidates for this can be the flock's health, numbers of boids lost, improvements in communication and decision making, the speed of adapting to strategies used by other flocks, and there is room for expansion here. Success of course depends upon the goals of different types of flock.

However, this isn't the main focus; the main thing that will be investigated is the impact these added abilities the boids within the flock will have due to their increased ability to communicate, learn and make decisions.
This will then be compared and contrasted to the performance of regular flocking algorithms which is where the aforementioned testing criteria may come in useful for comparison.

4. SUMMARY

In this research, the dynamics of the interaction between multiple flocks will be explored, with particular regard to promising AI techniques as applied to flocking explored in this paper, as well as taking advantage of the clear advances made in flocking algorithms found since its initial algorithmic conception.

While it is clear from researching this topic that flocking behaviour has been researched in depth in nature and in its algorithmic representation, the interaction between different kinds of flock has not been studied to the same kind of degree.

This leaves a lot of room for growth in the area, and so an observation of the kind of flocking behaviours that emerge due to this kind of interaction and how they can learn through that interaction is of interest.

Studying this area in more depth therefore paves the way for further research into the area. With more available papers on the topic, the easier it will be for more advanced techniques and incremental improvements to algorithms to be made.

This will be of use in the field of computer games as introducing more advanced kinds of flock (that can run in real-time) into games becomes easier, increasing the potential for more than one type of flock may interact. Having access to research that describes the behaviours that can arise from those interactions is immensely useful in understanding the impact that has on the game.

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