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Flocking Behaviors for Multiple Groups with Heterogeneous Agents

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***Abstract*—**Most of researches for conventional simulations were studied focusing on flocks with a single species. While there exist the flocking behaviors with a single species in nature, the flocking behaviors are frequently observed with multi-species. This paper studies on the flocking simulation for heterogeneous agents. In order to simulate the flocks for heterogeneous agents, the conventional method uses the identifier of flock, while the proposed method defines the feature vector of agent and uses the similarity between agents by comparing with those feature vectors. Based on the similarity, the paper proposed the attractive force and repulsive force and then executed the simulation by applying two forces. The results of simulation showed that flock formation with heterogeneous agents is very natural in both cases. In addition, it showed that unlike the existing method, the proposed method can not only control the density of the flocks, but also be possible for two different groups of agents to flock close to each other if they have a high similarity.

***Keywords*—**Flocking behavior, heterogeneous agents, similarity, simulation.

I. Introduction

FLOCKING is a collective behavior of certain agents that move according to speed and create a gathering. There are numerous examples such as groups of birds traveling in space, herds of animals moving across land, and fish that swim through the oceans [1]-[5], [12]. These flocking models are mathematical models according to biological intuition that simulate the animation of agent groups. In these models each agent determines the movement based on the environment surrounding it and certain rules of which they counteract with their neighbors in their group. Flocking is one of collective action models that can be applied in animation, robot control, data visualization depending on time and spatial crowd exploration. The basic flocking model suggested by Reynolds [1] is composed of three simple rules that must be applied to the agent for each frame [1]-[3]; (1) Separation rule – it tries to avoid collision with adjacent agents. (2) Alignment rule – it tries to coincide direction and speed with other neighboring agents. (3) Cohesion rule – it tries to move into the center of neighboring agents. These three simple local rules draw the global actions of the entire herd [1], [2], [4].

Conventional flocking simulations have always concentrated their studies on homogeneous agents [1]-[3], [13]. However what actually occurs in real-life flocking is that homogeneous flocking exists, while the heterogeneous flocking is not a rare sight, but frequently observed. Fig. 1 is examples of heterogeneous flocking. The left upper picture is a photo of two different kinds of birds flocking together, and the right upper picture is a photo of geese and chicken foraging for food together. The left lower picture is a photo of herd of impala and elephant which are both herbivores flocking together and the right lower picture is a photo of various types of fish swimming together in the sea.

Flocking has been used in movies and computer games in order to enhance realism [1]-[3], [8], [9], [11]. Especially, if the heterogeneous flocking which is easily observed in nature is introduced in movies and computer games, a more realistic and rich contents will be created. Also, as many researches require visualization of various scientific data, it can be applied to these data visualization depending on time. For instance, it can be utilized in simulating the process of separating impurities from liquid mixtures [7]. It can also be used in clustering massive amounts of documents, which is a kind of data mining [6], [10].

Fig. 1 Heterogeneous Flocking in Nature

The three basic rules of Reynolds are appropriate for homogeneous flocking. However it is far deficient for heterogeneous flocking. This paper focuses on studies for effective heterogeneous flocking. It adds a fourth rule to the basic three rules, which is the similarity rule. The rule enables agents with high similarity to form a group by moving closer and prevent agents with less similarity from forming a group.

The section II mainly discusses researches regarding steering force that has been applied in conventional flocking, and the

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section III defines similarity and suggests new steering forces based on similarity. The section IV explains the simulation results of heterogeneous flocking using the new steering forces mentioned above, and the section V concludes the paper.

II. Related Works

A. Steering Forces for Convention Flocking Behaviors

Homogeneous flocking mostly utilizes separation force, alignment force and cohesion force that were suggested by Reynolds. There have been many other studies ever since, and though the specific calculations may have differed, the basic structures were all similar to those of Reynolds [3]-[5], [8], [9], [12].

Let V_i be a group of agent which influences agent a_i to determine new location. The separation force $f_s(a_i)$, alignment force $f_a(a_i)$ and cohesion force $f_c(a_i)$ of agent a_i are defined like the following.

$$f_s(a_i) = -\sum_{\forall a_j \subseteq V_i} \frac{a_j.pos - a_i.pos}{|a_j.pos - a_i.pos|^k} \quad (1)$$

$$f_a(a_i) = \sum_{\forall a_j \subseteq V_i} \frac{a_j.dir}{||V_i||} \quad (2)$$

$$f_c(a_i) = \sum_{\forall a_j \subseteq V_i} \frac{a_j.pos}{||V_i||} - a_i.pos \quad (3)$$

In the above equations, $a_i.pos$ is the current location vector of a_i and $a_i.dir$ is the unit vector of the direction of which a_i is moving towards. $|v|$ indicates the magnitude of vector v, and $||V||$ indicates the number of elements forming group V. As shown in (1), separation force is in inverse proportion of the distance between two agents ($|a_j.pos - a_i.pos|$). In (1), k is determined by the type of agents and the simulation environment [2], [4]. In separation force, the negative sign signifies the repulsive force. Equation (2) is cohesion force, which enables agent a_i to move according to the location of neighboring agents. Equation (3) makes a_i move in the same direction with the neighboring agents.

B. Flocking Behaviors with Multiple Targets

Flocking proposed in [12] refers to agents forming multiple groups in a space. Here, a target is a characteristic representing the actions of each group. Therefore a target has a location and speed just like other agents.

Reference [5] suggests algorithms and theoretical backgrounds about various flocking behaviors of an agent, and [12] suggests flocking algorithms that track several targets in a large agent system. Assume that there are n number of agents and m number of targets, where n must be greater or equal to m. Each agent must be included in one target and one target must accept at least one agent. Reference [12] suggests two probabilities, p_{ik}^d and p_{ik}^ρ in the process of each agent selecting a target. The probability p_{ik}^d is one of relative distance of agent i to target k. This probability is in proportion to distance order to each target. The probability p_{ik}^ρ is the one that target k will accept agent i. If target k can accept agent i, the value of p_{ik}^ρ becomes 1, otherwise 0. In [12], targets are selected by calculating the value of $p_{ik} = 0.5p_{ik}^d + 0.5p_{ik}^\rho$. Therefore the target selection method in [12] is simply determined by the agent's primary location.

The method introduced in [12] can be used in heterogeneous flocking. Agents belonging to one target can be depicted as a homogeneous agent, and thus if there are m number of targets then it can be considered that there are m number of types of agents flocking according to their class. However, the flaw of this method is that there is no way to apply similarity to homogeneous agents that are similar species but not exactly "identical" species. For instance, consider a space where elephants, impala, and lion herds exist. In this case, elephant and impala are herbivores, while lion is a carnivore. There may be cases of animals flocking among each species, but it is most likely that herbivores would flock among themselves, like the right lower photo of Fig. 1. The method suggested in [12] may cover the former case, but not the latter case.

III. Steering Force based on Similarity

A. Feature Vector and Method to Estimate Similarity

The most important part in simulating multiple heterogeneous flocking is to divide agents into groups. Reference [12] forms a group where each agent must belong only to one target and one group must determine one target. Like mentioned above, this model cannot apply similarity between groups. In this paper, in order to solve those limitations, no agent is assigned to any particular group. Thus there will be no group from the first place. It is just that each agent has a feature vector that represents the features of each individual agent. The feature vector can be their type, speed, magnitude, weight, color and so on. These feature vectors mean that if their values are similar, they might be homogeneous. In opposite circumstances, they may be heterogeneous. This paper compares feature vectors to estimate similarities between agents and defines a new steering force which is in proportion to this similarity.

As mentioned above, the feature vector can be consisted of the speed, magnitude, weight, color and so on of an agent. This paper describes the feature vector $f_v(a_i)$ of agent a_i like the following.

$$f_v(a_i) = < x_{i1}, x_{i2}, \dots, x_{im} > \quad (4)$$

In (4), x_{ik} indicates the value of k^{th} property of agent a_i. For instance, in order to discriminate heterogeneous agents that are included in a simulation, the properties of the feature vector are consisted of "species" and "magnitude". In this case, x_{i1} and x_{i2} will be the values of "species" and "magnitude" of agent a_i respectively. Also, if we classify "species" into "carnivores", "herbivores", and "omnivores", we can construct a pure herbivore to assign a large negative value and a pure carnivore to assign a large positive value and an omnivore to assign values between the two values. In terms of “magnitude”, we can create a certain standard to give a large positive value to agents that have far exceeded the standard and a large negative value to agents far inferior to the standard. If the agent has similar values to the standard, it could be given a 0. If so, an agent a_i with values of $f_v(a_i)$ with <-10, 10> will be interpreted as a very large herbivore.

In general, there are two ways of estimating similarity. The first one is to calculate Euclidean distance, and the other is to calculate the dot product between two vectors. When vector represents a spatial coordinate, the former method is frequently used, and when it represents features of an object as a document, the latter method is used. In this paper, the feature vector represents features of animals, and so the latter is more appropriate. Let the feature vectors of two agents a_i, a_j be $< x_{i1}, x_{i2}, \dots, x_{im} >, < x_{j1}, x_{j2}, \dots, x_{jm} >$ respectively. The value of the similarity $S(a_i, a_j)$ is defined like the following.

$$\begin{aligned} S(a_i, a_j) &= \cos(\theta) \\ &= \frac{f_v(a_i) \circ f_v(a_j)}{|f_v(a_i)| \times |f_v(a_j)|} \\ &= \frac{x_{i1}x_{j1} + x_{i2}x_{j2} + \cdots + x_{im}x_{jm}}{\sqrt{x_{i1}^2 + x_{i2}^2 + \cdots + x_{im}^2} \times \sqrt{x_{j1}^2 + x_{j2}^2 + \cdots + x_{jm}^2}} \end{aligned} \quad (5)$$

In (5), the similarity is defined as the cosine value for the angle between the vectors. That is, if the two vectors have similar values then they will be 1 which leads to the cosine value of the angle 0. In the other hand, if the vectors have totally different values, they will point to opposite directions and the cosine value will be -1 (=cos (π)). Therefore, if the estimated similarity has a value close to 1, it can be considered that they are homogeneous agents. If the value is close to -1, it can be inferred that they are heterogeneous agents. Let’s review the example mentioned above. $f_v(a_1)$, $f_v(a_2)$ and $f_v(a_3)$ are each <-10, 10>, <10, 2>, <5, 5> respectively. According to (5), $S(a_1, a_2)$, $S(a_1, a_3)$ and $S(a_2, a_3)$ have a value of -0.55, 0 and 0.83 respectively. We can infer that agent a_1 is very different from agents a_2 and a_3 because $S(a_1, a_2)$ and $S(a_1, a_3)$ are low, while agent a_2 and a_3 are very similar to each other because and $S(a_2, a_3)$ is high.

B. Forces Applied to Each Agent

In order to simulate scattering of heterogeneous agents, a new steering force is required. It is needed to make agents naturally scatter with homogeneous species together. This paper utilizes the similarity mentioned above to create the steering force needed. These new steering forces can be determined into two categories. One is to operate attractive force between similar agents in order to gather homogeneous agents. The other is to operate repulsive force between relatively less similar agents so that heterogeneous agents separate. There are various ways to define attractive and repulsive force. In this paper, Newton’s law of gravity is adopted as the following.

$$f_p(a_i) = \sum_{\forall a_j \subseteq V_i} [S(a_i, a_j) - \alpha] \frac{a_i.pos - a_j.pos}{|a_i.pos - a_j.pos|^l} \quad (6)$$

In (6), if $f_p(a_i)$ has a negative value, it indicates repulsion force and in the case of positive values it represents attractive force. If the value of α has less than -1, $f_p(a_i)$ always maintains a positive value and thus operates attraction force, since $|S(a_i, a_j)|$ is always less than 1 according to (5). On the contrary, if the value of α is larger than 1, repulsion force is operated. If value of α equals to 0, $f_p(a_i)$ has a possibility of 50 % to operate either attraction or repulsion force. If the value of α is 0.7, the value of $|S(a_i, a_j)|$ is between -1.7 and 0.3 and so the possibility that $f_p(a_i)$ will operate 15 % as attraction force or 85 % as repulsion force. Thus, by appropriately setting the value of α, it is possible to control the rate of attraction and repulsion force. In the next chapter, we will observe changes in flocking depending on the value of α. In (6), the value of l must be determined by the characteristics of gathering and scattering of the given agents. In order to make heterogeneous agents flock, the total force $F(a_i)$ that is applied to a_i must be separation force, alignment force, cohesion force, attraction force and repulsion force. The following equation is the equation about the force totally applied to agent a_i.

$$F(a_i) = c_s f_{ps}(a_i) + c_c f_c(a_i) + c_a f_a(a_i) + c_p f_p(a_i) \quad (7)$$

In (7), c_s, c_c, c_a, and c_p are a constant number that represents weighting factor about separation force, alignment force, cohesion force, attraction and repulsion force. Those values must be experimentally found so that they express the animal’s characteristics in order to simulate a specific animal. For instance, “sparrows” flock in relatively dense areas and so the value of c_s must be small. In the other hand, “pigeons” flock in rather extensive areas leaving the value of c_s to be very large.

IV. Simulations

A simulation has been conducted in order to confirm that flocking of heterogeneous agents based on the proposed similarity works appropriately. As preprocessing of the simulation, values of c_s, c_c, c_a, and c_p have been determined throughout various experiments. The values of k and l in (1) and (6) are set to 3 and 1.5 respectively. These various constant values are normally determined by a number of experiments. In order to simplify the simulations, properties of the feature vector are limited to “species” and “magnitude”. The “species” property refers to carnivorous, herbivorous and omnivorous discriminations. The “magnitude” property is measured by setting a certain limit – which will be 1*m* in this case – and give positive values when it is larger than 1*m*, negative values when it is smaller than 1*m*. We created 128 agents for the simulation and distributed them to have the feature vectors like Fig. 2. We randomly placed them into any one of the four types of the feature vector. The important part of this simulation is that agents belonging to same types do not have identical value of the feature vector, but have only similar values. For example,

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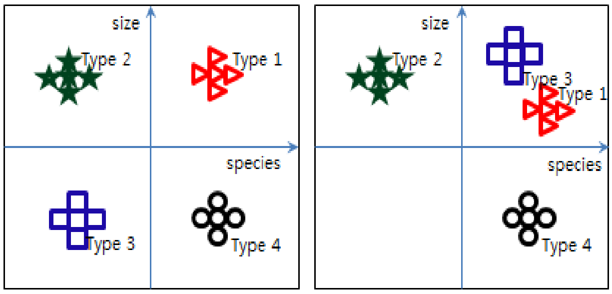
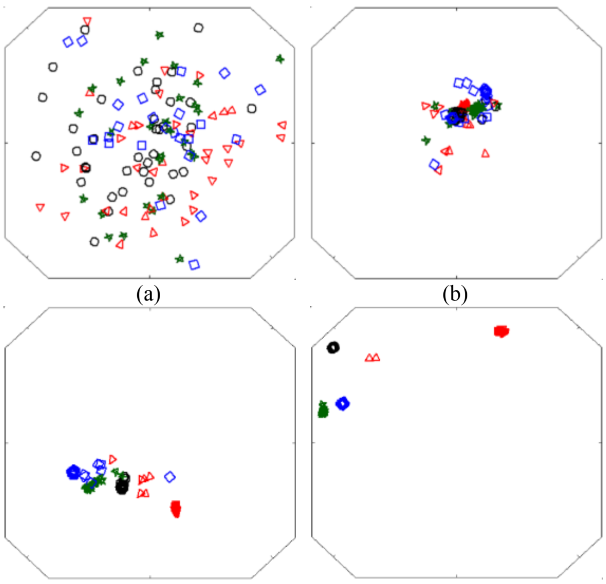
consider that there are two agents a_{21}, a_{22} that belong to type 2 and two other agents a_{41}, a_{42} that belong to type 4. And assume that a_{21}, a_{22}, a_{41} and a_{42} have <-1, 3>, <-2, 1>, <-1, 1> and <-1, 2> as the feature vector respectively. Then, a_{21} has more similarities with a_{22} than a_{41} because $S(a_{21}, a_{22})$ is high and $S(a2_1, a_{41})$ is low.



(a) (b)

Fig. 2 Types of agents by different features: (a) 4 types with four different features, (b) 4 types with three different features, where the type 1 has a high similarity with type 3

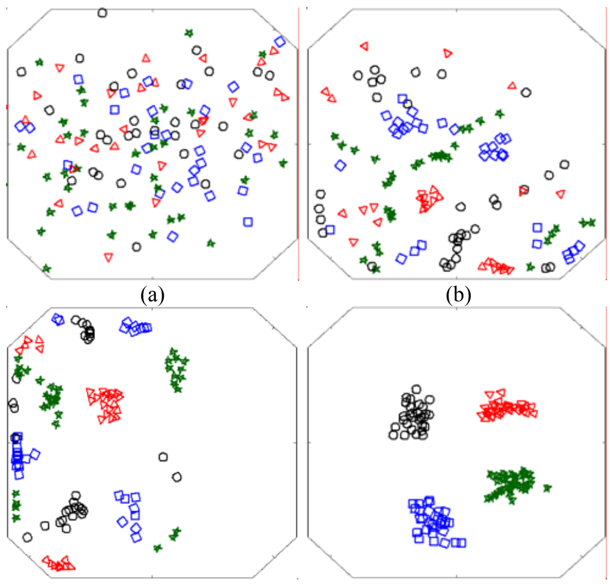


(a) (b) (c) (d)

Fig. 3 Simulation of heterogeneous agents with attraction force, where agents distributed with four different features like Fig. 2-(a) and α = -1: (a) distribution of agent at start, (b) distribution of agent after 5sec, (c) distribution of agent after 10 sec, (d) distribution of agent after sufficient time

The first experiment is to comprehend the differences in flocking depending on attraction and repulsion forces. In order to do so, we determined their feature vector by random functions so that the 128 agents are divided into 4 groups and that they are dispersed like Fig. 2-(a). On these agents, we set -1 or 1 as the value of α in order to operate attraction and repulsion force. Fig. 3 and Fig. 4 are each images of flocking by agents depending on attraction and repulsion force. As shown in (b) of Fig. 3 and Fig. 4, the characteristics observed after 5 seconds are totally distinguishable in the two cases. In Fig. 3, where attraction force is operated, agents with similar value of the feature vector gather rapidly to instantly form a group. Especially as time gradually passes, homogeneous agents gather and form a shape of a “large single agent”. It looks like as if there is one large agent. This is because the attraction force in (6) is larger than the separation force in (1). In Fig. 4, we can see that homogeneous agents slowly gather and form a group. Noticeable flocking is not observed in 5 seconds, but after 10 seconds the obvious flocking can be observed. As time passes, it is clear that homogeneous agents move towards their group.

The difference of flocking shown in Fig. 3 and Fig. 4 is the density. That is, contrary to the dense density observed when attraction force is operated just like in Fig. 3, repulsion force forms a relatively sparse group like those in Fig. 4. The results of simulation are very similar to those of [12]. It is similar to the results of simulating 4 targets (in this paper, “types”) in [12]. However, [12] is unable to control density, but the method proposed in this paper enables the control of density just by simply modifying the value of α.



(a) (b) (c) (d)

Fig. 4 Simulation of heterogeneous agents with repulsive force, where agents distributed with four different features like Fig. 2-(a) and α = 1: (a) distribution of agent at start, (b) distribution of agent after 5sec, (c) distribution of agent after 10 sec, (d) distribution of agent after sufficient time

The second experiment focuses on flocking of analogous species when agents belonging to type 3 have the feature vector similar to type 1. The results are shown on Fig. 5. This experiment fixes the value of α to 0.7. This is to observe cases where attraction and repulsion forces are mixed together. Like shown in Fig. 5-(a), the primary stage is similar to Fig. 3 and 4. However if you look at Fig. 5-(b), which is 5 seconds after the start, you can see a distinct difference with Fig. 3-(b) and 4-(b). If you see the right upper part where a circle is placed, you can see that agents belonging to types 1 and 3 are forming a group. In the left upper circle of picture 5-(c), it is more obvious that the two different types of agents are forming a group. What is peculiar is that even though they form a group with other types, inside that group they do not mix but form another group with identical types. This is similar to the left lower part of Fig. 1, that is, even if impala and elephant form a group, they are divided into two subgroups within the group. This phenomenon is more noticeable in Fig. 5-(d). In the circle of Fig. 5-(d), you can observe that agents of type 1 and 3 form a group but the left part of the circle is formed by agents of type 3(marked as a triangle) and the right part of the circle is formed by agents of type 1(marked as a square). The results are perfectly discriminated from [12]. In [12], targets can have absolutely no relation with other targets. Thus, it is impossible to control two different types to form a group with the methods suggested in [12]. The proposed method is possible only because groups are divided by similarities, and operated by different forces depending on similarities.

Another phenomenon observed through this experiment is that the groups of Fig. 5 are less dense than those of Fig. 3, and much denser than those of Fig. 4. This proves that density can be controlled in ways such as mixing attraction and repulsion force by manipulating the value of α.

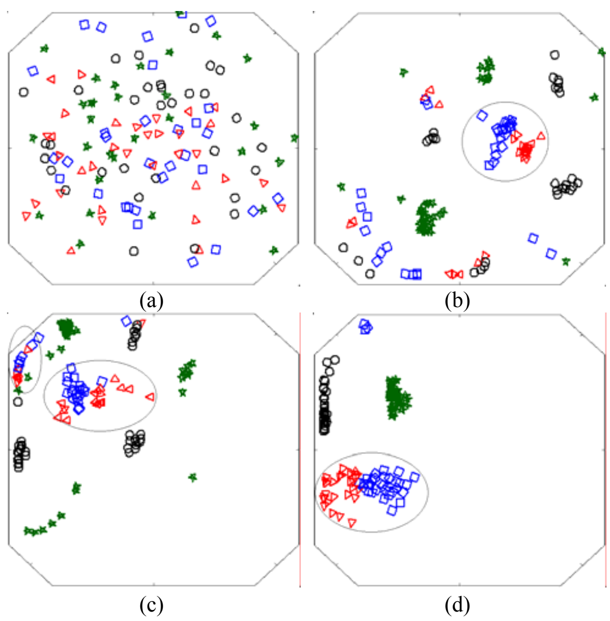


Fig. 5 Simulation of heterogeneous agents with three different features, where agents distributed with three different features like Fig. 2-(b) and α = 0.7: (a) distribution of agent at start, (b) distribution of agent after 5sec, (c) distribution of agent after 10 sec, (d) distribution of agent after sufficient time

V. Conclusion

Most of researches for conventional flocking simulation have focused on studying homogeneous agents. However in real-life flocking and other situations, homogeneous flocking does exist, but the heterogeneous flocking is not a rare sight, but frequently observed. This paper is a study about simulating heterogeneous agents flocking in spaces. In order to do so, instead of grouping agents by the identifier, we have defined the feature vector of an agent and compared them to estimate their similarities. We have also suggested new steering force based on similarities such as attraction and repulsion force. We have also conducted experiments applying all of our suggestions. Results have showed that both cases are able to naturally form multiple flocking. However, we were able to observe that the process and the consequences of the two cases were very different, and we will be able to selectively choose the results according to the environments to simulate.

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