Group Chase and Escape of Biological Groups Based on a Visual Perception-Decision-Propulsion Model

JINGTAO QI, LIANG BAI, YANDONG XIAO, WANSEN WU, AND LU LIU

ABSTRACT A relatively simple and local interaction between individuals produces coordinated and ordered collective behaviors that are widespread at all levels of biological groups. Group chase and escape is an important aspect in the field of collective behavior, particularly in regard to predation events in species interactions. Compared with other aspects of collective behavior, less research has been performed on this aspect, and the existing models are constructed only from the phenomenological perspective. We present an individual-based model named Visual Perception-Decision-Propulsion to explore the group chase and escape of biological groups and define several evaluation indicators to assess different aspects of this problem. Within this model, 2 types of self-propulsion individuals, i.e., predators and prey, are considered, and we consider the alignment and repulsion term between homogeneous individuals. Chase and escape are described as the escape (or chase) term between heterogeneous individuals. Based on the model, we identify and distinguish between 2 capture patterns, i.e., cooperative capture and separative capture. Then, we control the internal parameters to analyze the condition of these 2 patterns for production, and the external empirical parameters are adjusted to explore their effect on these 2 patterns. Hence, this paper provides a novel model for group chase and escape based on biological vision to compensate for the shortcomings of classical models and help apply the characteristics of biological groups to human-made swarm systems in the case of confrontation.

INDEX TERMS Collective behavior, visual perception, group chase and escape.

I. INTRODUCTION

Collective behavior, which is widespread at all levels of biological groups, is fascinating to most of us [1]. Related topics include shoals of fish [2]–[8], flocks of birds [9], [10], swarms of locusts [11]–[13], communities of bacteria [14], [15], groups of microtubules [16], masses of histiocytes [17], [18], streams of traffic and flows of humans [19], [20]. A relatively simple and local interaction between individuals produces coordinated and ordered collective behaviors such as these [21]. In this way, biological groups show various intelligent characteristics (distribution, self-adaption, and robustness) that cannot be achieved by a single individual in all kinds of situations. A conspicuous behavioral pattern [22] (e.g., aggregation, obstacle avoidance, group chasing and escaping [23]) is observed as a cohesive and highly coherent group. Research in this field is required to explain the complex emergent behaviors that are similar to the above patterns at the individual and group levels and to further apply these intelligent characteristics shown by biological groups to human-made swarm systems. Therefore, as an interdisciplinary subject, collective behavior modeling and mechanism exploration is a challenging area of focus.

Several models (e.g., the rule-based model, the random rotation model, and the Boids model) have been proposed to research collective behavior during the last several decades. The classical models of collective behavior are based on 3 simple behavioral rules [1]: separation (avoiding crowding local neighbors), alignment (steering toward the average heading direction of neighbors) and cohesion (moving toward the average position of neighbors), and this type of model was originally considered to demonstrate the quantitative and qualitative collective behavior observed in fish and birds. The random rotation and Boids models, which belong to this type of model, were presented by Aoki [24] and Reynolds [25], respectively. As a special case of the Boids model, the Vikesk
model [26], proposed by a physicist, takes the velocity alignment between individuals into consideration to explore the simplest conditions for collective behavior. Later, the Couzin model [27], developed by a biologist, was widely used in theoretical biology and extended to the coordinated control of swarm robotics.

The aforementioned models constructed from a phenomenological perspective have been basically mature in recent years. In these models, individuals follow 3 simple behavioral rules to interact with neighbors based on their positional and velocity information. However, these models narrowly focus on the understanding of decision and propulsion mechanisms while neglecting the understanding of perception mechanisms, which is a vital link between animal flocks and human-made swarm systems. Therefore, such approaches seriously hinder our understanding of the inherent complexity of collective behavior. In the field of sensory neuroscience, the recognition and research of visual perception are penetrating deeply and have made some new progress. Geisler and Albrecht [28] demonstrated that edge detection is performed in the visual cortex of higher animals. Since this discovery, numerous researchers have increasingly explored collective behavior based on visual projection from the perspective of sensory neuroscience, which is a promising direction for explaining the complex behavioral patterns shown by various biological groups. In the case of fish groups, Strandburg-Peshkin et al. [29] found that the structural features of visual interaction networks are different from those of measurement and topology by analyzing individual motion with visual perception information. Rosenthal et al. [30] revealed the nature of social contagion and provided full evidence of the feasibility of predicting complex cascades of behavioral changes by calculating the visual field of individuals. When the research objective was a group of birds, the simplest hybrid projection was presented by Pearce et al. [31] to provide a method for density control. For human crowds, Moussaïd et al. [32] reproduced the self-organization phenomena and crowd turbulence that have been observed during crowd disasters, guided by visual information. In the case of human-made swarm systems, Lavergne et al. [33] applied the principle that motility changes in individuals in response to visual perception in a real system to achieve the formation and cohesion patterns of collective behavior. Schilling et al. [34] achieved a vision-based flock based on a convolutional neural network.

Group chase and escape is an important aspect in the field of collective behavior, particularly in predation events in species interactions. Such problems often involve 2 types of individuals (predators and prey). For predators, their objective is to locate and catch the prey as quickly as possible. Conversely, the objective of prey is to escape and avoid getting captured. Related problems have been studied for a long time [35]; however, the extant studies on this problem are less common than those on other problems of collective behavior. Initially, mathematical tools (e.g., game theory and geometry) were used to study such problems [36], [37], but these methods lack relevant attributes (e.g., noise). Later, Kamimura and Ohira [38] defined a cost function to determine the optimal number of predators for a given number of prey. Angelani [23] proposed a simple individual-based model based on the Vicsek model and found two catch regimes. The model comprises 3 behavioral interactions: alignment and separation between homogeneous individuals and chase (or escape) between heterogeneous individuals. Matsumoto et al. [39] introduced new parameters to a simple group chase and escape model and classified the configurations of chasing and escaping in groups into three characteristic patterns. Yang et al. [40] introduced three aggregation strategies for predators and showed that the aggregation of predators increases the survival time of prey. Using a set of local interaction rules, Janosov et al. [41] considered time delay, external noise and limited acceleration to research the situation of predators chasing a much faster prey and showed how that group chase can significantly enhance the rate of capture.

According to the above research, more effective methods are needed in the field of collective behavior, and only a few studies consider group chase and escape. To study the internal mechanisms of group chase and escape and provide assistance for the construction of human-made swarm systems in the case of confrontation, we propose an individual-based model named Visual Perception-Decision-Propulsion to study the group chase and escape of biological groups. The major contributions of this paper are summarized as follows.

1) The Visual Perception-Decision-Propulsion model is proposed to explore the group chase and escape of biological groups and focuses on the process of perception represented by edge detection from a sensory neuroscience perspective. In addition, we clearly define several evaluation indicators used to evaluate the behavior of group chase and escape.

2) We prove that the model effectively achieves group chase and escape and find 2 capture patterns (cooperative capture and separative capture). For cooperative capture, multiple predators maintain a relatively long distance from one another to surround prey and approach to capture prey. In contrast, for separative capture, predators are separative, and prey are captured by a single predator. Additionally, we monitored the change in the number of clusters of predators when predation occurred to distinguish these 2 patterns.

3) The internal and external parameters are controlled to analyze these 2 patterns. We can observe cooperative capture when the effect of the repulsion term is moderate and smaller than the chase term, and it shows a better effect with relatively large number of predators and a large interaction range. The separative capture was achieved under the condition that the effect of self-propulsion and alignment term and the effect of repulsion term are balanced and the effect of escape term is small. Relatively large number of predators
are also required to catch quickly for separative capture, but they need either a small or large interaction range, which is different from the cooperative capture.

The remainder of this paper is organized as follows. In Section II, an individual-based Visual Perception-Decision-Propulsion model is presented to model the group chase and escape of biological groups. Based on this approach, in Section III, we define several evaluation indicators that are used to assess the behavior of group chase and escape. To further verify and explore our model, numerical experiments are performed, and the results are presented in Section IV. Our conclusions and a final discussion are provided in Section V.

II. THE VISUAL PERCEPTION-DECISION-PROPULSION MODEL

Group chase and escape are complex and unique in biological groups. It is notable that patterns are shown during predation events in species interactions. The movement of individuals in biological groups involves the following 3 processes: perception, decision and propulsion. For the perception process, individuals obtain the positional and velocity information of their neighbors. The decision process is the key link between the perception and propulsion processes and the appropriate action (e.g., acceleration, deceleration, and turning left and right) chosen by individuals to update their velocity based on the perception information in the decision process. The perception and propulsion processes are considered input and output by the decision process, respectively. During the propulsion process, individuals move at an updated velocity transferred from the decision process. Therefore, to explore the mechanism of group chase and escape, an abstracted and representative model is critical. In this section, an individual-based Visual Perception-Decision-Propulsion model is presented to characterize this problem. The flow of the model is given as follows.

Algorithm 1 The Visual Perception-Decision-Propulsion Model

Input:

- Positions of individuals in the last moment, \( \mathbf{r}(t-1) \);
- Velocities of individuals in the last moment, \( \mathbf{v}(t-1) \);

Output:

- Positions of individuals in the current moment, \( \mathbf{r}(t) \);
- Velocities of individuals in the current moment, \( \mathbf{v}(t) \);

1: The perception process: obtaining the velocity information (\( \mathbf{v}_j(t), j \in S^d_i \)) and visual information (\( \hat{\theta}_i^{rep} \) and \( \hat{\theta}_i^{CT} \)), as shown in Fig. 1;
2: The decision process: calculating the change in \( \mathbf{v}_i^{int}(t) \) for each individual based on Eq. 1;
3: The propulsion process: calculating \( \mathbf{r}(t) \) and \( \mathbf{v}(t) \) for each individual based on Eq. 7;
4: return \( \mathbf{r}(t) \) and \( \mathbf{v}(t) \).

A. PERCEPTION

We consider 2 groups of organisms: predators (or chasers C) and prey (or targets T). The number of predators \( N_C \) is constant in the simulation, while \( N_T \) is the number of prey that can decrease over time because of the occurrence of predation events. Individuals are described by their position \( \mathbf{r} \) and velocity \( \mathbf{v} \) vectors in 2 dimensions. We consider \( N = N_C + N_T(0) \) individuals as round with radius \( BL \) and perform a simulation in a square box with periodic boundary conditions. The length of this box (\( L \)) depends on the density \( \rho \), \( N_C \) and the number of initial prey \( N_T(0) \), and not change as prey are captured; that is, \( L = \sqrt{(N_C + N_T(0))/\rho} \).

For the perception process, individual \( i \) obtains the velocity and visual information of other individuals. The self-propulsion and alignment term obtains the velocity information of individuals of the same group (including individual \( i \)) within a round range of radius \( r_0 \) surrounding individual \( i \) (Fig. 1A); that is, \( \mathbf{v}_j(j \in S^d_i) \). The visual information of individuals of the same and different groups within this range (Fig. 1B and C) is obtained for the repulsion and escape (or chase) term. The visual information is reasonably represented as \( \theta_i \) by performing edge detection, which is demonstrated to be performed in the visual cortex of higher animals [28, 31]. However, it is difficult to reproduce the visual perception of organisms in the real world. Therefore, we calculate the edge detection of each individual as an interval of an angle based on the positional information and then consider the overlapping of the visual information of different individuals to obtain the union of these intervals, the boundaries of which are used to approximate the result of edge detection.

B. DECISION

Based on the perception information, we consider the self-propulsion and alignment term (\( \mathbf{v}_i^{al} \)), repulsion term (\( \mathbf{v}_i^{rep} \)) and escape (or chase) term (\( \mathbf{v}_i^{CT} \)) to define the decision equation as

\[
\mathbf{v}_i^{int}(t + \Delta t) = \phi_{al} \mathbf{v}_i^{al}(t) + \phi_{rep} \mathbf{v}_i^{rep}(\theta_i^{rep}, t) + \phi_{CT} \mathbf{v}_i^{CT}(\theta_i^{CT}, t).
\]  

(1)

where \( \mathbf{v}_i^{int} \) is a unit vector, hat (‘\( \hat{\cdot} \)’) denotes a normalized vector, and the coefficients in all terms are taken to obey

\[
\phi_{al} + \phi_{rep} + \phi_{CT} = 1. 
\]  

(2)

The self-propulsion and alignment term (Fig. 1A) that takes the velocity information obtained in the perception process as the input considers inertia and intragroup interactions to reproduce the coherence of biological groups by accumulating the velocity vector, and its definition is as follows:

\[
\mathbf{v}_i^{al}(t) = \sum_{j \in S^d_i} \mathbf{v}_j(t).
\]  

(3)

The repulsion term (Fig. 1B) that takes the visual information obtained in the perception process as the input considers
intragroup interactions to avoid crowding local neighbors and
is defined as

\[ v_i^{rep}(t) = -\sum_{j=1}^{N_i^{rep}} \frac{\theta_i^{rep} - \theta_{ij,0}}{2 \sin \theta_i^{rep} + \theta_{ij,0}} \left[ \frac{\cos \left( \theta_i^{rep} - \theta_{ij,0} \right)}{2} \right] \]  

(4)

Similarly, the escape (or chase) term (Fig. 1C), which takes the visual information obtained in the perception process as the input to make prey move away from predators and avoid getting captured (predators get closer to prey and catch them), considers intergroup interactions and is defined as

\[ v_i^{CT}(t) = p \sum_{j=1}^{N_i^{CT}} \frac{\theta_i^{CT} - \theta_{ij,0}}{2 \sin \theta_i^{CT} + \theta_{ij,0}} \left[ \frac{\cos \left( \theta_i^{CT} - \theta_{ij,0} \right)}{2} \right] \]  

\[ p = \begin{cases} +1 & \text{individual } i \text{ is a predator} \\ -1 & \text{individual } i \text{ is prey.} \end{cases} \]  

(5)

The last 2 terms in Eq. 1 use projections of the central unit vector of the occlusion area of the visual field (cos \( \frac{\theta_i^{CT} + \theta_{ij,0}}{2} \) and sin \( \frac{\theta_i^{CT} + \theta_{ij,0}}{2} \)) to characterize the effect of direction on velocity. The closer the distance between individuals is, the wider the angle of the occlusion area of the visual field. Therefore, the angle of the occlusion area also reflects the distance between individuals, and we take a weighted average of the angle of the occlusion area to characterize the effect of distance.

C. PROPULSION

The propulsion process is taken as output by the decision process. We assume that the velocity magnitude of individuals is constant and focus only on the change in the velocity direction of individuals. Predators and prey move at constant velocity magnitudes \( v_c \) and \( v_r \), respectively. Based on the above description, the positions and velocities of individuals are considered to be updated based on the studies of Chaté et al. [42] in the following propulsion equation:

\[ r_i(t + \Delta t) = r_i(t) + v_i(t + \Delta t)\Delta t \]  

\[ v_i(t + \Delta t) = \begin{cases} v_c \hat{v}_c^{rep}(t + \Delta t) & \text{individual } i \text{ is a predator} \\ v_r \hat{v}_r^{rep}(t + \Delta t) & \text{individual } i \text{ is prey.} \end{cases} \]  

(6)

where \( \Delta t \) is the unit time, and we set the upper limit of time \( t = t_{\text{total}} \). Additionally, if any predators are closer than the radius of capture area \( r_c \) to prey, then the prey is captured and eliminated.

III. EVALUATION INDICATORS

According to the above Visual Perception-Decision-Propulsion model, we define the following indicators that represent different aspects of group chase and escape. The prey may be eliminated during the simulation; therefore, we monitor only the following indicators for the group of predators.

For the research on group chase and escape, the indicator total catch time \( t_{\text{total}} \) when all prey are captured (\( N_i(t) = 0 \)) is necessary to assess the quality of capture for the predators and the prey. When \( t = t_{\text{total}} \) or \( t = t_{\text{max}} \), the simulation is stopped.

We set indicator \( \bar{v}_c \) to assess the coherence of predators, which is frequently described by the absolute value of the
average normalized velocity:

\[
\bar{v}_e = \frac{1}{N_c v_c} \sum_{i=1}^{N_c} v_i(t)
\]  

(7)

The closer \( r_c \) approaches 1, the better the coherence of the group. However, for the group chase and escape, predators chase different prey, which perform as several clusters. Therefore, it is necessary to monitor the number of connected clusters of predators \( N_{c\text{cluster}} \). To define clusters, we defined a network of interactions that contains the predators (nodes) and edges. An edge exists between 2 predators if they are closer to each other than \( r_0 \). Hence, \( N_{c\text{cluster}} \) is the number of connected components of the network of predators.

To assess the cohesion of predators, we present the average closest neighbor distance \( d_{c\text{min}} \), as given below.

\[
d_{c\text{min}} = \frac{1}{t_{\text{end}}} \sum_{t=1}^{t_{\text{end}}} \min_{i=1,j=1,i\neq j} d_{ij}(t),
\]  

(8)

where \( d_{ij}(t) \) is the distance between predators \( i \) and \( j \).

### IV. CASE STUDY

To evaluate the quality of the group chase and escape, we conduct a number of experiments to analyze the model based on the above evaluation indicators. At the beginning of each experiment, we randomly place individuals with a random velocity direction \( (v_i = v_0[\cos \psi_i, \sin \psi_i]^T, \psi_i \in [-\pi, \pi]) \) into a square box of length \( L \) with periodic boundary conditions. In our simulation, we fix 6 parameters and control for the other parameters (Table 1). We first show 2 capture patterns and distinguish them by monitoring the evaluation indicators. Then, we evaluate the influences of 3 internal parameters to explain the cause of these patterns. Finally, 2 external empirical parameters are controlled to analyze their influences on these patterns.

### A. CAPTURE PATTERNS

The model achieves 2 capture patterns, i.e., cooperative and separative capture, under different parameters, as shown in Fig. 2. We show the cooperative capture with \( \phi_{al} = 0.15 \), \( \phi_{rep} = 0.35 \) and \( \phi_{CT} = 0.5 \), and the separative capture is performed with \( \phi_{al} = 0.5 \), \( \phi_{al} = 0.45 \) and \( \phi_{CT} = 0.05 \). Fig. 2A and B indicate the 2 patterns with \( r_0 = 10 \), \( N_c = 8 \) and \( N_i(0) = 1 \). Additionally, we also conduct another experiment with \( r_0 = 10 \), \( N_c = 18 \) and \( N_i(0) = 18 \) and monitor indicators \( N_i(t)/N_i(0) \) and \( N_{c\text{cluster}}/N_c \) for the 2 patterns (Fig. 2C and D). In reality, predators cooperate to surround and capture prey when the prey is relatively larger in size than are they. The model achieves this pattern as cooperative capture. With moderate \( \phi_{rep} \), multiple predators keep a relatively long distance from each other to surround prey and approach to capture prey because of large \( \phi_{CT} \) and \( \phi_{CT} > \phi_{rep} \) (Fig. 2A). In the case of separative capture, \( \phi_{al} \) accounts for a large proportion, so the group of predators performs with better coherence. However, since the self-propulsion and alignment term contains self-propulsion, that is, the inertia of the individual when moving, even if the escape term exists, the prey cannot escape in time and will be captured by a single predator (Fig. 2B). Moreover, predators are separative due to large \( \phi_{rep} \), which makes it more probable that the prey will be captured by a single predator. This pattern corresponds to the situation in which predators attempt to catch a small animal in reality. Comparing the indicators \( N_i(t)/N_i(0) \) and \( N_{c\text{cluster}}/N_c \) of the 2 patterns (Fig. 2C and D), we find that the value of \( N_{c\text{cluster}}/N_c \) of the cooperative capture is smaller than that of separative capture. In addition, with the occurrence of capture events, the value of \( N_{c\text{cluster}}/N_c \) of the cooperative capture increases stably after first descending. Multiple predators come together from different directions to form a cooperative capture. Once the prey is captured, it is eliminated. Therefore, the chase term no longer works, and the repulsion term is dominant, which leads to the predators dispersing in all directions and finding new prey. Inside, the value of \( N_{c\text{cluster}}/N_c \) of separative capture is almost unchanged. The results suggest that our model reproduces predation events as cooperative and separative capture.

### B. INTERNAL PARAMETERS

Under the combination of different internal parameters (\( \phi_{al}, \phi_{rep} \) and \( \phi_{CT} \)), we conduct 50 experiments with fixed parameters (\( r_0 = 5 \), \( N_c = 50 \) and \( N_i(0) = 50 \)) and monitor the indicators \( t_{\text{end}}, N_{c\text{cluster}}, v_c \) and \( d_{c\text{min}} \), as shown in Fig 3. The 2 blue areas in Fig. 3A correspond to the 2 capture patterns in Fig. 2, where the large blue area at the top is cooperative capture, and the small blue area at the bottom is separative capture. In the case of cooperative capture, fixing \( \phi_{al}, \phi_{rep} \) increases, we find that \( N_{c\text{cluster}}/N_c \) and \( d_{c\text{min}} \) increase; that is, predators become sparser, and \( t_{\text{end}} \) of cooperative capture rises at the beginning and then decreases. When \( \phi_{rep} \) is too small, the distance between predators becomes narrow, and thus, they cannot surround prey, which is in line with the finding of Yang et al., in which the aggregation of predators increases the survival time of prey [40]. In contrast, predators cannot get close to prey to reach the capture range even if they can surround the prey when \( \phi_{rep} \) is too large. When \( \phi_{rep} \) is moderate and \( \phi_{rep} < \phi_{CT} \), predators can surround and approach prey to...
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FIGURE 2. Patterns of group chase and escape with fixed parameters ($r_0 = 10$). The red and blue disks are predators and prey, respectively. The corresponding red and blue arrows are their velocity directions. (A) The pattern of cooperative capture in 5 moments ($N_c = 8, N_t(0) = 1, \phi_{al} = 0.15, \phi_{rep} = 0.35$ and $\phi_{CT} = 0.5$). (B) The pattern of separative capture in 5 moments ($N_c = 8, N_t(0) = 1, \phi_{al} = 0.5, \phi_{rep} = 0.45$ and $\phi_{CT} = 0.05$). (C and D) Comparison of cooperative capture ($N_c = 18, N_t(0) = 18, \phi_{al} = 0.15, \phi_{rep} = 0.35$ and $\phi_{CT} = 0.5$) and separative capture ($N_c = 18, N_t(0) = 18, \phi_{al} = 0.5, \phi_{rep} = 0.45$ and $\phi_{CT} = 0.05$) with the timeline of $N_{\text{cluster}}/N_c$ and $N_t(t)/N_t(0)$. The blue and orange curves show $N_{\text{cluster}}/N_c$ and $N_t(t)/N_t(0)$, respectively. The gray areas represent the example for the occurrence of capture events.

C. EXTERNAL EMPIRICAL PARAMETERS

In nature, the predation between different species corresponds to different external experience parameters (the ratio of the number of predators to prey $N_c/N_t(0)$ and the radius of the interaction area $r_0$), so we control for them and perform 50 experiments to explore cooperative capture ($\phi_{al} = 0.15, \phi_{rep} = 0.35$ and $\phi_{CT} = 0.5$) and separative capture ($\phi_{al} = 0.5, \phi_{al} = 0.45$ and $\phi_{CT} = 0.05$). We control for $N_c/N_t(0)$ with $r_0 = 5$ and $N_t(0) = 10$ and control for $r_0$ with $N_c = N_t(0) = 50$. As shown in Fig. 4, we analyze the role of these parameters in the 2 patterns based on indicators $t_{\text{end}}$ and $N_{\text{cluster}}/N_c$. With the increase in $N_c/N_t(0)$, cooperative and separative capture show better effects (Fig. 4A and B). In the case of cooperative capture, the larger the number of predators is, the better they surround the prey and leave it...
FIGURE 3. Results of different evaluation indicators for simulations with 50 predators and 50 prey under different internal parameters ($\phi_{\text{al}}, \phi_{\text{rep}}$ and $\phi_{\text{CT}}$) of the Model. (A to D) Under the fixed parameter $r_0 = 5$, evaluation indicators $t_{\text{end}}, N_{\text{cluster}}/N_c, \tau_c$, and $d_{\text{mean}}$ are observed as functions in the ternary plot of $\phi_{\text{al}}$ (red axis), $\phi_{\text{rep}}$ (green axis) and $\phi_{\text{CT}}$ (blue axis) in simulation. The values of these indicators correspond to color, which is shown as a color bar on the right.

With less space to escape. However, when $N_c/N_t(0)$ increases to a certain number, the predators will surround the prey, and the effect will optimal. That is, increasing the number of predators cannot reduce the time required to capture prey. When $N_c/N_t(0)$ is small, the number of predators is insufficient. To achieve cooperative capture, predators can capture prey only one by one. Therefore, an increase in predators in this situation means an increase in $N_c$ and a decrease in $N_{\text{cluster}}/N_c$. In contrast, when $N_c/N_t(0)$ is large, predators can capture prey at the same time. An increase in predators leads to an increase in $N_{\text{cluster}}/N_c$ in this case. $\rho$ and $N_t(0)$ are constant; therefore, the density of predators increases (Eq. 10). For this reason, separative capture performs better with the increase in $N_c/N_t(0)$ because of the increase in the probability of predation, and $N_{\text{cluster}}/N_c$ decreases with the increase in $N_c/N_t(0)$.

$$\rho_c = \frac{N_c}{L^2} = \frac{N_c}{N_c + N_t(0)} \rho$$  \hspace{1cm} (9)

With the augmentation of $r_0$, the $t_{\text{end}}$ of cooperative capture decreases because predators have an effect on remote prey, surround them and then approach to capture. Because $\phi_{\text{CT}}$ is greater than $\phi_{\text{rep}}$, the chase term makes the predators become more aggregative when multiple predators perceive the same prey at the same time. Additionally, $r_0$ is used to construct the interaction network of predators to define clusters, so the increase in $r_0$ will also make predators more aggregative. For separative capture, although predators can surround prey, $\phi_{\text{rep}}$ is greater than $\phi_{\text{CT}}$, so they disperse before the capture condition is achieved. Therefore, when $r_0$ is small, multiple predators can approach the prey without the effect of the repulsion term, and as the interaction range increases, the prey can perceive remote predators and take action earlier to avoid capture. However, when $r_0$ is large, prey perceive too many predators, so they are confused and cannot choose a good direction to escape.

In this case, because the definition of cluster is related to $r_0$, $N_{\text{cluster}}/N_c$ increases. From the above analysis, cooperative capture shows a better effect with relatively large number of predators and a large interaction range. Similarly, relatively large number of predators are required to catch quickly for separative capture, but they need a small or large interaction range, which is different from the requirements of cooperative capture.
V. CONCLUSION

Group chase and escape is an important aspect in the field of collective behavior, particularly in predation events in species interactions. Two types of individuals, i.e., predators and prey, are the main research objects. Predators attempt to catch prey as soon as possible, while prey attempt to escape to avoid being caught. On the one hand, the research on this topic can help us understand biological species interactions, and on the other hand, we can construct human-made swarm systems with biological characteristics in the case of confrontation based on a deep understanding of the collective behavior of biological groups. Compared with other aspects of collective behavior, less research has been performed on this aspect, and the existing models are constructed only from the phenomenological perspective. The models focus on the decision and propulsion process of biological groups, but they ignore the cognition of the perception process, which is a vital link among animal flocks and human-made swarm systems. Therefore, it is necessary to attach importance to research the group chase and escape from the essence of species interactions.

To compensate for these shortcomings and provide help in constructing human-made swarm systems with biological characteristics in the case of confrontation, we propose an individual-based Visual Perception-Decision-Propulsion model to explore group chase and escape from the sensory neuroscience perspective [43], which offers a new direction in this field. This model considers the interaction between homogeneous individuals (the self-propulsion and alignment term and the repulsion term) and between heterogeneous individuals (the escape or chase term). On the basis of this model, we found 2 capture patterns of biological capture and analyzed the internal and external parameters. We can observe cooperative capture when the effect of the repulsion term is moderate and smaller than the chase term, and it shows a better effect with relatively large number of predators and a large interaction range. Our model achieves separative capture under the condition that the effect of the self-propulsion

![FIGURE 4. Results of different evaluation indicators for 2 capture patterns under different empirical external parameters ($r_0$ and $N_c/N_t(0)$). The blue and red curves indicate cooperative capture ($\phi_{al} = 0.15$, $\phi_{rep} = 0.35$ and $\phi_{CT} = 0.5$) and separative capture ($\phi_{al} = 0.5$, $\phi_{rep} = 0.45$ and $\phi_{CT} = 0.05$). (A and B) The total catch time and the number of clusters of predators are shown as functions of $N_c/N_t(0)$ with $N_t(0) = 10$ and $r_0 = 5$. (C and D) The total catch time and the number of clusters of predators are shown as functions of $r_0$ with $N_c = 50$ and $N_t(0) = 50$.]

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*Cooperative capture ($\phi_{al} = 0.15$, $\phi_{rep} = 0.35$, $\phi_{CT} = 0.5$)*

*Separative capture ($\phi_{al} = 0.5$, $\phi_{rep} = 0.45$, $\phi_{CT} = 0.05$)*
and alignment term and of the repulsion term are balanced and the effect of escape term is small. Relatively large number of predators are also required to catch quickly for separative capture, but they need a small or large interaction range, which is different from the requirements of cooperative capture.

Although the model effectively reproduces the group phase and escape of biological groups, it still has the following shortcomings. The model is constructed from the sensory neuroscience perspective. However, it still contains the alignment term, which requires the velocity information of neighbors, which is difficult to obtain in human-made swarm systems and, thus, is a quite challenging task; therefore, it clearly presents a large challenge for the construction of human-made swarm systems, and we need to improve this model based purely on biological vision in future work [44]. In our model, to reduce the parameters of the model, predators and prey make decisions based on the same Eq. 1. However, in reality, the strategy of predators is different from that of prey. In addition, we mainly focus on the capture pattern from the predator standpoint while ignoring the escape pattern from the prey standpoint, and thus, we need to improve this focus as well. Generally, theoretical models of collective behavior should be critically evaluated based on their correlation with real-world biology or human-made groups, which conforms to the purpose of the research on collective behavior. Hence, the analysis of actual biological data should be performed in the future. Furthermore, more work is required on the theoretical models to research a specific biological group and the comparison between realistic and experimental data.

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JINGTAO QI received the B.E. degree in simulation engineering from the National University of Defense Technology, Changsha, China in 2018. He is currently pursuing the M.E. degree in control science and engineering.

His current research interests include studying complex systems with a combination of theoretical tools and data analysis, modeling heterogeneous information networks, analyzing the development of complex collection intelligence based on network methodologies, exploring collective behavior driven by biological data, and modeling collective motion with a physical model.

LIANG BAI received the B.E. and B.M. degrees from Xi’an Jiao Tong University in 2002 and the M.E. and Ph.D. degrees from the National University of Defense Technology in 2005 and 2008, respectively.

He is currently a Professor with the School of System Engineering, National University of Defense Technology. His research interests include multimedia content analysis and access, particularly for video and images, big multimedia data, complex system modeling, and network analysis. He is a member of the Chinese Computer Federation.

YANDONG XIAO received the B.E. degree in information system engineering and the Ph.D. degree in system engineering from the National University of Defense Technology, Changsha, China, in 2012 and 2018, respectively.

From 2015 to 2017, he was a joint Ph.D. candidate and a Research Trainee with Harvard University, Boston, MA, USA. His research interests include complex system modeling, artificial intelligence, swarm intelligence, and interdisciplinary principles for community ecology and social networks.

WANSEN WU received the B.E. degree in simulation engineering from the National University of Defense Technology, Changsha, China, in 2018. He is currently pursuing the Ph.D. degree in control science and engineering.

His research interests include cognitive architecture and knowledge graph.

LU LIU received the B.S.Med. degree in clinical medicine and the Ph.D. degree in oncology from The Second Military Medical University, Shanghai, China, in 2008 and 2013, respectively.

Her research interests include exploring collective behavior driven by biological data and modeling collective motion with a physical model.