BSwarm: Biologically-Plausible Dynamics Model of Insect Swarms

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Figure 1: *A variety of insect swarms can be simulated by our approach: (left) a swarm of fruitflies in a huge glass box, (middle) a swarm of male flies compete for a female (the green one), and (right) a large swarm of migratory locusts passes through a village.*

Abstract

We present a biologically plausible dynamics model to simulate swarms of flying insects. Our formulation, which is based on biological conclusions and experimental observations, is designed to simulate large insect swarms of varying densities. We use a hybrid formulation that combines a force-based model to capture different interactions between the insects with a data-driven noise model, and computes collision-free trajectories. We introduce a quantitative metric to evaluate the accuracy of such multi-agent systems and model the inherent noise. We highlight the performance of our dynamics model for simulating large flying swarms of midges, fruit fly, locusts and moths. In practice, our approach can generate many collective behaviors, including aggregation, migration, phase transition, and escape responses, and we highlight the benefits over prior methods.

CR Categories: I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Virtual Reality I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation;

Keywords: insect swarm, validation, crowd simulation

1 Introduction

Collective biological behaviors are frequently observed in the real world. Such behaviors are used to characterize the coordinated behavior of large groups of similar animal. They have been well studied in computer graphics and related areas, such as social networks, artificial intelligence, sociology, and biology. Sociologists and ethologists have proposed many models to understand collective animal behaviors and these models are frequently used for character AI in computer games, virtual reality, and animation [Reynolds 1987; Funge et al. 1999]. This includes creating intelligently behaving non-player characters, generating special effects, and modeling social dynamics in multi-player games.

In this paper, we address the problem of modeling the collective behaviors and trajectories of swarms of flying insects. Insects are among the most diverse groups of animals on the planet, and there are more than a million described species representing more than half of all known living organisms. Insect swarms exhibit many collective behaviors that are different from other animals, such as aggregation, phase transition, positive phototaxis, large migration, escape response, etc. [Rauch et al. 1995; Rogers et al. 2003]. As a result, a major challenge is to develop models that can generate all these collective behaviors.

Research advances in capture technologies and high-speed imaging have yielded experimental evidence that offers new insights on how insect swarms dynamically form and evolve. It has been shown that individual insects interact via forces [Couzin et al. 2002; Puckett et al. 2014]. Another key swarm characteristic is inherent noise, which corresponds to the random movement of insects in a swarm [Buhl et al. 2006; Yates et al. 2009]. In addition, it has been shown that the insect density within a swarm can vary considerably; for example, mosquito swarms exhibit a very high density around the swarm centroid.

Main Results: We present a biologically-motivated dynamics model for insect swarms (BSwarm). Our approach is governed by biological conclusions and experimental observations. We describe a force-based model that can capture different interactions between the insects and computes a collision-free trajectory for each individual insect. We also present a novel quantitative metric for evaluating such multi-agent systems that takes into account the inherent noise in the dynamics model. The two novel components include:

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

Figure 2: *Competition for mates: (a) at first, males fly freely in a swarm; (b) the males close to the female chase her; (c) other males detect the female neighbor movements; and (d) after a period of time, most of the males found the female.*

1. Dynamics Model: Our dynamics model is based on hybrid formulation and consists of three components: interaction forces, self-propulsion forces and inherent noise forces. Moreover, we use a data-driven approach to model the induced-noise force as Curl noise; our noise model is derived using our quantitative metric and real-world datasets. We perform local collision avoidance using the reciprocal velocity obstacles algorithm. The overall formulation is stable and can simulate large swarms with varying densities.

2. Model Evaluation: We present a quantitative metric that can be used to evaluate the performance of multi-agent simulation algorithms in relation to real-world trajectory datasets. We use a statistical formulation that inherently accounts for noise in the dynamics model. We use seven time-varying metrics to evaluate the collective behaviors of insects and compute the optimal parameters for our dynamics model using a genetic algorithm. We also use the metric to evaluate the performance of different simulation models.

We have implemented the overall algorithm and have used it to simulate the trajectories and collective behaviors of various insects including midges, fruit fly, locusts, moths as well as bats (non-insects) over large indoor and outdoor environments. Our dynamics model can generate many collective behaviors including aggregation at different scales, locust migration, competition for mates, phase transition in terms of density passing a critical point, positive phototaxis, and escape responses to predator-like objects. Our approach can simulate very large swarms with tens of thousands of insects and handle high swarm densities. We also validate our model using two real-world datasets and highlight the benefits over prior methods for simulating insect swarms.

2 Prior Work

In this section, we give a brief overview of agent-based models and other techniques used to simulate insect behaviors.

2.1 Agent-Based Collective Behavior Models

Insect swarm simulation can be regarded as a type of simulation for collective behaviors known as *multi-agent simulation*. Multi-agent simulation techniques have been widely studied in computer graphics, robotics, artificial intelligence, and related areas. To simulate swarming insects using these multi-agent techniques, we treat each insect as one of the interacting intelligent agents within an environment.

Many algorithms have been proposed to simulate the behavior or compute the trajectory of each agent based on global path planning, local navigation, collision avoidance, and motion synthesis. The Boids model [Reynolds 1987] and other rule-based approaches [Musse and Thalmann 2001] use simple rules to govern the movement and behavior of different agents. Other techniques are based on social forces [Helbing and Molnár 1995], the cellular automata [Burstedde et al. 2001], velocity-based reasoning or optimization [van den Berg et al. 2011], etc. Most of these techniques have been used primarily for human-like crowd simulation, though Reynolds' Boids model has also been used to simulate movements of birds and fishes.

Some recent work in computer graphics on insect simulation includes a hybrid model based on noise function and potential fields [Wang et al. 2014] and a data-driven model for visual simulation [Li et al. 2015]. In contrast with these models, we propose an agent-based model to describe the dynamics of each individual and simulate the collective behaviors of the entire group. There is large scientific literature on collective behaviors of animal groups and many specific agent-based models have been proposed [Couzin and Krause 2003]. Our dynamics model is different from these methods and is able to generate many collective behaviors for different insects.

2.2 Evaluation and Validation Techniques

Many techniques are proposed to evaluate the results or improve the accuracy of multi-agent and crowd simulation algorithms. Most of these techniques compare the algorithms' output with real-world sensor data. Pettré et al. [2009] compute appropriate parameters based on Maximum Likelihood Estimation. In order to learn accurate parameters from real-world datasets, learning techniques have also been used [Ju et al. 2010; Charalambous and Chrysanthou 2010]. Wolinski et al. [2014] and Berseth et al. [2014] present parameter optimization-approaches to make the simulated trajectories matching real-world datasets. Guy et al. [2012] propose an entropy-based evaluation approach to quantify the similarity between real-world and simulated trajectories. But most of these techniques have been designed for and applied to pedestrians or human crowds. In contrast, our evaluation approach is designed for insect swarm trajectory datasets, and robustly handle the inherent noise to be found both in the trajectory data and in our model.

3 Background and Overview

In this section, we give an overview of our approach. We provide some background on insects and insect behaviors, introduce the notation, and finally highlight key aspects of our approach.

3.1 Insects and Insect Behaviors

An *insect* is a small autonomous entity flying in three dimensions that can perceive other insects and the obstacles in the environment. An *insect swarm* refers to a spatial aggregation of insects of similar sizes with collective (but no cooperative) behaviors. In our paper, we mainly deal with flying insects.

There is considerable research on studying actual behaviors of insect swarms nature [Morse 1963; Rauch et al. 1995]. This research is aimed at understanding the biological rules at the lower scale (i.e. the insect level) which engenders the collective phenomena at higher scale (i.e., the swarm) [Lukeman et al. 2010]. Many researchers have analyzed experimental datasets to model or predict the behaviors of insect swarms. During the past decade, many researchers have argued that these behaviors or group patterns occur due to simple individual rules; they agree that there are at least three interaction rules for each individual in a group: a short-range repulsion, an intermediate-range tendency for an insect to align its motion with its neighbors, and a long-range attraction [Couzin et al. 2002].

3.2 Overview

Our goal is to develop an agent-based mathematical model to describe the dynamics of each individual insect and use them to simulate the collective behavior of insect swarms. In our force-based model, we regard insects as identical self-driven agents with mutual interactions. A swarm consists of N agents with unit mass (i.e., the mass is 1). We use the symbol $\mathbf{F}_i$ to represent forces for a given insect i ($i = 1, \ldots, N$). Our dynamics formulation uses a force-based model to generate a preferred velocity for each insect. This includes different type of forces. We also use reciprocal velocity obstacles to compute each insect's actual velocity to avoid collisions with other insects and the obstacles [Li et al. 2015]. As shown in Figure 3, the equation to describe the dynamics of each insect in the swarm is given as:

$$\dot{\mathbf{v}}_{i,pref} = \mathbf{a}_i = \mathbf{F}_{i,int} + \mathbf{F}_{i,pro} + \mathbf{F}_{i,\xi}. \tag{1}$$

As described in Section 3.1, we model two types of forces for each insect. The first type of force in Equation 1 is the interaction force $\mathbf{F}_{i,int}$, which consists of a short-range repulsion, an intermediate-range tendency for an insect to align its motion with its neighbors, and a long-range attraction. Lumen et al. [2010] suggest that $\mathbf{F}_{i,int}$ can also be fitted into a concentric zonal model (i.e., individual-based concentric zones of forces; see the leftmost side of Figure 3), in which an insect interacts with all neighbors within a certain distance.

The second type of force is called self-propulsion force $\mathbf{F}_{i,pro}$. This force represents all external factors that contribute to the insect's trajectory. $\mathbf{F}_{i,pro}$ is formulated as:

$$\mathbf{F}_{i,pro} = \mathbf{F}_{i,fric} + \mathbf{F}_{i,res}, \tag{2}$$

where $\mathbf{F}_{i,fric}$ is the friction force corresponding to the drag on the movement of an insect, $\mathbf{F}_{i,res}$ is the response forces that arises when an insect senses danger or things of interest in the environment.

Insects also exhibit noise-induced behaviors and instinct responses to the environment. In other words, these forces are exerted on each insect even if it is the only individual insect present in a swarm. The force exerted by inherent noise, an important characteristic of insect swarms, is represented here by the term, $\mathbf{F}_{i,\xi}$. In order to model the noise function, we consider different choices for the stochastic term, including white noise ($\mathbf{W}$), Gaussian white noise ($\mathbf{G}$), Perlin noise ($\mathbf{P}$), and curl noise ($\mathbf{C}$) [Bridson et al. 2007]. Our experimental results, based on our evaluation metric (see Section 5), indicate that curl noise provides us the best result. The noise term is represented as:

$$\mathbf{F}_{i,\xi} = \mathbf{C}(\mathbf{r}_i), \tag{3}$$

where $\mathbf{C}(\mathbf{r}_i)$ denotes the curl noise function we used.

It is important to prevent collisions, both between insects in the swarm and with obstacles in the environment. One key issue is to ensure that our approach can deal with large and dense simulations of swarms. There are some widely-used collision avoidance algorithms used for multi-agent simulation and human crowds, such as the ones based on social forces [Helbing and Molnár 1995] and reciprocal velocity obstacles (RVOs) [van den Berg et al. 2011]. However, algorithms based on social forces can have stability problems in dense scenarios and the resulting simulation needs to take very small time steps. Therefore, we use the geometric optimization algorithm based on RVOs to compute collision free trajectories for each insect. The underlying collision avoidance algorithm f_R is stable, in terms of using large time steps, and also works well in dense situations. The preferred velocity $\mathbb{V}_{pref} = \{\mathbf{v}_{i,pref} | i = 1 \ldots N\}$ for each insect is generated by Equation (1), and is used as an input to f_R. We use RVOs to obtain the actual velocity $\mathbb{V} = \{\mathbf{v}_i | i = 1 \ldots N\}$:

$$\mathbb{V} = f_R(\mathbb{V}_{pref}).$$

Finally, we use the actual velocities $\mathbb{V}$ to update insects' positions at each time step: $\dot{\mathbf{r}}_i = \mathbf{v}_i$.

4 Insect Dynamics Model

In this section, we give details of our dynamics model that is inspired by biological observations. As introduced in Section 3.2, insect behaviors are dominated by three type of forces: interaction force, self-propulsion force, and inherent-noise force.

4.1 Interaction Force

Interaction force depends on an insect's neighbors and on the transition zones depicted by concentric circles (or the spheres in 3D). The borders of zones for repulsion, alignment, or attraction for a given insect are defined by the radii r_{rep}, r_{ali}, and r_{att} with the conditions $r_{att} \geqslant r_{ali} \geqslant r_{rep} \geqslant 0$ [Couzin et al. 2002], as shown in Figure 3. For a given insect i , if another insect j is within its range r_{att}, then j is classified as a neighbor of i. The interaction force of i is computed as an average of the influences exerted by neighbors:

$$\mathbf{F}_{i,int} = \sum_k \mathbf{F}_{i,k}, \;\; \mathbf{F}_{i,k} = \frac{\chi_k}{N_k} \sum_{j=1}^{N_k} (g(r_{ji})\hat{\mathbf{r}}_{ji} + (1 - |g(r_{ji})|)\hat{\mathbf{v}}_{ji}). \tag{4}$$

In this equation, repulsion force $\mathbf{F}_{i,rep}$, alignment force $\mathbf{F}_{i,ali}$, and attraction force $\mathbf{F}_{i,att}$ are represented as $\mathbf{F}_{i,k}$ with $k = \{rep, ali, att\}$; $\chi_k \geqslant 0$ stands for weighting parameters for each force, respectively; N_k is the number of neighbors located in the corresponding zone for that function. Other notations are described as follows: $r_{ji} = \|\mathbf{r}_j - \mathbf{r}_i\|_2$, $\hat{\mathbf{r}}_{ji} = (\mathbf{r}_j - \mathbf{r}_i)/r_{ji}$, $\hat{\mathbf{v}}_{ji} = (\mathbf{v}_j - \mathbf{v}_i)/\|\mathbf{v}_j - \mathbf{v}_i\|_2$. The piecewise function $g(x)$ is used to distinguish these zones:

$$g(x) = \begin{cases} -1; & 0 \leqslant x < r_{rep}, \\ 0; & r_{rep} \leqslant x < r_{ali}, \\ 1; & r_{ali} \leqslant x \leqslant r_{att}. \end{cases}$$

4.2 Self-propulsion Force

The self-propulsion force $\mathbf{F}_{i,pro}$, introduced in Equation (2), is based on real observations. "Self-propulsion" means that the external forces arise from the insect's reaction to the environment or other factors, not from its neighbors. $\mathbf{F}_{i,pro}$ is composed by $\mathbf{F}_{i,fric}$ and $\mathbf{F}_{i,res}$.

The friction function is expressed as $\mathbf{F}_{i,fric} = -\gamma \parallel \mathbf{v}_i \parallel \mathbf{v}_i$, where γ is the friction coefficient. The second term $\mathbf{F}_{i,res}$ denotes the response to environmental stimuli, such as predators approaching or prey passing by. In general, there are two types of stimuli for insects: predator-like objects, which create escape behaviors, and food/females, which create pursuit behaviors in male insects. According to the experimental results presented in [Domenici et al. 2011], insects usually escape away from the threat with relatively high variability and a limited angular sector (mainly $90 - 180°$). On the other hand, the pursuit behavior of insects is simple; they just directly fly towards the target [Lukeman et al. 2010]. Since there is little chance that insects will engage in escape and pursuit behaviors at the same time, we assume that the insects are responding to only one type of stimulus at any given

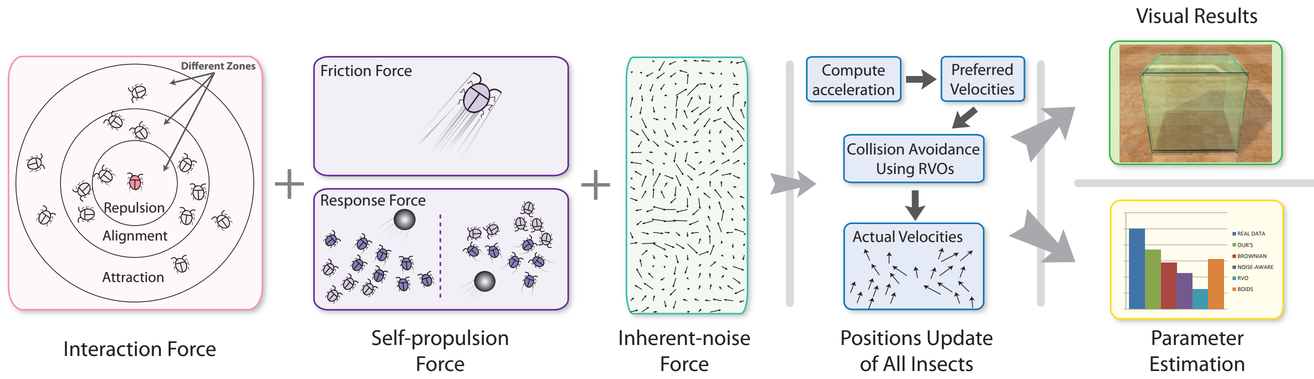

Figure 3: ***Our Model:*** *Overview of our biologically-driven insect swarm model (illustrated in 2D view). We highlight different components of our algorithm used to calculate the position of each insects at each time step, including two sets of forces: interaction forces and self-propulsion forces. Interaction forces are represented by individual-based zones: insects follow forces that are represented in concentric zones of repulsion, alignment, and attraction to their neighbors. We use these forces to compute the acceleration and preferred velocity for each insect, and use velocity obstacles to perform collision avoidance and compute the actual velocity. The parameter estimation step is performed to compute the optimal parameters for our model.*

time. Let $\mathbf{r}_e$ denotes the position of an environmental stimulus, r_{res} denotes the visual range of all insects. $\mathbf{F}_{i,res}$ is defined as:

$$\mathbf{F}_{i,res} = \chi_{res} H(r_{res} - r_{ie})(s_e \hat{\mathbf{r}}_{ie} \mathbf{R}(\mathbf{n}, \theta) - (1 - s_e)\hat{\mathbf{r}}_{ie}).$$

Here $\chi_{res} \geqslant 0$ is the weighting parameter. $H(x)$ is the Heaviside step function, which reflects whether an insect "sees" the stimuli. The rotation matrix $\mathbf{R}(\mathbf{n}, \theta)$ is adopted to generate an escape direction, where $\mathbf{n} = (0, 1, 0)$ is a rotation axis and θ is a random angle perturbation that obeys uniform distribution on $[-\frac{\pi}{2}, 0]$. The symbol variable s_e reflects the type of stimuli. $s_e = 1$ denotes the predator-like object and $s_e = 0$ denotes food or female to be chased.

In Section 6, we evaluate the accuracy of each of these noise functions into our dynamics model by plugging $\mathbf{F}_{i,\xi} = \{\mathbf{W}, \mathbf{G}, \mathbf{P}, \mathbf{C}\}$. We observed that the Curl noise function can provide us the most accurate results both in simulation experiments and evaluation results.

5 Model Evaluation

The simplest technique for evaluating a model is to render the trajectories and observe the insect movements. However, it is not sufficient to evaluate whether a given dynamics model can capture all aspects of insects emergent behaviors based on visual rendering [Puckett et al. 2014]. We present a novel quantitative approach to evaluate our insect dynamics model by using real-world trajectory datasets. Our approach takes into account some key aspects of insect behaviors and trajectories, based on seven time-varying metrics.

Recent work in evaluating crowd simulation algorithms with respect to real-world trajectories is based on statistical and optimization methods [Guy et al. 2012; Wolinski et al. 2014; Berseth et al. 2014]. Due to the inherent noise formulation in insect swarms [Wang et al. 2014], these methods are not directly applicable. It is possible that two different swarms with noisy trajectories may exhibit similar swarm behaviors even though their trajectory positions are quite different. Our approach uses discrete probability density distribution functions (PDFs), which are generated from the time-varying metrics and it reflects the global characteristics of insect swarm; as a result, the influence of a small amount of data abnormality or noise can be ignored.

Our evaluation model is represented by the following equation which contains seven energy terms:

$$E = 1 - \sum_{\phi \in \Phi} w_\phi E_\phi. \tag{5}$$

Inspired by the biological and physical research [Kelley and Ouellette 2013; Flash and Hogan 1985; Buhl et al. 2006], we select seven time-varying metrics for calculating energy terms in Eq. 5, that is, $\Phi = \{v, a, \omega, \alpha, \mu, d, \eta\}$. v the velocity, a the acceleration, ω the angular velocity, α the angular acceleration, μ the Cartesian jerk, d the shortest distance, and η the velocity difference. We propose two new metrics to characterize the insect swarm behavior: Cartesian jerk $\mu = \left\| \frac{\Delta \mathbf{v}_1 - \Delta \mathbf{v}_2}{(\Delta t)^2} \right\|_2$, where μ is the magnitude of the second order differential of velocity, $\Delta \mathbf{v}_1$, $\Delta \mathbf{v}_2$ are the velocity changes of one insect in neighboring time points; and velocity difference $\eta = \frac{|v_{nei} - v|}{d}$, where v_{nei} denotes the magnitude of velocity of the nearest neighbor. More details about these metrics are given in [Ren et al. 2015]. E_ϕ denotes the energy term about the metric ϕ, and w_ϕ denotes the weight of E_ϕ.

For a metric ϕ in Φ, E_ϕ is the energy term which represents the difference in discrete PDF between the real-world data and the simulation data. We formulate E_ϕ as

$$E_\phi = \left\| \mathcal{Q}_\phi^{real} - \mathcal{Q}_\phi^{sim} \right\|_1, \tag{6}$$

where $\mathcal{Q}_\phi^{real}$ denotes the discrete PDF of an insect swarm's metrics from real-world captured data and $\mathcal{Q}_\phi^{sim}$ represents discrete PDF of an insect swarm's metrics from our swarm simulation model. We compute E_ϕ in four steps as follows:

Step 1: Sample the real data and the simulation data for the metric ϕ;

Step 2: Normalize the samples with the z-score method which is refers to a mean shift followed by a standard deviation scaling;

Step 3: Compute the discrete PDFs [Billingsley 2008] of the real-world data and the simulator's data with normalized samples from Step 2;

Step 4: Compute the energy term E_ϕ.

We normalize the energy terms in Equation 6:

$$E_\phi = \frac{\left\| \mathcal{Q}_\phi^{real} - \mathcal{Q}_\phi^{sim} \right\|_1 - p_{1\phi}}{p_{2\phi}}, \tag{7}$$

where $p_{1\phi}$ and $p_{2\phi}$ are normalization parameters. The computation of $\left\| \mathcal{Q}_\phi^{real} - \mathcal{Q}_\phi^{sim} \right\|_1$ is the same as in Equation (6).

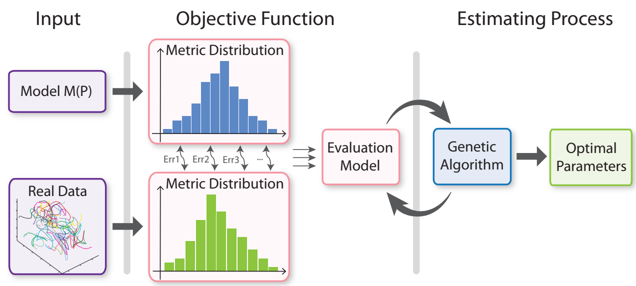

Figure 4: *Parameter-estimation algorithm (Par-Est algorithm). For a given real world trajectory data of insect swarm, we compute the discrete PDFs of the seven time-varying metrics with that data. Meanwhile, we use the parameterized dynamics model to simulate insects and compute the discrete PDFs of the seven time-varying metrics with the simulation data. Next, we evaluate the function given in Equation (5) and use that as an objective function for the genetic algorithm to compute the optimal parameters.*

5.1 Model Evaluation with Entropy Weight

In this section, we describe our evaluation algorithm. The overall evaluation has two components: optimizing the dynamics model parameters and optimizing the weights of seven energy terms.

We evaluate our dynamics model of an insect swarm with estimated optimal parameters (see Figure 4). The performance of our dynamics model is sensitive to the choice of underlying parameters. Therefore, we use a genetic algorithm to compute the optimal parameters by maximizing the evaluation function in Equation 5. However, when we use the evaluation model to evaluate different simulation techniques for insect swarms, it may require assigning a different weight to each energy term. Instead, we compute the weights of all energy terms automatically, and then compute the final weighted score to evaluate different insect simulation models for fair comparisons. We use the entropy-based evaluation method described in [Zou et al. 2006] to compute the weights of the evaluation model in Equation 5, as they can provide reliable results. More details are given in [Ren et al. 2015].

6 Results and Analysis

In this section, we highlight the performance of our dynamics model on different insect swarms. We also analyze the accuracy using two real-world trajectory datasets and compare the performance with other multi-agent algorithms.

6.1 Implementation

We have implemented our approach in C++ on a PC with Intel 2 Duo CPU E7500 and 4GB memory. Our current implementation uses the fixed-radius nearest neighbors search algorithm [Dickerson and Drysdale 1990] to accelerate spatial proximity queries to calculate $\mathbf{F}_{int}$). All the timing results reported in this paper are generated using a single core. The results were rendered using Autodesk Maya 2014. The supplementary video shows the collective behaviors for different flying insects. We use the Curl noise to model the noise force. We use the RVO2 library [van den Berg et al. 2011] for local collision avoidance. We use our simulator to generate collective behaviors for midget, fruitfly, and locust. Furthermore, our dynamics model can also be used to simulate collective behaiviors of non-insects, such as bats.

6.2 Real-World Datasets

We use two insect trajectory datasets to compute the appropriate noise model and estimate the parameters of our dynamics models. Both these datasets were captured in an indoor setting with state-of-the-art motion capture systems. The dataset-1 from [Kelley and Ouellette 2013] was captured in a transparent $91cm$ cubical enclosure with laboratory swarms of the midge *Chironomus riparius*. The total number of midges vary from 12 to 111 per frame. The three other datasets, dataset-2, dataset-3, and dataset-4 were captured in a cube of $2m$ edge length with hundreds of *Drosophila* (fruit fly) [Wu et al. 2011]. All these four datasets correspond to time-resolved measurements of the positions, velocities, and accelerations of individual insects, so we can compute the discrete PDFs of the seven metrics easily. We choose 500 frames from each of these four datasets.

Parameter Estimation: Our dynamics model, described in Section 4, can be regarded as a parameterized dynamics model. The computation of different forces is governed by 11 parameters. 7 of them, including γ, χ_{rep}, r_{rep}, χ_{att}, r_{att}, $scale$ and $gain$, are estimated based on the real-world datasets. The other four parameters: χ_{ali}, r_{ali}, χ_{res} and r_{res}, cannot be estimated since our real-world datasets do not exhibit significant alignment tendency [Kelley and Ouellette 2013] or there is no specific external stimuli. As a result, we estimate them based on empirical observations, including alignment information [Lukeman et al. 2010] and the flying speeds and the visual range of the insects.

Noise Estimation: Figure 5 shows the comparison results of the models based on the four different noise types with four different datasets. The Curl noise provides the most accurate results with respect to our four datasets.

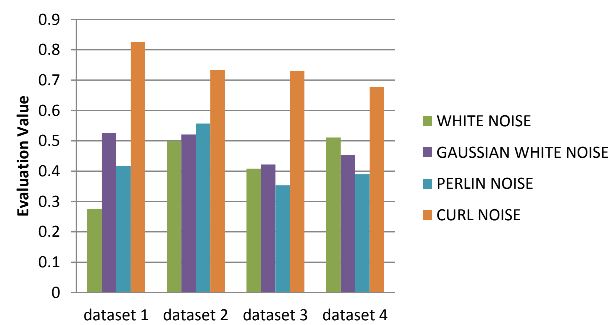

Figure 5: *The comparison results of our model with the four different noise functions. The evaluation value is the value of Eq. 5.*

The parameter estimation method is described in Section 5.1, and the values of the parameters used to generate our results are given in Table 1.

6.3 Collective Behaviors

(a) (b) (c)

Figure 6: *Aggregation: (a) and (b) simulated swarms of midges moving in the environment with* 500 *and* $3,000$ *midges, respectively. Other parameters are shown in Table 1; (c) a photo captured using a camera.*

Aggregation: We generated aggregation behaviors of midges at different scales. Figure 6(a) contains 500 midges and Figure 6(b)

Table 1: *Simulation performance and parameter settings of our results. In order to express the radii conveniently, we use the radii differences* $r^*_{att} = r_{att} - r_{ali}$, $r^*_{ali} = r_{ali} - r_{rep}$ *instead.*

	Midge	Aggreagtion		Fruitfly	Mating	Escape	Bats	Locust		Phase	Phototaxis
#insect	100	500	3,000	100	100	100	500	2,000	200,000	20 ∼ 200	20 ∼ 80
γ	11.16			8.76			10.21	13.0		8.76	15.0
$scale$	2.20			2.75			2.20	1.72		0.72	3.42
$gain$	2.51			1.79			2.51	0.36		0.10	2.0
χ_{rep}	5.61			1.74			8.0	3.0		5.0	3.0
r_{rep}	0.17			1.48			2.0	0.45		0.2	0.2
χ_{att}	14.29			10.39			25.0	5.0		7.0	8.0
r^*_{att}	5.12			4.49			10.0	5.0		9.2	10.0
χ_{ali}	0	5.0		0	3.0	3.0	20.0	5.0		10.0	0
r^*_{ali}	0	1.0		0	10.0	10.0	3.0	0		2.2	0
χ_{res}	0	0		0	10.0	20.0	10.0	60.0		0	1.0
r_{res}	0	0		0	2.0	8.0	10.0	25.0		0	5.0
Simulation FPS	489.87	34.41	1.49	442.37	146.79	420.60	37.25	13.48	0.018	134.37	528.19

is simulated with 3,000 midges in the same environment. The swarm flies erratically (i.e., the swarm center hardly changes) with different densities, $9,469.7/m^3$ and $56,818.2/m^3$ (with their body length set to 0.01m), respectively.

(a) (b) (c)

Figure 7: *Locust Migration: (a) and (b) simulated migratory locusts pass through a village. The number of locusts is* 2,000 *and* 200,000*, respectively; (c) a photo captured from a video camera.*

Locust Migration: Figure 7 shows migratory locusts passing through a village. The locusts formed in a cuboid shape with $24.0m$ length, $5.0m$ width and $0.5m$ height. In this environment, we set a large stimulus for locusts to pursue (e.g. crop) . The locust swarm simulated has: (a) 2,000 locusts with density $34.2/m^3$ (we set locusts' body length to $0.04m$); (b) 200,000 locusts with density $342/m^3$ in the same space.

Competition for mates: Figure 2 shows a swarm of male flies competing for a female (shown as glowing green). We generated this behavior by regarding the female fly as a pursuit stimulus. The collective behavior is generated based on known behaviors of males and females [Dublon and Sumpter 2014].

Phase transition: This behavior occurs when the increasing density of a swarm passes through a critical point. Viscek et al. [1995] generate such behaviors by continuously manipulating the parameters. We model it by decreasing the noise force and increasing the alignment component, χ_{ali}.

Positive phototaxis: In this scenario, a succession of moths gather around a street lamp. We set the lamp holder as an external stimulus to attract the moths towards it. We also mark the lamp as an obstacle to avoid collisions with moths based on RVOs.

Startle/escape response: Figure 8 highlights the fly swarm's responses to a predator-like object. In this scenario, we use the sphere as an external danger. When it approaches, each insect will choose a determined direction in which to escape.

Swarm of bats in a cave: Although bats are not insects, bat swarms often exhibit similar patterns as insect swarms. Bats have the ability to respond rapidly due to echolocation. In Figure 9(b), we show a

(a) (b)

Figure 9: *Interior swarm of bats rapidly responding due to echolocation simulated using our dynamics model: (a) a snapshot of the simulated bats by our model; (b) a real photo of bats.*

real-world image of a bat swarm flying as a ring-shape in a dark cave. We simulate echolocation behavior by setting a changing stimulus in front of each bat (Figure 9(a)).

6.3.1 Comparisons and Benefits

We have compared 4 *parameterized multi-agent simulation models* based on the algorithm described in Section 5.1: RVO model [van den Berg et al. 2011], the Boids model [Reynolds 1987], the Noise-aware model for simulating insects [Wang et al. 2014], and a Brownian dynamics model [Schweitzer et al. 1998]. For each model, we used our parameter estimation algorithm to compute the optimal parameters. Figure 10 shows results comparing the five models with four different ground truth datasets, and highlight the relative benefits of our approach.

All the forces in our model are useful. If we remove the RVOs, insects can have collisions. If we remove $\mathbf{F}_\xi$, insects will not exhibit noise-induced behaviors. If we remove $\mathbf{F}_{pro}$, we cannot simulate bats, mating behaviors of flies, and the escape responses.

As compared to prior methods, our model has many advantages. Some recent methods [Wang et al. 2014; Li et al. 2015] cannot simulate phase transitions and escape behaviors due to lack of interaction forces and escape forces; Vicsek et al. [1995] cannot simulate mating and escape behavior, due to lack of response forces; Boids model [Reynolds 1987] cannot generate positive phototaxis and phase transitions due to lack of noise forces and can result in collisions in dense simulations. Moreover, none of the prior methods can simulate the bats behaviors and mosquito swarms (with a very high density around the centroid), as shown in video.

Our approach is complimentary to [Li et al. 2015]. Our formulation of the dynamics model (Section 4) is driven by observed biological behaviors. Our approach for using a data-driven noise model uses

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

Figure 8: *Startle/escape response: When a predator-like object (the sphere) approaches the swarm, insects escape and disperse quickly to avoid it. They aggregate again after the danger disappears.*

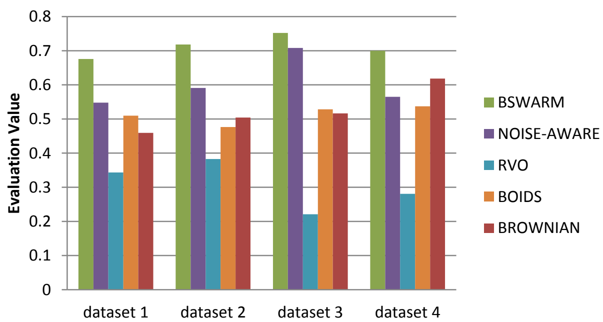

Figure 10: *We compared different multi-agent simulation with the real-world datasets. The evaluation value is the value of Eq. 5. Our biologically-plausible dynamics model provides higher accuracy with respect to the real-datasets as compared to other models.*

parameter evaluation techniques, which have been used for crowd and insect simulation. [Li et al. 2015] used density distribution to compute the waypoints that are used to compute insect trajectories to preserve their spatial swarming patterns. In contrast, our metric takes into account discrete probability density distribution functions, as explained in section 5. Moreover, our approach allows us to intuitively change the parameters to generate different swarm behaviors (Section 6.3.2).

6.3.2 Generating Different Swarm Behaviors

As mentioned above, our model has 11 parameters. These parameters can be modified to generate different swarm behaviors. For example, Increase the value of r_{rep} will make insects fly apart away from each other so the swarm will result in a lower density. if we increase the value of r_{ali}, insects will tend to follow its neighbors' purposes (e.g., exhibiting the mating behavior). Larger r_{att} will bring more dense swarms and results in mosquitoes-like aggregation (see the video). Please refer to [Ren et al. 2015] for more details. Increasing r_{res} will expand the visual range of all insects, and make them escape much before the predator arrives close to them.

If we increase the weighting variables $\chi_{\{rep,ali,att,res\}}$, the corresponding forces applied on insects will increase (and vice-versa). i.e., insects will accelerate faster to move away from (or close to) others when χ_{rep} (or χ_{att}) increases, or escape quickly when χ_{res} is large (the escape behavior). Please refer to [Ren et al. 2015] for more details. Decreasing the noise parameter $scale$ will result in more noisy trajectories (and vice-versa), we can use it to generate different insect swarms with different noise frequencies (e.g. midge has a smaller $scale$ while moth has a larger one). Increase in the $gain$ value will directly increase the noise speeds of the insects. If we decrease $gain$ and increase χ_{ali}, it will result in phase transition behavior. Finally, the friction coefficient γ is usually decided by the type of insects. The animals with large wings (moths, bats) will overcome more air drag, so they will be assigned to a larger value of γ.

7 Limitations, Conclusions and Future Work

We have presented a biologically-plausible dynamics model (B-Swarm) to simulate insect swarms. We use a force-based model that is based on biological conclusions and experimental observations. We also present a novel evaluation metric for multi-agent simulation algorithms that can take into account the inherent noise both in the model and in the real world datasets. We use these datasets for estimating the parameters of our dynamics model and use Curl noise to model insect trajectories. We have used our model on different flying insects and can generate many emergent behaviors and trajectory patterns.

Limitations: Our current approach is mainly designed for adult flying insects, and may not be applicable to walking or swimming insects. Furthermore, it is not applicable to some eusocial insects (e.g. ants, bees), as the interaction rules may not be applicable. The accuracy of our parameterized dynamics model is governed by the accuracy and the different behaviors captured in real-world datasets. For example, the two specific datasets did not exhibit alignment tendency and had no major external stimuli. The evaluation model is based on statistical assumptions about the noise, which may not hold for all datasets.

Future Work: There are many avenues for future work. In addition to overcoming the limitations, we would like to extend the model to simulate some very large swarms (e.g. millions of locusts). As we gather more outdoor datasets related to insect swarms, they can be used to improve the accuracy of our parameterized dynamics model. It would be useful to augment our metric with perpetual factors. Moreover, we would like to extend our dynamics model to other animal groups, and use them for computer games and special effects.

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