Modelling and Analyzing Moth's Phototaxis behaviour using Braitenberg Vehicles

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***Abstract*—Bio-inspired artificial agent models are widely used to imitate animal behavior. The paper presents a Braitenberg vehicle-based model to analyze moth's navigation patterns in a light source environment. The analysis of the model is performed in different parameter settings to understand the characteristics of moth eclipse. Furthermore, a support vector regression-based prediction method is suggested to predict the emergent characteristics of the model. The results of experiments indicate the moth path-planning and effective eclipse forming tendencies and a possible robotic application in decision making in unmanned aerial vehicles.**

Keywords – Moths, Phototaxis, Braitenberg Vehicle, Support Vector Regression

I. Introduction

Our world is advancing towards intelligent systems to solve challenging and complex problems. Bio-inspired artificial life models are increasingly being used to solve some of these difficult problems in an unconventional way. These models propose innovative computing architectures and novel problem-solving paradigms. Computing models such as artificial neural networks [1], genetic algorithms [2], and swarm intelligence [3] are major constituent models of the bio-inspired approach. The application of such models includes robot control, robot manufacturing, practical robots, computer graphics, natural phenomenon modeling information processing and the list goes on.

Insect-inspired, Swarm intelligence (SI) models originate from collectivistic behavior of scattered self-organizing systems. These models can provide useful insights to entomologists regarding the insect behavior patterns, such as the model introduced in [4] improved understanding of biologists regarding social flying patterns in fruit flies and the model described in [5] pointed out some interesting information about foraging behavior of honeybees. In addition to this, these models can be used as the basis for the development of many meta-heuristic algorithms such as Artificial bee colony models that provide robust optimization techniques as mentioned in [6], [7] and [8]. Furthermore, SI models such as Stochastic diffusion search [9] for agent-based probabilistic global search, Particle swarm optimization [10] .for global optimization algorithms and Artificial Swarm Intelligence [11] for amplifying the collective intelligence of networked human groups have been introduced in recent past and have proposed unconventional architectures for solving these optimization problems effectively. The real-world applications of the above-mentioned models include controlling unmanned vehicles [12], understanding astronomical planetary mapping [13] and controlling nanobots for curing diseases within human bodies [14], etc.

Bio-inspired behavior-based robotic models have been implemented extensively using Braitenberg vehicles [15], which provide a simple and memory-efficient way to characterize animal behavior as artificial agents. Braitenberg vehicles feature simple motor-sensor coupled architecture to imitate simple animal psychological behaviors such as fear, aggression, love, and explorer towards/from a stimulus [15]. Braitenberg vehicles-based models have been used to mimic chemotaxis and phototaxis insect behaviors in models introduced in [16], [17], and, [18] and have been the basis for building many intelligent chemical-sensing robot swarms.

In this paper, a moth-based bio-inspired model is formulated using Braitenberg vehicles. Moths use phototaxis to align their orientation in the dark and follow optimal trajectories to avoid collisions in different environment settings [19]. This model can be used to understand moth's interaction with the environment and for predicting the behavior of this insect in different environment settings. Furthermore, the model's emergent properties can suggest some useful applications in robotics.

II. Biological Background and Model Formulation

A. Moth Behavior and Its Characteristics

Moths are a polyphyletic group of insects that includes all members of the order *Lepidoptera*. The majority of these insects are usually active at night and drink nectars, rotting fruits, and bird droppings to get nutrients [20]. Moths feature simple and compound eyes for vision, setae (sensory hairs) for tactile senses, and use antennae for olfactory senses [19]. These organisms exhibit positive phototaxis to avoid predators and navigation [21]. To sense pheromones and food sources, most of the moths use olfactory senses evincing the avoid collisions with surrounding particles using the tactile positive chemotaxis behavior. Furthermore, these insects avoid collisions with surrounding particles using the tactile senses and vision senses [22]. Younger moths (caterpillars) tend to have a weaker vision and only have simple eyes with low sensitivity towards light, whereas the adult moth features both compound and simple eyes with a heightened sense of vision [19], This contrast in sensitivity causes different behavioral patterns in moth species. Furthermore, moths tend to plan their trajectory in dense terrains to avoid collisions from other insects [21], these flight patterns can provide inspirations for decision making in autonomous aerial vehicle applications.

This paper presents a rational agent-based model and its analysis, to imitate the behavior of moths in a light source environment. The model focuses on the ability of insects to orient towards the light source and to follow their trajectory towards the source avoiding collision from neighborhood agents. These behaviors can be implemented using the Braitenberg vehicles as described in the section below.

B. Braitenberg Vehicles

In behavior-based robotics, Braitenberg vehicles are rational agents, which can be used to imitate complex animal behaviors by building up vehicles with sensors wired to their wheels. The models based on Braitenberg vehicles are simple in terms of control and analysis and provide a good approximation as forward moving animals suffer from nonholonomic restrictions to motion [23]. Braitenberg vehicles 2a and 2b exhibiting "fear" and "aggression" towards light source representing positive and negative-phototaxis respectively are explained below [15].

Fear: A positive direct connection between light sensors and vehicles in a two-wheeled vehicle (shown in Fig.1(a)) results in a "Fear" behavior from the source [15] i.e. the vehicle starts moving away from the source.

Aggression: A positive cross-connection between light sensors and vehicles in a two-wheeled vehicle (shown in Fig. 1(b)) results in an "Aggression" behavior towards the light source [15] i.e. the vehicle starts moving towards the source and does not stop until it reaches the source.

A combination of these sensor-based models can be used as described in [15], to integrate multiple behaviors in an individual agent. To mimic the moth behavior, the aggression model can be used towards the light source and the fear model can be used for proximity repulsion to avoid collisions from surrounding neighbors.

C. Formulating the moth model using Braitenberg vehicle

The above-described model can be implemented using Khepera I robots [24] which feature 8 infra-red sensors (as shown in Fig.2) on either side of robots. These sensors provide information about light intensity and proximity of objects sensed by the agents via light and distance sensors.

As a high value of light intensity corresponds to the low value of light sensor reading, the proportional light intensity is calculated by normalizing the light intensity reading as described by (1). The distance sensors sense the amount of light intensity reflected by the nearby object and hence a

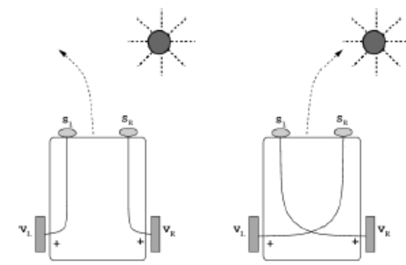


Fig.1 (a) Fear behavior and (b) Aggression behavior exhibited by Braitenberg Vehicles [23]

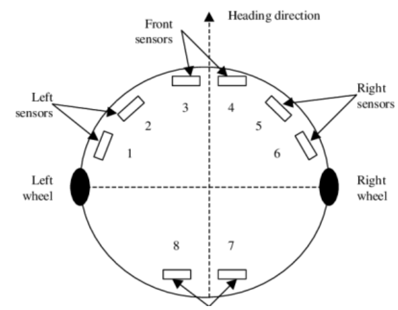


Fig.2 Khepera I top view with sensors [25]

higher reading of the distance sensor corresponds to the closer proximity to the closer proximity of another object. The values these sensors are also normalized to achieve adequate scaling as described by (2).

$$N_{l_i} = (Max_l - l_i)/\,Max_l \tag{1}$$

$$N_{d_i} = d_i/\,Max_d \tag{2}$$

Here, N_{l_i} is normalized light sensor reading corresponding to i^{th} light sensor, Max_l is the maximum value that can be read by a light sensor and l_i is light sensor reading taken by the i^{th} sensor at the current time step. Also, N_{d_i} is normalized distance sensor reading i^{th} distance sensor,, Max_d is the maximum value that can be read by distance sensor and $d_i$is distance sensor reading taken by the i^{th} sensor at the current time step (refer Appendix A).

Moths phototaxis behavior is modeled by using a cross-connection of light sensors (0,1,2 on the left side and 3,4,5 on the right side) with a coefficient of aggression as K_a. Furthermore, neighbor proximity repulsion can be modeled using direct connection of distance sensors (0,1,2,7 on the left side and 3,4,5,6 on the right side) with a coefficient of proximity repulsion as K_f . Inspired by Grey Walter's tortoise model [26], orientation control can be added to Braitenberg vehicles by rotating the Khepera robot as it senses light on the opposite end of its facing direction. This can be performed by multiplying the normalized light sensor (opposite to the facing direction of Khepera I) reading of one the wheel by an orientation coefficient K_o. Using this technique, the equation for Left wheel speed; L_{speed} and

Right wheel speed; R_{speed} for the Braitenberg vehicle can be described by (3) and (4).

$$L_{speed} = K_a (N_{l_3} + N_{l_4} + N_{l_3}) + K_f (N_{d_0} + N_{d_1} + N_{d_2} + N_{d_7}) + K_o (N_{l_6}) \quad (3)$$

$$R_{speed} = K_a (N_{l_0} + N_{l_1} + N_{l_2}) + K_f (N_{d_3} + N_{d_4} + N_{d_5} + N_{d_6}) + (N_{l_7}) \quad (4)$$

Moths with different sensitivities behave contrastingly in different environment settings. The difference in these sensitivities can be attributed to age, species, and sex of the moth [19]. Furthermore, the moths might follow wider trajectories while navigating through insect dense areas to prevent collision amongst each other. These biological characteristics of the moth form expected behavioral patterns for the Braitenberg based model described by the equations (3) and (4). These behavioral characteristics are formed as hypotheses for the artificial agent-based moth model as described below:

Hypotheses: Based on the above model of the moth, the following hypotheses are tested for the model by performing single-agent and multi-agent experiments. These hypotheses are derived from the behavior patterns of the moth as an individual entity and behavior of moth as part of moth eclipse as described in the above section:

H1: An increase in the agent's aggression sensitivity towards the light source would cause the rational agent to take less time to reach the source.

H2: As the light source intensity increases, the time taken by the agent to reach nearby the source decreases.

H3: In a fixed light source environment with a fixed value of K_a and with a fixed value of K_f, as the number of agents in the system increases, the trajectory of agents becomes comparatively wider and agents travel more distance to reach a near the light source.

H4: In the fixed light source environment with a fixed number of agents and a fixed value of K_a, as the value of K_f increases, the trajectory of agents becomes wider and agents cover longer routes in a fixed time.

III. EXPERIMENTS

Two types of experiments are performed to test the proposed moth model for above mentioned hypotheses, these experiments include single agent systems and multi agent system systems. The simulation set up and experiment methodology for these experiments is described below.

A. Simulation set up

The simulations for the experiments are conducted in webots [27] software. As described in Fig. 3, a circular arena of radius 1 meter is used as a simulation environment and a point light source is placed at center of the circular arena with a height of 0.2 (along y-axis) meters, to act as a stimulus for a rational agent which mimic moth's umwelt. A circular patch of 0.2 meters radii is also placed at the center of the circular arena, to record the time taken and distance covered by a rational agent to reach 0.2 meters from the light source.

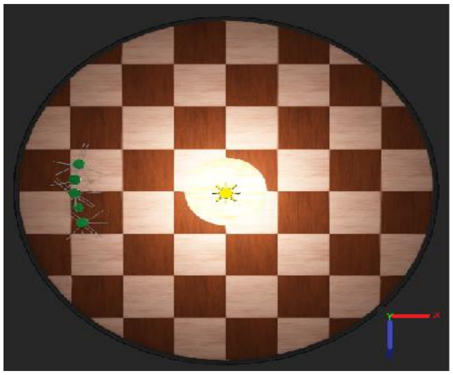


Fig.3 Simulation Environment

Initially, the rational agents are placed at a Euclidean distance of 0.75 meter from the center facing towards the center. For simulations featuring multiple agent system a Manhattan distance of 0.01 meters maintained along each x and z axis between adjacent artificial agents. To maintain symmetry the with respect to number of agents for multiple agent systems, odd numbers of agents are used for experiment and are placed evenly with respect to central agent. The position of central agent is kept fixed at (-0.75,0,0) for single agent and multiagent system experiments. The controller code for an individual artificial agent is written in webot's python extension (refer Appendix A).

B. Experiment Methodology

The experiment methodology for single and multi-agent experiments is described below, each observation is taken five times and average value is recorded for analysis and outliers are removed while noting down average values for analysis:

1) Single Agent Experiments

These experiments were carried out to observe the behavior of rational agents for different values of the coefficient of aggression towards light and light source intensities. Since there are no neighboring insects in the simulation, the value of K_f, is kept fixed as zero for these two experiments.

a) *Experiment A: Fixed Light intensity source with variations in the coeffcient of aggression of the autonomous agents*

In this experiment, the sensitivity of rational agents towards the light source is varied to imitate the behavior of moths of different vision sensitivities in similar source environments. For the simulation analysis, a point source of 1 Watt per meter square is kept at the center of the circular arena, the time taken to reach 0.2 meters distance from the light source is measured for various settings of aggression coefficient K_a, ranging from 0.1 to 2.0 meters cube per joule with an increment step of 0.1 meters cube per joule. In order to critically evaluate the experiment results, the experiment is repeated with a point light source of intensity of 0.5 and 2 Watt per meter square kept at the center of the arena.

b) *Experiment B: Variations in light source intensity with a fixed value of the coefficient of aggression for autonomous agents*

For this experiment, the intensity of the light source is varied to imitate the behavior of moths with similar light sensitivity characteristics in different light source environments. To carry out simulations for this experiment, the value of K_a is kept fixed at 1 meter cube per Joule, while source intensity is increased in steps of 0.1 from 0.1 meter cube per joule to 2.0 Watt per meter square. The calculation methodology for time for single-agent experiments is explained in Appendix B.

2) *Multi-Agent Experiments*

In a multi-agent system, the experiments are conducted to understand the behavior of an agent in a group of agents with variations in the size of the group and the degree of repulsion among each individual agent. The Following two sets of experiments are conducted for multi-agent systems. Since there are neighboring agents in these experiments, the value of K_f is kept non-zero for these experiments.

a) *Experiment C: Variation in the number of agents for fixed values of light source intensity, K_a and K_f*

To understand how multiple rational agents behave in a similar environment, the observations are taken for a fixed value of K_f =3 and the number of agents(A) are varied as A = 1,3,5,7 and 9. Furthermore, in order to understand the behavior of a group of rational agents with different aggression sensitivities, the experiment is performed for different K_a values as 0.5, 1 and 2 meter cube per joule. The time to reach 0.2 meters from the source, total distance covered to reach 0.2 meters from the source and trajectory followed in 60 seconds by the central agent is noted for analysis. The calculation methodology for time and distance for these experiments is explained in Appendix B.

b) *Experiment D: Variation in values of K_f with a fixed number of agents, fixed light source intensity and K_a*

To understand how proximity repulsion sensitivity causes different behavior patterns to emerge in these systems, the simulations are carried out for a fixed number of agents (A=3,5,7,9) and with variations in K_f values as 1,2,3,4 and 5 meter cube per joule. For analysis of this behavior, the trajectory of all agents is recorded, along with the distance covered by all of the agents in the multi-agent system for 60 seconds from the starting position of these agents. The calculation methodology for time and distance for these experiments is explained in Appendix B.

IV. Results and Discussion

The experiment results and their relevance with moth's characteristics are explained below, also the experimental data is used to train a predictive model that can be used for evaluating and predicting artificial agent model characteristics for different parameter settings.

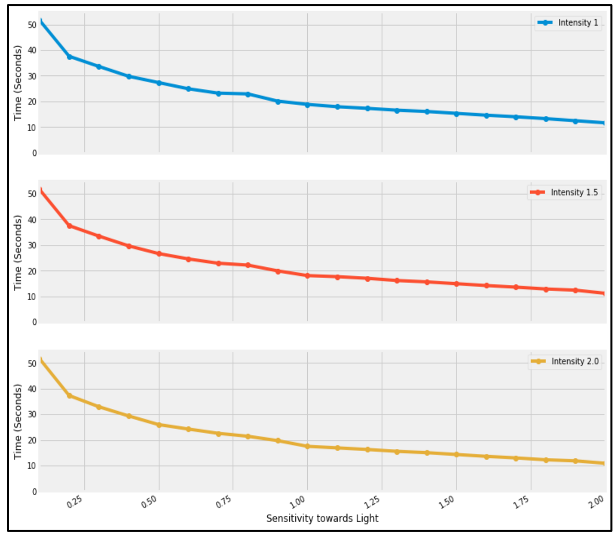


Fig.4 Time taken to reach 0.2 meters near the source Vs. K_a plot from the observation from experiment A

A. *Experimental results and their evaluation in comparison to real-world moths' characteristics*

Fig. 4 represents the time vs light sensitivity plots for experiment A observations, it shows the average taken by a single agent to reach 0.2 meters from the light source for different values of K_a ranging from 0.1 to 2 meter cube per joule at intensities of 0.5,1 and 2 Watt per meter square. It can be observed that, as we increase the sensitivity of agents, the time taken by these agents to reach near the source decreases linearly. These observations can be understood from the equations (3) and (4), as an increase in vehicle velocity due to high K_a values causes less time for vehicle to reach near the light source. Therefore, hypothesis H1 can be claimed as true. The increase in light sensitivity can be interpreted as the growth of moth from a newborn to an adult. The increase in this sensitivity can be related to the

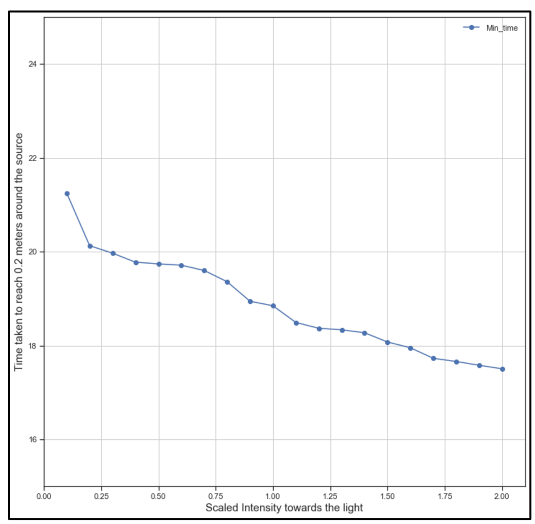
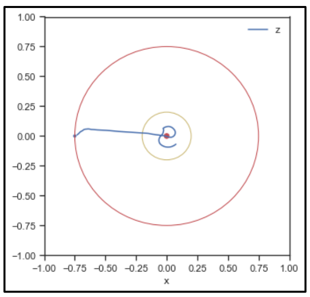


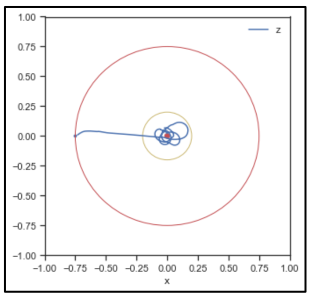
Fig.5 Time taken to reach 0.2 meters near the source Vs. Intensity for observations from experiment B

development of vision senses in moths i.e. as moths grow their visual senses, their ability to navigate improves with time. Furthermore, experimental results obtained from experiment A can provide insights for understanding the behavior of different moth species based on their sensitivity towards the light source.

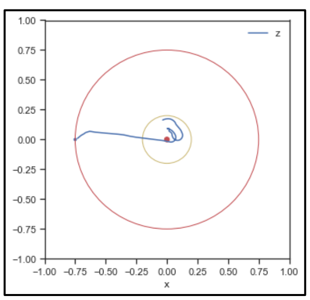
The experiment B observations at K_a =1 Watt per meter square for variations in light source intensities are plotted in Fig.5 These results indicate that an increase in source intensity results in an approximately linear decrease in time taken by an artificial agent to reach 0.2 meters to the light source. These results are also supported from the model equations (3) and (4) as the sensor readings are proportional to the light source intensity, an increase in light intensity results in an increase in agent's speed which in turn results in less time taken by the agent to reach nearby the source. Biologically, this explains the degree to which moths are driven towards the source, it shows the urgency to react to a stimulus by taking less time to reach a nearby source,



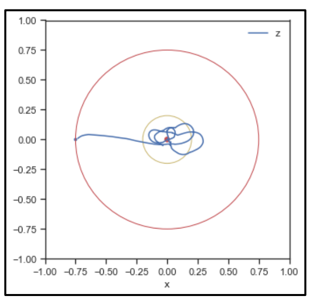
(a) A = 5, K_a = 0.5 m^3/J



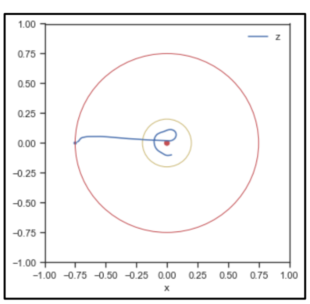
(b) A = 5, K_a = 2 m^3/J



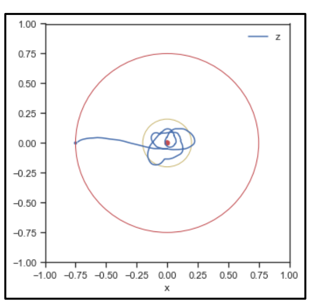
(c) A = 7, K_a = 0.5 m^3/J



(d) A = 7, K_a = 2 m^3/J



(e) A = 9, K_a = 0.5 m^3/J



(f) A = 9, K_a = 2 m^3/J

Fig.6 Trajectory of agents (blue in color, red dot at center represents light source) for a light source of 1 W/m^2 and at coefficient of proximity repulsion = 3 m^3/J, A and K_a values are described as above for different observations.

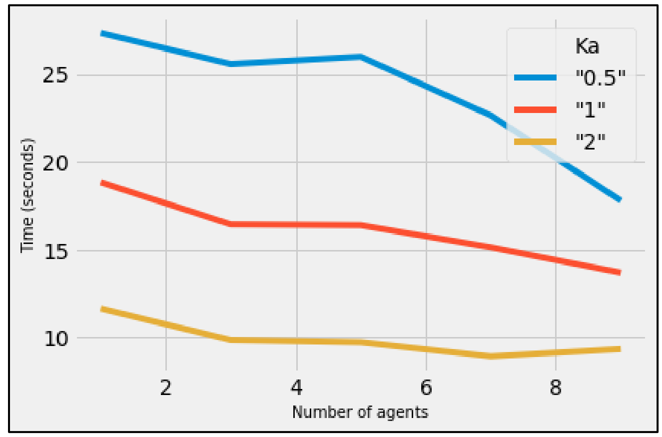


Fig.7 Plot for time taken to reach 0.2 meters from source vs Number of agents from experiment C observations for different K_a values

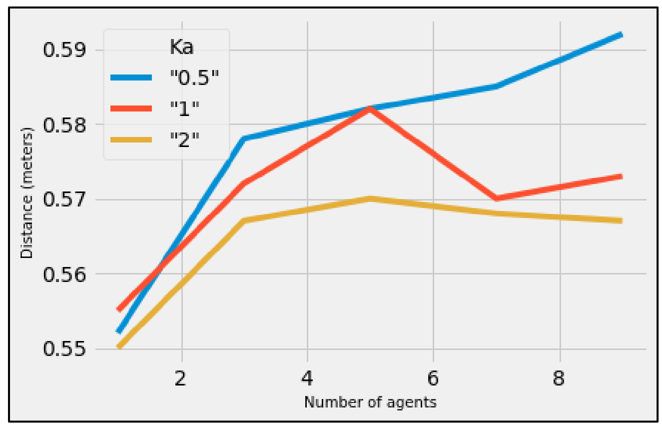
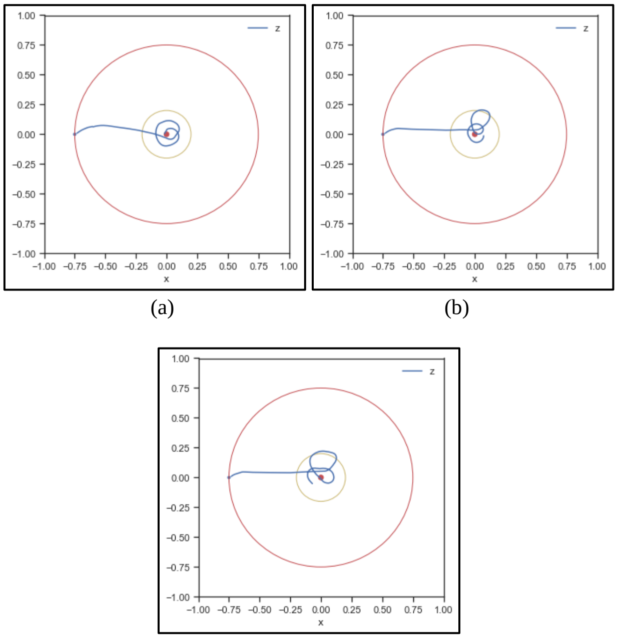


Fig.8 Plot for distance traveled to reach 0.2 meters from source vs Number of agents from experiment C observations for different K_a values

satisfying the hypothesis H2 as explained above. The observations from experiment B can be used along with moth's chemotaxis behavior towards pheromones and food-sources to understand the decision making in moths while responding to a multi-stimulus environment.

Fig.6 shows trajectories of central agent obtained from experiment C for A equal to 5,7 and 9 with variations in K_a values as 0.5 and 2 meter cube per joule. These trajectories represent the path taken by the central agent to reach near the light source exhibiting the positive phototaxis behavior along with agent's ability to orient itself towards the light source. Comparing Fig.6 (a), (b) with (c), (d) and (e), (f) it can be observed that the trajectory of the central agent nearby the light source does not always get wider as the number of agents increases in the environment, this reflects how the agents might try to distance themselves from other agents before reaching the light source. This behavior explains how moths pre-plan their trajectories in the forests [16], which help these creatures to avoid prey and follow intelligent trajectories. In addition to this, looking at Fig.6 (a), (c), (d) and (b), (e), (f), it can be observed that agents which are more sensitive to light tend to follow more complex trajectories nearby light source compared to the ones exhibiting lower sensitivity towards light. This complex



(a) (b) (c)

Fig.9 Trajectory (blue in color, red dot at center represents light source) at an Intensity = 1 W/m^2, Number of agents = 3, K_a = 1 m^3/J, For Figure 9 (a) K_f = 1, (b) K_f = 3 and (c) K_f = 5 m^3/J

behavior can be understood from the (3) and (4), as both K_a and K_f actuate the wheels in opposite directions.

Fig.7 shows the plot for distance traveled central agents to reach 0.2 meters to the light source with respect to the number of agents in the environment for K_a values equal to 0.5,1 and 2, and Fig.8 represents the plot for the time taken to cover the distance as described in Fig.7 with respect to the number of agents. Looking at Fig.7 and Fig.8 It can be said that the time taken, and distance covered to reach 0.2 meters to the light source cannot be positively related to the number of agents present in the surrounding for different values of K_a , thus hypothesis H3 can be rejected. These plots provide an idea of emergence in the multi-agent system, the non-linear behavior for different K_a values can be attributed to the change in velocity of agents in the presence of multiple agents. This provides evidence that not only phototaxis, but insect crowding can also cause an increase in the velocity of moths. Furthermore, it shows that for a given environment there might be an optimal value of the number of moths in a moth eclipse, at which number, the moths can use minimal resources (cover less distance or take less time) to navigate properly without colliding with neighbor insects.

The trajectory obtained from experiment D for A = 3, and for K_f values as 1,3 and 5 are described in Fig.9, it can be observed that An increase in K_f value for agents in multi-agent systems, results in the trajectory of agents to be wider. This result can be interpreted from (3) and (4), i.e. for a fixed number of agents, the higher proximity coefficient drives the agent to such a trajectory that helps to avoid collisions, and thus resulting in wider trajectories. Table I shows the

Table I: Experiment D observations

Intensity = 1W/m^2 , K_a = 2m^3/J and A=3		
K_f	Distance (in meters)	Time (in seconds)
1	1.764	16.914
2	1.75	16.496
3	1.655	16.448
4	1.725	16.496
5	1.656	16.448

observations obtained for experiment D; distance traveled by the central agent in 60 seconds and time taken by the central agent to reach 0.2 meters from the source at a light source intensity of 1 watt per meter square and at A equals to 3 for different K_f values. These results indicate that the distance traveled by these agents in a fixed time and time taken to reach nearby the light source does not always increase with an increase in proximity sensitivity of the agent, therefore hypothesis H4 can be rejected. The model behavior regarding the distance covered can be attributed to an increase in the velocity of the agent due to higher K_f values as can be understood from (3) and (4). As per entomology, these observations can provide a basis for why certain moth species with higher sensitivity towards proximity repulsion, still tend to form a moth eclipse with a higher number of moths [16].

The time and distance data from experiments A, B, C and D can be found in Appendix C, also trajectories of all the observations obtained from these experiments can be found in Appendix D. Observations for these experiments show some non-linear relationship between time to reach nearby source and value of K_f as well as between time to reach the nearby source and A. Thus, the response of an agent with variations in experiment parameters cannot be predicted by linear extrapolation of data with respect to parameters. The section below presents a machine learning approach to predict and evaluate the non-linear time characteristics of artificial agents in a group with variations in environment settings.

B. *Predicting And Evaluating The Moth Behavior In Multi-Agent Environment*

Machine learning models such as artificial neural networks [28] and support vector regression [29] have been used extensively to learn patterns from the simulations. The merged and extended data (Appendix C) from experiments C and D can be used to predict the result of simulations for different values of experiment parameters. The parameters such as light source intensity, K_a , K_f and A can be used as independent predictor variables and minimum time taken by the central agent (the middle agent as shown in the simulation set up) to reach the nearby (0.2 meters) the light source can be analyzed as the outcome variable. Since the number of observations is small, the Support vector regression method [30] is preferable over neural network-based methods. Thus, the above-mentioned data is used to train a kernel support vector regression model (SVR) and linear regression, since the data follows a nonlinear pattern as discussed above, the performance of the support vector regression (using radial basis function as kernel) method is expected to be better as it uses a kernel-based approach.

1) Training methodology: Total merged data from experiments C and D with 180 observations (Appendix C) is randomly split among two sets, 80% of this data is used for training the regression models whereas 20% is used to test the performance of trained models. Furthermore, a 5-fold validation set is used for tuning the hyperparameter of the Support vector regression model.

2) Model Performance: The accuracy of machine-learning-based prediction models is calculated using root mean square error on predicted and observed data. The average accuracy of SVR based models on training data is 0.76 seconds whereas the average accuracy of linear regression on training data is 2.36 seconds. The Fig.10 shows the comparison of linear regression vs kernelized support vector regression for square root absolute error on training and testing data respectively, the average accuracy achieved for the Support vector regression method is 0.21 seconds whereas average accuracy achieved for the linear regression model is 2.09 seconds. The model parameters for SVR models can be found in Appendix E.

From the plots shown in Fig.10 and the model performance it can be understood that a kernel SVR model performs better on the data compared to the linear method used in linear regression, this further provides evidence of a nonlinear relationship among the environment parameters and time taken by the central agent to reach nearby the source(0.2 meters).

The SVR model predicts the time taken by the agent to reach 0.2 meters from source with an average absolute error less than that of 0.7 seconds. The similar SVR models can be used to predict and evaluate the patterns in the average time taken by all agents to reach a nearby source, maximum time taken by an agent to reach nearby the source and many more characteristics of multi-agent systems subjected to various environmental features. This SVR method-based approach can be used as a tool for understanding the moth phototaxis behavior with variation in environment dynamics.

V. MODEL SIGNIFICANCE AND APPLICATIONS

The artificial agent model described in this paper can be used for understanding the variations in moth behavior in different light source environments. The observations from experiments C and D can provide useful information to entomologists regarding the behavior of moths in multi-agent environments, their path planning tendencies and how eclipse sizes of moths are emerged to navigate efficiently. The experiments A and B can also provide insights to compare different moth species based on their sensitivity to phototaxis and can be useful to study evolution and the lifecycle of moths in different parts of the world.

The SVR based predictive model can further be used to analyze the above model-based patterns for a specific number of agents and light source intensity for a moth species.

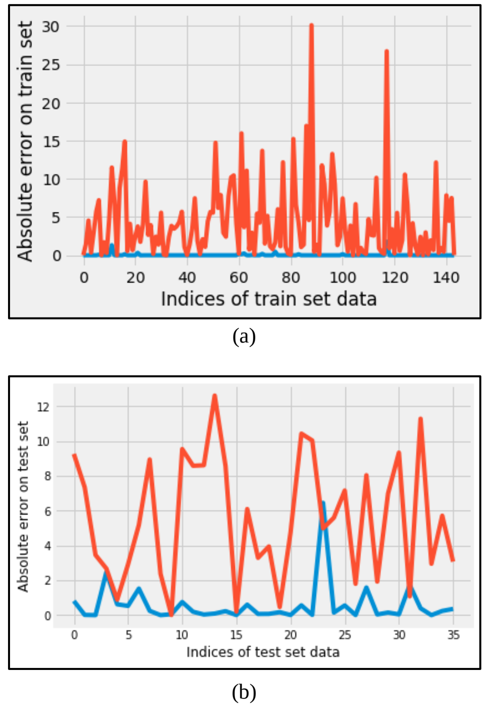


Fig.10 Performance of SVR and Linear regression on (a) train set and (b) test set, blue one represents absolute error for SVR method and red one represents absolute error for linear regression.

Though the SVR model can predict artificial agent model time-based behavior for the given data, it would require more data for efficient prediction for parameters that vary too much from the training data. In addition to this, a better prediction model can be built implementing artificial neural networks (ANN) collecting a large sample data by carrying out more simulations. However, the SVR or ANN-based approach can provide accurate prediction with low error bounds, these approaches still lack interpretability and are expensive in terms of memory utilization compared to interpretable linear methods. Therefore, these methods may not be used by entomologists for interpreting the effect of an individual environment parameter on predicted emergent characteristics.

The described artificial agent-based model only considers moth's phototaxis behavior, however, moth's behavior can be affected drastically in presence of pheromones and food sources thus further work considering chemotaxis in moths can improve the relevance of the model significantly. In addition to this, the simulation set up used for multi-agent systems is an approximate representation of the moth's real-world in two dimensions excluding moth's Levy flight patterns [31], which may not be directly applicable in describing the moth eclipse's behavior completely in three dimensions.

The rational agents in the model described in this paper orient themselves towards light sources and follow an intelligent trajectory considering the presence of obstacles around. An extended moth model representing three-dimensional motion can be used for decision making and solving optimization problems related to unmanned aerial vehicles [32], [33] and have applications in military and as an aerial explorer for gathering planetary information [34]. Furthermore, these multi-agent models can be used in applications where it is hazardous for humans to go such as navigation through confined spaces such as reactors and vessels used in nuclear [35] and hydrocarbon industries [36].

VI. CONCLUSION

Braitenberg vehicle-based bio-inspired models can be implemented to understand the moth's phototaxis behavior. The model described in this paper mimics the light-based navigation in moths, the experimental observations bring out some interesting emergent observations for models in multi-agent environments, the results of these experiments show how moths might tend to preplan their trajectory in dense environments and why a certain number of moth might form an efficient size of moth eclipse while trying to avoid collisions among themselves. Moreover, the emergent behavior of artificial agents mimicking moth can be predicted using non-linear machine learning methods using the simulation data. The machine-learning model along with the artificial agent model can be used to study the emergent patterns in moth eclipse. In addition to this, these emergent model properties can be used in decision making for various practical robot applications such as robotic navigation in unmanned aerial vehicles.

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