

A Critical Analysis of an Ant Excavation Model

Colton Cunov, Emil Jansson, Johan Laberg Nilsson, and Xinlei Li

(Dated: January 10, 2021)

From empirical data Buhl, et. al. created a model for digging activity in ant colonies that reproduces the observed positive linear relationship between excavation volume and the number of ants in a colony, as well as incorporates feedback in the form of recruitment via pheromones. Included in the model were a higher probability for ants to dig when in a depression, or anfractuosity. In this paper, we reproduce the model and find that the depression aspect is likely not necessary to reproduce these relationships, as well as present new evidence to support the authors' assertion that the logistically-shaped excavation dynamics result from an interplay between recruitment and ant density.

I. INTRODUCTION

Ants are social insects with complex colonies that rely on many individuals to cooperate in order for the colony to succeed. In addition to their ubiquity, these factors have led to ants being extensively studied in biology [1] as well as used for inspiration in other areas of science such as engineering and computer science [2], [3], [4].

Understanding more about ant behaviour is a key to better deal with ants as a pest and to understand their role in ecosystems [5], [6]. There is also value in learning more about ants as inspiration for other fields of science.

One way to understand ants is through behavioural modeling. Since ants are relatively simple agents and are part of large societies, many of their high level behaviours can be recreated in agent based simulations [7], [8], [9]. In this paper we examine one such model presented in a paper by Buhl, et. al. in [10].

The main claim of the model presented in [10] is that the excavation dynamics of ants are logistically shaped due to an interplay between recruitment processes and ant density. Logistic shapes are often indicative of a double feedback system, where positive feedback results in an initial exponential growth phase and negative feedback results in a saturation phase [11]. In this case they hypothesize that the recruitment through pheromones leads to the growth and that this effect is saturated when the ants reach a critical density. After first conducting experiments with biological ants, they were able to reproduce the observed dynamics with their model, but do not provide any further evidence or quantification supporting their assertion that recruitment and density are causally linked to the excavation dynamics.

To further evaluate the hypothesis this report examines the model's ant recruitment process via a proxy measure for local ant density and compares it to the excavation dynamics. It also examines if the realistic tunneling behavior is a critical component of the model.

II. MODEL

The model used is based on the simulations described in [10] and was implemented to recreate the dynamics of the system. The original model was inspired by real-world experiments of biological ants digging into a disk of sand in an enclosed arena. It is comprised of a 2-D grid of cells, with a one layer thick disk of sand in the center. Ants are initialized randomly about the remaining space around the disk.

During the simulation ants can dig, carry sand, and move about in space. The ants' behavior is modified by pheromones which introduces the self-organizing behavior.

A. Ant Body and Perception

In the model ant bodies occupy multiple cells. Their decision making process is probabilistic and is modified by their perceived surroundings. An ant perceives cells in a square around it's body as seen in Fig. 1. This square is divided into perceptive areas which represent what the ant perceives in a certain direction. It is these squares the ant uses to detect pheromones, avoid obstacles, discover grains of sand, and decide if it is in a depression or not.

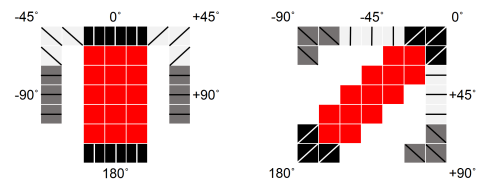


FIG. 1. Ant body and perception area of ants in the 0° and $+45^\circ$ configurations. Red squares are occupied by the ant body and gray-scale squares are perceptive areas for different directions.

B. Pheromone deposition, diffusion, and evaporation

While an ant is digging it will deposit a quantity of digging pheromone below and immediately in front of itself. After the sand has been extracted, the ant will lay an initial quantity of trail pheromone as well as a decreasing quantity at each subsequent time step until the sand is dropped.

The two pheromones are subject to evaporation at each time step and diffuse to surrounding cells in the Moore neighborhood via a diffusion coefficient.

C. Digging behavior

An ant that is eligible may spontaneously dig, which means it is unable to move for a period of time. The probability that an ant starts digging is higher when in a depression than when facing a homogeneous wall of sand, see Fig. 2. This is also the case if an ant is under the influence of digging pheromones. During the influence of pheromones ants' digging probability is calculated as $f_p = \frac{X^2}{X^2 + K^2}$, where K is a constant that is smaller if the ant is in a depression and X is the amount of digging pheromone in her vicinity. Once the ant is finished digging it enters the transporting state where it carries a sand pellet.

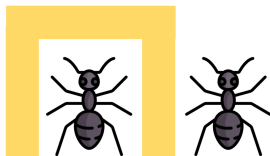


FIG. 2. The ant to the left is considered to be in a depression since the amount of sand surrounding it exceeds a threshold, while the ant on the right is not.

D. Ant movement

In each time step, an ant is eligible for movement if it did not dig, pick up, or drop sand. Each eligible ant moves to a cell in the Moore neighborhood (Fig. 3) subject to the weights given in the movement matrix, which favors forward movement. These values are modified by the addition of the amount of trail pheromone present in the surrounding cells.

III. METHODS

We firstly implemented the model described in [10], taking care to resolve ambiguity with reasonable assumptions. We validated these assumptions by reproducing


46	100	46
6		6
0	1	0

FIG. 3. Relative probabilities of the movement matrix M_d before pheromones are added. Note that an ant occupies more than one cell (Fig. 1).

the authors' results, namely the linear relationship between ant colony size and excavated volume, the excavation rate, as well as the tunneling behavior seen in Fig. 4.

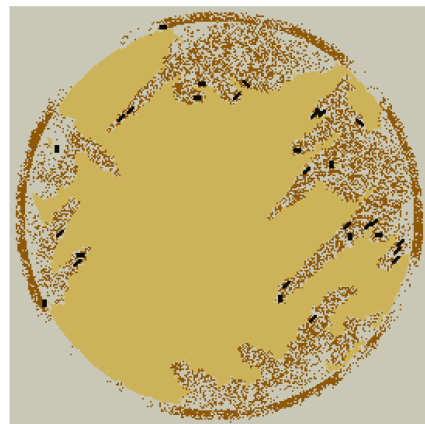


FIG. 4. Simulation in progress: ants, sand and excavated sand pellets are in black, yellow, and brown respectively.

Because the authors hypothesized that pheromones and ant density alone are responsible for the logistic excavation dynamics, we created an alternative model by making an ant no more likely to dig in a depression than when faced with a homogeneous wall. This removes the tunneling behavior observed in nature. We analyzed the excavation rate and relationship between colony size and excavated volume, and compared the results to the unmodified model.

Some [12] have hypothesized that because the excavation dynamics are driven by interactions, as the local density of ants decreases due to tunneling there are fewer opportunities for interactions, and the digging rate will decrease. As a proxy measure for average local density we used the inverse mean inter-ant distance (ρ_l), which reflects the degree to which ants are close to each other. Ants that are close together will contribute highly to this value, while ants that are far away will contribute little. This gives us a measure that is invariant to the

number and size of groups and has arity 0, as opposed to cluster analysis methods such as k -nearest neighbors. Using MATLAB's *fit* function with the '*smoothingspline*' option and a suitable smoothing parameter, a curve was fit to the simulated data ($R^2 = 0.942$, Fig. 6).

We ran 10 simulations with 50 ants using the same parameter values as [10], the only exception being Δt which was set to 1 due to computational constraints. In the next section we define pheromone exposure as the level of pheromone in the perceptive areas of all ants.

IV. RESULTS

Fig. 5 shows a clear correlation between the digging rate and exposure to digging pheromones. Recruitment through digging pheromone seems to be a dominant aspect determining excavation rate.

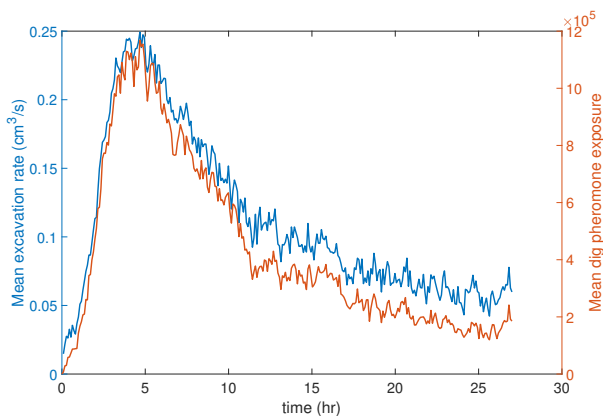


FIG. 5. Digging rate and dig pheromone exposure.

In Fig. 6 the local ant density increases over time before converging to a fixed value. This is indicative of an initially rapid coalescence of the ants, before the attracting and repelling factors affecting them reach an equilibrium.

Fig. 9 shows the rates of change for the trail pheromone exposure Δq and local density $\Delta \rho_l$ over time. The influence that the trail pheromones have on ant movement can be seen through Δq since trail pheromones stimulate ants to move from low to high concentration areas, giving a large Δq . The change in local density $\Delta \rho_l$ can be seen as the speed at which ants are grouping together, a signal of spatial recruitment. We can therefore infer that spatial recruitment is correlated with trail pheromone influence, along with the excavation rate from Fig. 5

Using the alternative model where ants ignored depressions, we found excavation dynamics similar to that of the original model. This can be seen when comparing Fig. 7 and Fig. 8 to the results in [10] in addition to Fig. 5.

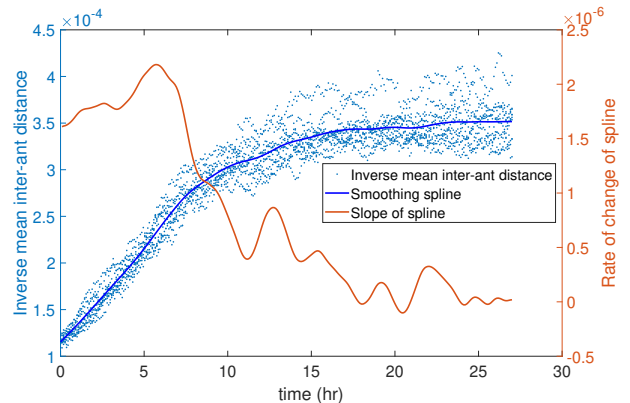


FIG. 6. Local density ρ_l measured in cell^{-1} , with smoothing spline and slope of the spline ($\Delta \rho_l$).

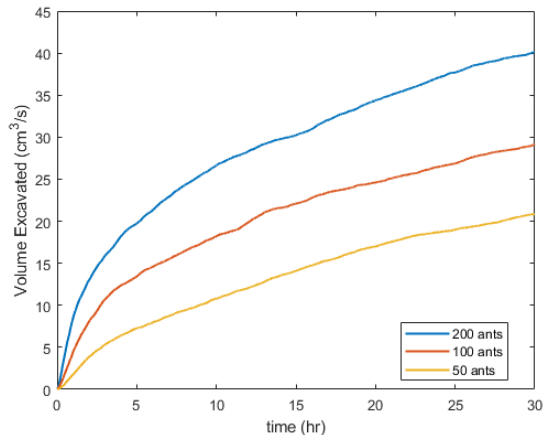


FIG. 7. Excavated volume of sand over time for different colony sizes with depression aspect removed.

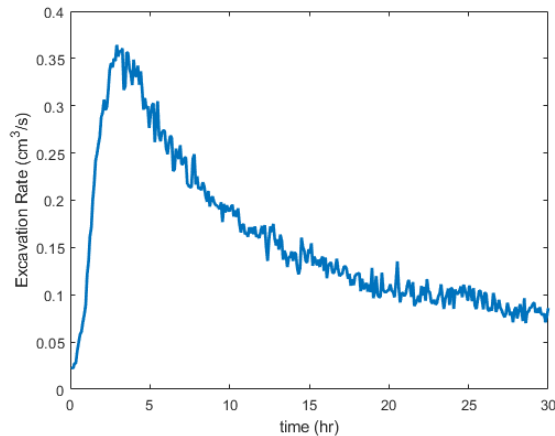


FIG. 8. The excavation rate over time for an ant colony with 100 ants with the depression aspect removed.

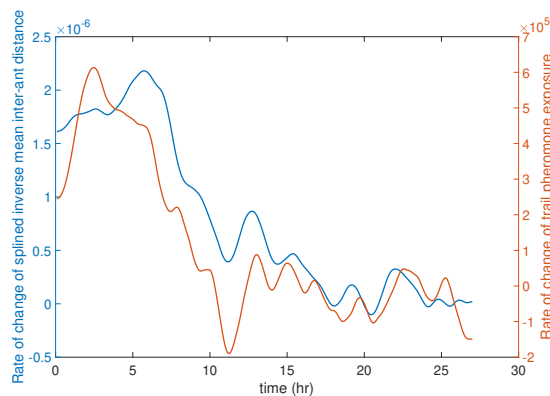


FIG. 9. Rates of change of local density ($\Delta\rho_l$) and average trail pheromone exposure (Δq). Linear correlation coefficient of 0.9079

V. DISCUSSION

What differs between the results presented here and in Buhl, et. al. is the numerical values. We cannot be sure what causes this discrepancy since the paper was not completely transparent on all parts of the model and we have had to make some assumptions. The one parameter we know is different between our simulation and the original one is Δt , the time step.

To reduce the time taken for each simulation we have used a time step of 1 second instead of 1/20. This allowed us to try new changes and experiment with simulations completing within 2 hours instead of 2 days, a requirement for producing results on time. This disparity may be significant because ants move one cell per time step, meaning a higher Δt yields fewer movements and pheromone depositions, or in other words, slower excavation. This is a strong candidate for the disparity in numerical results between our simulation and the paper.

The simulations run with and without rules for encouraging ants to dig in depressions are qualitatively similar with respect to digging rates. This indicates that ants being stimulated by depressions and, consequently, digging tunnels are not necessary factors to recreate the excavation rates observed in biological ants.

An interesting feature to note is that in Fig. 9 the rate of change of pheromone exposure (Δq) leads the rate of change of local density ($\Delta\rho_l$) in the beginning. The lead seems to disappear as we approach 10 hours, where it starts to lag. We speculate that initially there is spatial recruitment via trail pheromones until a critical point, at which a saturation and subsequent degradation of spatial recruitment occurs. This saturation may be due to pheromone diffusion, causing a fuzzy and widespread pheromone distribution and resulting in meandering ants. Further investigation may lead insight into the role of this dynamic in the negative feedback implied by the logistic dynamics.

VI. CONCLUSIONS

By removing the depression aspect from the model presented in [10] and obtaining comparable excavation dynamics, we call into question the importance of this inclusion. It is certainly necessary for producing tunnels, however the authors based the model's validity on its ability to reproduce the excavation dynamics and did not consider the produced networks. Further study of the resulting networks may produce insight into model improvements.

In this paper we noted a strong correlation between the digging rate and digging pheromone exposure, which suggests the ants recruit each other to dig. Additionally we showed correlations between trail pheromone exposure, local density, and digging rate, suggesting a relationship between spatial recruitment and excavation dynamics. These findings suggest that a causal relationship between the excavation dynamics, recruitment, and density may exist, and lends credence to [10]'s assertion that the excavation dynamics are likely attributable to an interplay between recruitment and density.

CONTRIBUTIONS

Johan

Colton

- Proposed research area.
- Participated in simulation debugging.
- Data analysis and figure generation.
- Participated in conclusion formation.
- Participated in writing and editing report and presentation.

Emil

- Participated in coming up with a research area and posing research questions.
- Modeled and implemented the simulation in Matlab.
- Participated in analyzing the results of the simulation and forming conclusions.
- Participated in writing and editing the report and presentation.

Xinlei

- Discussed the research question and scope.
- Helped prepare presentation material and final presentation.
- Editing of the report.
- Participated in debugging and implementation discussions.
- Research area background investigation.
- Participated in simulation debugging.
- Participated in presentation, and recording and editing the presentation video.
- Editing part of the report and discussing the conclusions.

-
- [1] E. O. Wilson, The social biology of ants, *Annual Review of Entomology* **8**, 345 (1963).
 - [2] J. Dupeyroux, S. Viollet, and J. Serres, Antbot is able to go home like desert ants (2019).
 - [3] A. D. McKinnon, S. R. Thompson, R. A. Doroshchuk, G. A. Fink, and E. W. Fulp, Bio-inspired cyber security for smart grid deployments, in *2013 IEEE PES Innovative Smart Grid Technologies Conference (ISGT)* (2013) pp. 1–6.
 - [4] R. Mullen, D. Monekosso, S. Barman, and P. Remagnino, A review of ant algorithms, *Expert Systems with Applications* **36**, 9608 (2009).
 - [5] T. M. Della Lucia, L. C. Gandra, and R. N. Guedes, Managing leaf-cutting ants: peculiarities, trends and challenges, *Pest Management Science* **70**, 14 (2014), <https://onlinelibrary.wiley.com/doi/pdf/10.1002/ps.3660>.
 - [6] C. S. Lofgren, *Fire ants and leaf-cutting ants: biology and management* (CRC Press, 2019).
 - [7] A. Drogoul, B. Corbara, and S. Lalande, Manta: New experimental results on the emergence of (artificial) ant societies (1995).
 - [8] E. J. Robinson, F. L. Ratnieks, and M. Holcombe, An agent-based model to investigate the roles of attractive and repellent pheromones in ant decision making during foraging, *Journal of Theoretical Biology* **255**, 250 (2008).
 - [9] A. Drogoul and J. Ferber, Multi-agent simulation as a tool for modeling societies: Application to social differentiation in ant colonies, in *Artificial Social Systems*, edited by C. Castelfranchi and E. Werner (Springer Berlin Heidelberg, Berlin, Heidelberg, 1994) pp. 2–23.
 - [10] J. Buhl, J. L. Deneubourg, A. Grimal, and G. Theraulaz, Self-organized digging activity in ant colonies, *Behavioral ecology and sociobiology* **58**, 9 (2005).
 - [11] P. Meyer, Bi-logistic growth, *Technological Forecasting and Social Change* **47**, 89 (1994).
 - [12] J.-L. Deneubourg and N. R. Franks, Collective control without explicit coding: the case of communal nest excavation, *Journal of insect behavior* **8**, 417 (1995).