

Reading and Research Report

Problem Domain

Communication is an important factor in the foraging performance of social insects, like ants. During foraging, ants keep track of the food sources by using memory (site fidelity) or communicating it through pheromones [1]. If food is spatially clustered, then ants recruit nest mates to collect from large clusters. However, we don't know how large a food pile needs to be for recruitment to occur. Goal of our research was to investigate the answer of this question and develop a model to detect the recruitment in the field data.

Background Study

Previous study has showed that, seeds with less information are found faster [1, 2]. Colony size is also an information factor in the foraging performance of ants. More large colony size means more external communication(via chemical/Pheromone) which leads to better foraging performance [3]. We have used the field data of the experiments of [1] to detect the changes in the foraging rate. Since the data is been collected manually, we are assuming that, there may be some errors while collecting the data. So we have decided to use the simulator to generate the data for our experiment. We have used the iAnt argos simulator developed in Biological Computation Lab of UNM. It uses the Central Place Foraging Algorithm [1] which uses individual agents. iAnts have the ability to sense food and count food near food source that they find, as well as deposit and follow pheromone at locations, and remember previously found locations. The CPFA is an example of a complex system in that it is a system represented by small components, iAnts which use signaling and information processing(pheromone, site fidelity and counting) to adapt to their environment in order to collect the most food in a given time frame without a central decision [4]. The CPFA focuses on seven changeable parameters that govern its behavior. The rate of laying pheromone or pheromoneRate. The rate at which site fidelity is used or siteFidelityRate. The rate of pheromone decay, how fast pheromone evaporates, or pheromoneDecayRate. The rate of informed search decay (informedSearchDecay) which governs how long an iAnt spends searching a previously known good location. The uninformed search variation (uninformedSearchCorrelation) which governs the turning angle of an iAnt during search. The probability of giving up on search and returning to nest, searchGiveupProbability. And finally the probability of switching to searching which governs when an iAnt will give up on its traveling to a location and switching to searching at its current location (travelGiveupProbability).

Methods

To simulate the behavior of ants we have used Argos simulator which uses CPFA. We have tuned the parameters of CPFA using the GA. We prepared specific environment for our GA. We have looked at evolving the CPFA on a larger arena size, 20 by 20, with more seeds, power rank 5 which has 1280 seeds in varying size clusters. We evolve two types of genetic algorithms (GAs) in this environment: one that limits the pheromone rate and one that uses the full range of values of the CPFA. We look at finding when swarms are able to collaboratively collect from piles and see if this collaborative collection causes an increase in collection rate [5]. We use change point detection through the CUSUM method. We are able to detect change points that seem to match the data but the results are not completely conclusive as they require manual intervention to match data. We wanted to take a closer look at when a pile is discovered by ants. To do so we have used our developed CUSUM module. We traced collection time for all of the seeds. Then we have separated seeds according to their distribution type. To detect the discovery of piles or a collective recruitment, we have used CUSUM algorithm which is capable of detecting change points. We have created timelines of collected seeds using sliding windows of 60 seconds with varying sliding

amounts based on the pile type. This timeline contains the rate of seed collection. To get the optimum results for change detection.

Our Results

We analyzed foraging rates on different sizes of piles in simulation. Using a power law distribution to arrange seeds in piles of different sizes, we observed that for significantly large piles of seeds, the ants take more time to discover a pile, but once discovered, seeds are collected at an increased rate from that pile (Figure 1). We also observed that ants may repeatedly lose track of found piles and then re-find them. Using change point analysis on seed intake time series, we were able to trace the discovery and loss of a piles by detecting changes in the foraging rate. We found multiple positive and negative change points for single large piles of foods and no change points for small clusters of foods, which suggests that ants do not recruit to small clusters of food. We have tried to trace the discovery of piles by detecting abrupt changes in their foraging rate. We have varied sliding window size and sliding amount to get the optimum result for detecting changes. We are able to detect change points for one, four and sixteen large piles by varying the thresholds and drifts. It can be inferred from Figure 2 that if the piles are not significantly large then detecting of changes in collection of seeds are difficult. But for sixty four piles of four seeds it was not possible to detect the changes as the distribution is close to a random distribution of seeds.

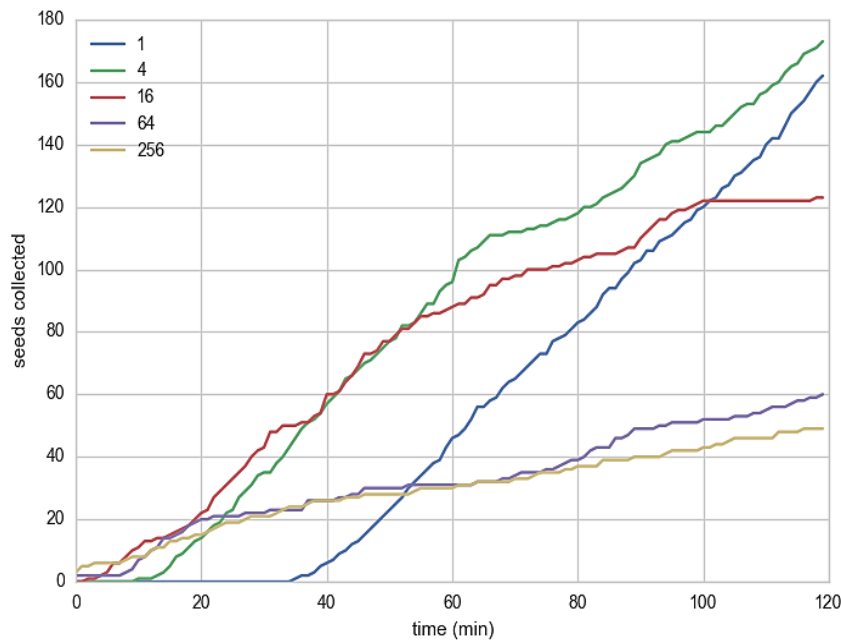
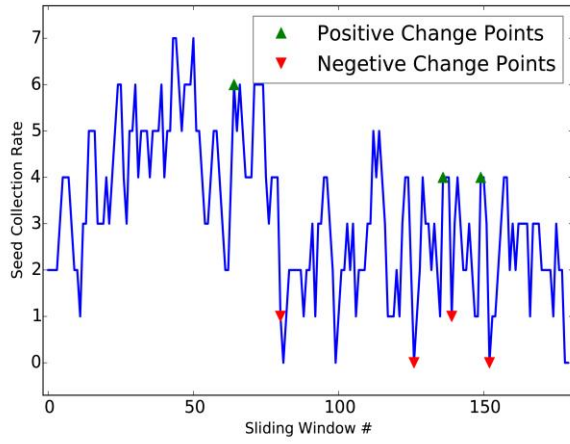


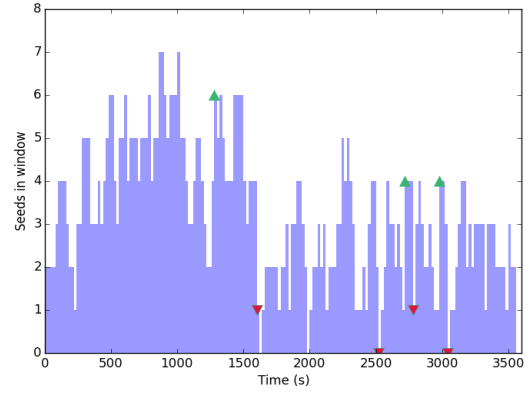
Figure 1: The time series is generated from one experiment of simulated iAnt data. It shows the rate of collecting seeds from different types of piles. Blue line is for 1 large pile of 256 seeds. Green line is for 4 piles of 64 seeds. The red, purple and yellow lines are for 16 piles of 16 seeds, 64 piles of 4 seeds and 256 random seeds respectively. It can be inferred from the figure that large piles takes more time to be discovered, but once they are discovered, the foraging rate from that pile increases.

The drifts, threshold values, sliding windows and their sliding amounts are given in the table for different types of pile size of seeds.

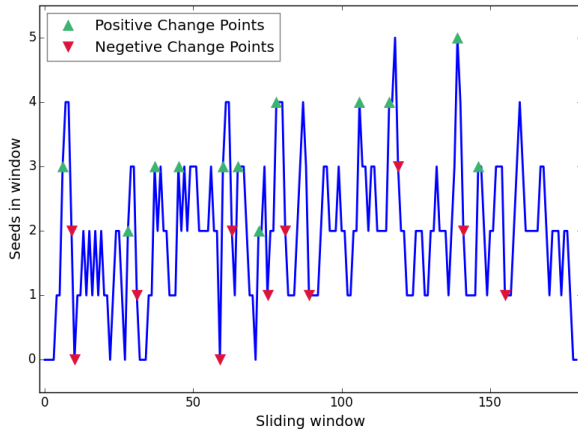
Seeds in Pile	Sliding Window	Sliding Amount	Threshold	Drift
256	60	10	1	1
64	60	20	1.5	0.8
16	60	40	1	0.5



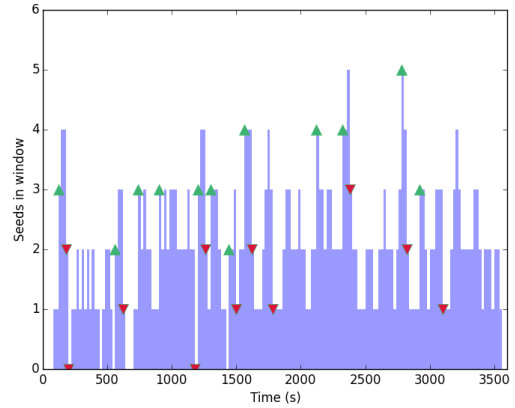
(a)



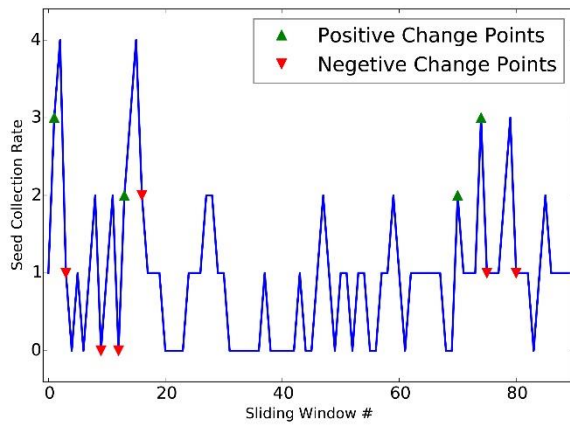
(b)



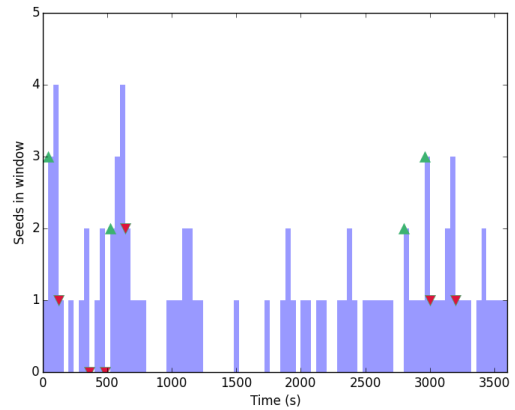
(c)



(d)



(e)



(f)

Figure 2: 2a and 2b shows the discovery of one large pile multiple times. 2a detects the change points in the sliding windows and 2b shows the actual time that the changes occur. 2c represents the change points for Four piles in the sliding window and 2d represents actual change points in time. 2e and 2f detects the changes in foraging rate for Sixteen Piles.

Future Work

At this point, we have tried to tune all the parameters. Next we are going to tune all other parameters except site fidelity (We will keep it to zero). The reason behind this is to check the foraging performance with zero site fidelity and only pheromone. Before applying the change point detection algorithm on the data set we will detrend the data set. The purpose of detrending is to make the change points more detectable. We assume, the recruitment from large piles are inflated by pheromone. To find a correlation between pile size, pheromone and recruiting we will trace the increment in pheromone value along with time and try to correlate the change points with the pheromone value.

References

- [1] T. Paz Flanagan, K. Letendre, W. Burnside, G. M. Fricke and M. Moses, "How ants turn information into food," in *Artificial Life (ALIFE), 2011 IEEE Symposium on*, IEEE, 2011, pp. 178--185.
- [2] M. E. Moses, K. Letendre, J. P. Hecker and T. P. Flanagan, "In vivo, in silico, in machina: ants and robots balance memory and communication to collectively exploit information," in *Proceedings of the European Conference on Complex Systems 2012*, Springer, 2013, pp. 621--628.
- [3] R. Beckers, S. Goss, J.-L. Deneubourg and J.-M. Pasteels, "Colony size, communication and ant foraging strategy," *Psyche: A Journal of Entomology*, vol. 96, no. 3-4, pp. 239--256, 1989.
- [4] J. P. Hecker and M. E. Moses, "Beyond pheromones: evolving error-tolerant, flexible, and scalable ant-inspired robot swarms," in *Swarm Intelligence*, Springer, 2015, pp. 43--70.
- [5] T. P. Flanagan, K. Letendre, W. R. Burnside, G. M. Fricke and M. E. Moses, "Quantifying the effect of colony size and food distribution on harvester ant foraging," *PloS one*, vol. 7, p. e39427, 2012.