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Improving Multi-Agent System Coordination Via Intensity Variation

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Abstract

In this work, we explore the impact of inter-agent variation in intensity of effort on the ability of a swarm of artificial agents to achieve a goal. Variation in intensity models biological phenomena such as individual differences in size and strength and increased adeptness for a task due to experience. Focusing on experience, we implement inter-agent variation in intensity, with dynamic values that increase and decrease with an agent's activation or non-activation for a task. Examining intensity variation alone and in combination with activation threshold variation, we find that the desynchronizing effects of variation in thresholds in concert with the increase in agent efficiency due to experience with a task, dramatically improves the swarm's goal achievement.

1 Introduction

Swarm-based systems consist of large groups or swarms of agents that have a common goal and work collectively to perform the tasks associated with that goal (Beni 1992). In general, each agent in a swarm is capable of performing multiple, perhaps all, of the tasks required of the swarm. Therefore, the division of labor, selecting which agents perform which tasks, is neither predetermined nor obvious. A self-organizing swarm is one in which coordination of the activities of agents in the swarm is decentralized. Thus, each agent in the swarm decides independently if and when to undertake one of the tasks in service of the global goal. An important feature of natural swarms is inter-agent variability, differences in how or when agents select and perform tasks (Jeanson and Weidenmüller 2014). We introduce variation in intensity of effort, a form of inter-agent variation that reflects some agents' ability to complete more work than others.

In nature, swarms are common, particularly in the insect world. The tasks individuals perform in pursuit of a global goal are often critical to survival of the hive or colony. For example, bee hives are highly sensitive to temperature variation. Members of the hive act collectively to maintain the hive's core temperature in a narrow range, 35 to 37 °C. When the temperature drops, bees intentionally shiver to generate heat. When the temperature rises, bees flap their wings to move air and cool the hive. Additionally, some bees may move into or out of the core to increase or decrease population density, which also affects core temperature. This latter action allows for a low-cost method of temperature regulation as it requires a much lower degree of energy expenditure than shivering or flapping. This is important as the hive has a limited supply of honey, their energy source (Seeley 2010). In another example, some bee species form clusters as part of their reproductive cycle. Maintaining the cluster, which is critical for reproductive success, requires that the swarm change the shape of the cluster in response to environmental stimuli such as wind or a shaking tree branch. Individual bees decide when and where to move to achieve the desired cluster shape (Peleg et al. 2018).

Importantly, the bees' actions are decentralized: each bee decides if and when to shiver or flap. If members of the hive were uniform in their decisions, the hive temperature would oscillate. For example, when the temperature reaches a threshold value, all bees would begin to flap and continue until the temperature dropped sufficiently and all bees stopped flapping. Then the temperature would rise again and the process would repeat. This is avoided due to variation in the bees' behaviors under the same conditions (Jones et al. 2004; Weidenmüller 2004). Some bees will, for example, begin shivering or flapping before others, for longer or shorter periods, and with more or less energy.

Artificial swarms consist of some number of computational *agents* and are modeled after natural swarms such as bees or ants. As with natural swarms, artificial swarm task performance can be improved through inter-agent variation. Common sources of inter-agent variation in natural systems include activation thresholds (Jones et al. 2004; Weidenmüller 2004) and probability that an agent will activate (Weidenmüller 2004). As in the bee hive example, variation in activation thresholds desynchronizes agent actions by preventing simultaneous activation by all agents that will perform a task (Krieger and Billeter 2000; Riggs and Wu 2012; Wu et al. 2012; 2020). A side effect of this variation is that early activators will work on a task much more frequently than late activators. This will result in some agents gaining more experience and, therefore, being much more adept at the task. In this work, we model this increased experience through another form of inter-agent variation: variation in intensity of task performance.

Variation in intensity models different abilities of agents (Dornhaus et al. 2008; Oster and Wilson 1978). From the biological perspective, this could model factors such as strength, size and stamina in addition to experience. For example, some bees are bigger and/or stronger than others and may, therefore, shiver or flap more vigorously. Further, an individual may change their intensity of effort to accommodate changes in the needs of the colony (Jeanne 1996).

From an engineering perspective, agent intensity may refer to an agent's working capacity or efficiency which may vary due to wear and tear, amount of time active, and the functional capabilities of the agent. In both cases, variation in intensity means that agents will have different impacts on the goal which may affect when and which other agents respond and gain expertise.

Research in the biology community suggests that experience plays a role not only in individual task efficiency but also in collective colony performance and individual task selection (Ravary et al. 2007; Langridge, Franks, and Sendova-Franks 2004). In at least one ant species, individuals that find early success in foraging activities choose to forage again, whereas those individuals that were unsuccessful are more likely to choose to care for young in the nest (Ravary et al. 2007). In another ant species, task repetition improved colony performance for emigration, the task of moving the colony to a new nesting location (Langridge, Franks, and Sendova-Franks 2004). Efficient emigration is critical as the entire colony is exposed during the process.

We hypothesize that intensity variation, which differentiates agents within a swarm, facilitates more successful goal achievement. Further, because intensity variation is not a form of desynchronization, its effect may be orthogonal to that of activation threshold variation, allowing the two forms of variation to perform well in combination. We implement a model of inter-agent variation and perform experiments to test these hypotheses. In the remainder of this paper, we describe our model, the problem on which we test it, the experiments we perform and the results we observe.

2 Our Model

The testbed problem we use is a simple 2D tracker. In this problem, a *target* object moves in the plane, either at random or according to a predefined path. The agent swarm pushes a *tracker* object (such as a box) attempting to trace the target path in real-time. Agents independently choose to remain idle or undertake one of four tasks: `push_north`, `push_east`, `push_south`, or `push_west`.

A run is divided into a number of discrete time steps. During each of these time steps:

- The target moves a fixed number of distance units, creating frequently changing task demands.
- Each agent chooses and performs a task.

The tracker, pushed by the swarm, may move farther in a time step than does the target. This allows the swarm to catch up to the target should it fall behind or even move ahead of the target. Though the latter is unlikely to be desirable with respect to goal attainment, it reduces constraints on swarm behavior. An example random path is shown in Figure 1.

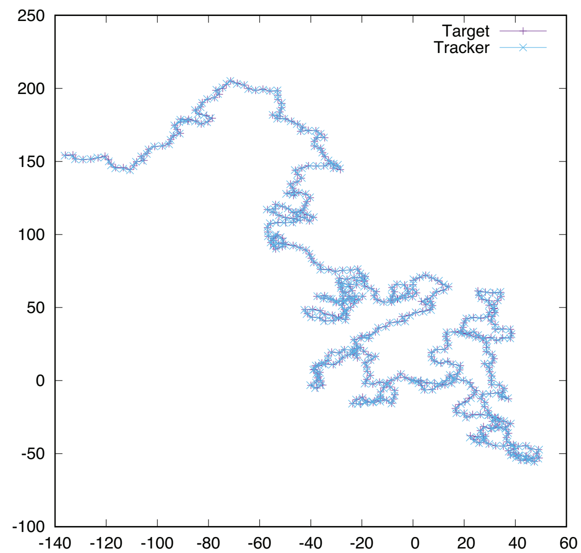


Figure 1: An example random target path (purple) and corresponding tracker movement (blue) over 500 time steps.

In support of the high-level goal of tracing the target path, the measurable goals of the swarm are:

Goal 1. *Minimize the average difference, per time step, between the target location and the tracker location.*

Goal 2. *Minimize the difference between total distance traveled by target and the total distance traveled by the tracker.*

Both criteria are required to gauge how well the tracker follows the target since the tracker can remain close to the target, following the path at a macro level, while performing poorly at a micro level. For example, the tracker may zigzag back and forth across the target path. While the difference in position at any time step is small, the swarm does considerably more work than necessary which is be reflected in the total path length but not the average difference. Conversely, the path lengths may be similar while the tracker is never very close to the target, taking short cuts in some places while straying significantly in others.

At each time step, we record the tracker's distance from the target. In addition, we record the total distance traveled by the target, total distance traveled by the tracker, the number of time steps in which each agent pushes in each direction, the number of times an agent does not perform a task (remains idle), and the number of times an agent changes from one task to another.

Agents know the values of $\Delta x = \text{target}.x - \text{tracker}.x$ and $\Delta y = \text{target}.y - \text{tracker}.y$. In addition, each agent has the following relevant attributes:

- an activation threshold value for each task
- an intensity multiplier value for each task

For this problem, each threshold value represents the maximum acceptable Δ between the target and tracker in the direction specified for that task. If the Δ exceeds the threshold,

Parameter	Values
Population Size	200
Time steps	500
Target step length	3
Tracker step multiplier	2
Task selection	Random
Threshold distribution	Constant 0.5
	Gaussian
	Uniform
Intensity variation	Off
	On
Intensity dynamic	Off
	On
Intensity multiplier range	$\mathcal{N}(1.0, 0.09)$
	$\mathcal{N}(1.0, 0.0625)$
	$\mathcal{N}(1.0, 0.0275)$
Intensity increment	0.15
Intensity decrement	0.05

Table 1: Parameter values for the experiments we perform.

the agent may activate for that task. To illustrate by example, if agent a_i has a push_north threshold of 0.7 and Δy is 0.8 (the target is 0.8 units north of the tracker), then a_i could activate for push_north, whereas if the target is only 0.5 units north of the tracker a_i could not activate for that task. If none of an agent's activation thresholds are met, the agent remains idle. If multiple of an agent's thresholds are met, the agent chooses from those tasks at random. Note that, for this problem, at most two thresholds can be met at once.

As indicated previously, intensity variation can model at least two natural phenomena: differences in an agent's physical ability (strength, stamina, size) and differences in an agent's adeptness (experience). *Dynamic intensity values*, per task gains or losses in intensity due to activation or non-activation for a task, allow us to model either phenomenon.

If dynamic intensity is enabled, an agent's intensity multiplier for a task increases each time the agent activates for that task and decreases each time the agent activates for another task or remains idle. Thus, an agent's intensity multiplier for a task will decrease more often than it increases. For this reason, the magnitudes for increasing and decreasing dynamic intensity multipliers are asymmetric. Intensity multipliers are applied to the base intensity value of 1.0. Thus, an agent with an intensity multiplier of 1.5 pushes 50% harder than an agent with an intensity of 1.0. Figure 2 illustrates changes in dynamic intensities over the course of a run.

3 Experiments

We perform a number of experiments to gauge the effect of variation in intensity of effort on a swarm's ability to achieve a goal. To explore this, we run experiments with the following intensity values:

- Static, homogeneous intensity multipliers of 1.0
- Static, heterogeneous intensity multipliers set according to a Gaussian distribution

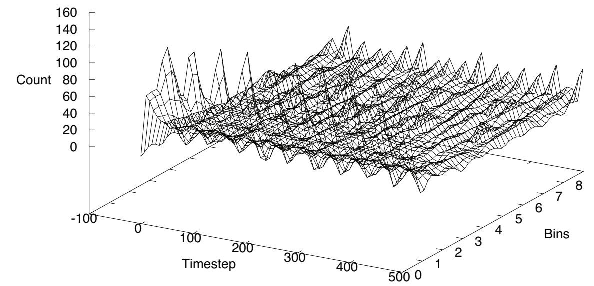


Figure 2: This histogram tracks changes in agent intensity values for task push_north over the course of a run for target path s-curve. The intensity range has been partitioned into 10 uniformly-sized bins. Height represents the number of agents in a bin at a given time step. Intensity multipliers increase with bin number.

- Dynamic, heterogeneous intensity multipliers, set according to a Gaussian distribution, and that vary within a specified range

Figure 3 provides a comparison of these experiments for one of our target paths.

The Gaussian distributions used to determine initial intensity multiplier values appear in Table 1. The resulting intensity ranges are approximately: $[0.1, 1.9]$, $[0.25, 1.75]$, and $[0.5, 1.5]$. We also test dynamic intensities with constant initial values of 1.0. We note that use of this alternatives makes virtually no difference in achievement of the swarm's goal. Thus, we report results only for initial intensity values set according to the Gaussian distributions.

To gauge the interaction between variations in activation thresholds and intensity, our experiments include three distributions for threshold values: constant $= 0.5$, Gaussian $\mathcal{N}(0.5, 0.0275)$, and uniform in [0, 1]. Constant threshold values allow us to gauge the effect of intensity variation with no variation in activation thresholds, while the uniform and Gaussian distributed thresholds allow evaluation of the combined effect of the two forms of variation.

We test our model on four different target paths: random, sharp, s-curve (sinusoidal), and zigzag (sawtooth). s-curve, and zigzag are reasonably self explanatory. The random path, calculates an angle change, in radians, at every time step. The change is Gaussian $\mathcal{N}(0.0, 1.0)$. Sharp is a randomized path in which a new heading and probability p of changing direction are chosen in every time step. The heading is chosen uniformly in $[0, 360]$ and p is in $[0.1, 0.5]$. Thus, turns are sharper than in the random path.

Experiments are run for 500 time steps with a population size of 200. With a target step length of 3, the target path length is 1500 units in all cases. We execute 50 runs for each of 60 different experiments: 4 paths $*$ 3 activation threshold distributions $*$ 5 intensity variations.

The relevant parameters and the values used during the experiments reported here appear in Table 1.

4 Results and Analysis

The experiments performed test our hypothesis: inter-agent variation in intensity of effort on individual tasks improves a swarm's success in goal achievement. In this section we report these results:

- the combination of heterogeneous activation thresholds and heterogeneous intensities dramatically improves swarm performance
- choice of intensity range for a given threshold distribution significantly impacts results
- static intensity variation performs no better than homogeneous intensities
- with dynamic intensities modeling experience, agents specialize and a relative few do much of the work

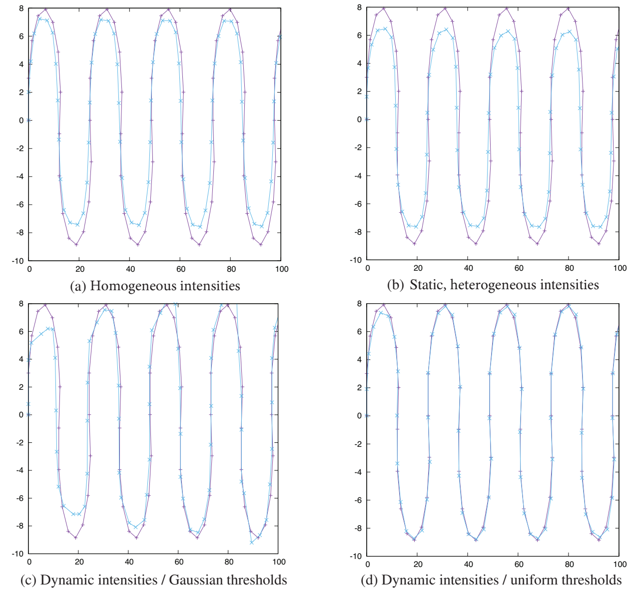
Figure 4 provides an overview of the results. Data presented are averaged over 50 runs for each experiment. Results are grouped by target path.

Twenty-four experiments combine dynamic, heterogeneous intensities with uniform or Gaussian activation thresholds. Significantly, all 24 outperform all but 2 of the 36 experiments in which at least one of the forms of variation (thresholds or intensities) is absent. The only outliers are uniformly distributed thresholds with homogeneous intensities (`uniform-no_intensity`) and uniformly distributed thresholds with static, heterogeneous intensities (`uniform-no_dynamic`) for the random target path only. These were slightly better than only one combination of threshold and intensity variations: uniformly distributed thresholds with dynamic, heterogeneous intensities in $[0.1, 1.9]$ (`uniform-0.1-1.9`). This is unsurprising since, as discussed below, uniform thresholds work best with dynamic, heterogeneous intensities in a smaller range. In all other cases and for all target paths, combinations of threshold variation with intensity variation outperform the absence of one or both forms of variation.

Threshold variation alone improves swarm performance while intensity variation alone does not. Together, the two forms of inter-agent variation produce dramatic improvement. These results strongly confirm the hypothesis that a combination of these two forms of inter-agent variation significantly improves swarm success.

We observe that the choice of activation threshold distribution for a given intensity multiplier range makes a significant difference in performance. The effect is easily seen in Figure 4. When all results are sorted by average difference, for each of six possible threshold distribution / intensity range combinations ($\{$uniform, gaussian$\} \times \{[0.1, 1.9], [0.25, 1.75], [0.5, 1.5]\}$), the results for the four target paths are consecutive. Uniform activation thresholds with intensity range $[0.5, 1.5]$ are best followed by Gaussian activation thresholds with intensity range $[0.1, 1.9]$.

This highlights the interaction between intensities and activation thresholds. As intensity multipliers increase with experience, accurate tracking requires fewer agents to activate. Uniform activation thresholds result in about the same number of agents at the extremes of the threshold range as near the middle. Thus, lower intensity multipliers are desirable. Conversely, with Gaussian activation thresholds, low thresholds are in the tail of the distribution resulting in few agents with these thesholds. With this smaller number of agents activating, we need a larger intensity range to allow agents to push harder. This effect also explains why with uniformly distributed activation thresholds and a large intensity range of $[0.1, 1.9]$, we see a dramatic increase in tracker path length. Notably, with either threshold distribution, we observe strong results with at least one intensity range.



(a) Homogeneous intensities
(b) Static, heterogeneous intensities
(c) Dynamic intensities / Gaussian thresholds
(d) Dynamic intensities / uniform thresholds

Figure 3: Target paths (purple) and tracker paths (blue) for s-curve. With homogeneous intensities (a) and static, heterogeneous intensities (b), the tracker follows the target well except for shortcuts in the turns. With variation in activation thresholds and intensities (c) and (d), the swarm tracks much closer to the target. With uniform thresholds in particular, the target and tracker paths are nearly indistinguishable.

The data also demonstrate that static, heterogeneous intensity multipliers (`no_dynamic`) do not improve swarm performance compared to homogeneous intensity multipliers fixed at 1.0 (`no_intensity`). With both uniform and Gaussian activation thresholds, `no_intensity` and `no_dynamic` intensity multipliers are clustered in the middle of the pack (see Figure 4). Tracker path lengths in these cases are significantly below the target path length. Thus, variation in intensity values improves performance only when the values are dynamic, changing to reflect agents' increased adeptness for a task. Figure 5 illustrates the role of experience. The data are sorted by activation threshold. Agents with low thresholds for a task activate more frequently for that task and, therefore, gain experience, increasing their intensity multiplier. Modeling the limits of experience for improving efficiency, intensity values are bounded.

Figure 2 shows changes in the swarm's intensity values for task `push_north` throughout a trial for target path s-

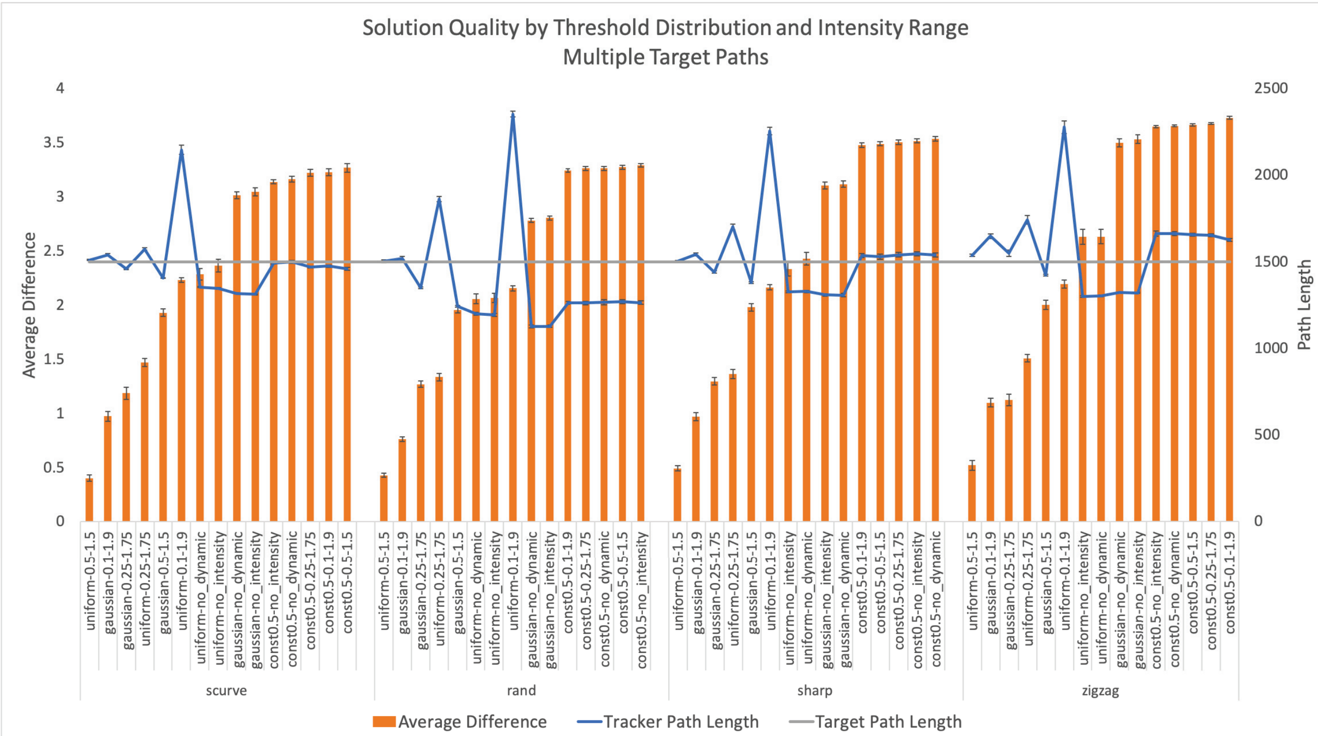


Figure 4: Average values over 50 runs for average difference (bars) and tracker path length (blue line) grouped by the four target paths. Data are sorted by average difference. The gray line shows the target path length. Error bars represent the 95% confidence interval. The experiment labels indicate: `threshold_distribution-intensity_range`. Dynamic, heterogeneous intensity values with heterogeneous activation thresholds achieve the best performance.

curve. The number of highly adept agents (bin 9) pushing north decreases when the target changes direction to east or south, as agents lose experience, and rebounds when the target begins moving north again, as agents gain experience.

Figure 3 illustrates the implications this has for goal achievement. The runs depicted in (3a) and (3b) use homogeneous and heterogeneous, static intensities, respectively. There is considerable variation between target and tracker paths. With heterogeneous, dynamic intensities, shown in (3c) and (3d), performance is considerably improved. When Gaussian activation thresholds are used (3c), improvement is delayed, resulting from the higher intensity values required for each agent due to fewer agents with low activation thresholds from that distribution. With uniform activation thresholds, the swarm's path is very close to the target.

5 Conclusions and Future Work

In this work, we explore the effect of variation in intensity of effort on task completion in a swarm of artificial agents. We experiment with intensity variation in isolation and in combination with activation threshold variation. While both forms of variation are known to exist in natural swarms, such as in bees and ants, only activation thresholds have been extensively studied in artificial swarms. We find that variation in intensity, when combined with variation in activation thresholds, dramatically improves swarm performance. While variation in activation thresholds significantly improves swarm performance in the absence of intensity variation, introducing dynamic, heterogenous intensities dramatically increases the effect.

Variation in activation thresholds is known to desynchronize the actions of agents in a swarm, allowing for better task completion in many domains. We find that variation in intensity further differentiates agents within a swarm, improving swarm performance beyond the effects of threshold variation, when intensity values are dynamic, changing with agent activation. Such dynamism in intensity values models natural agents becoming more adept at a task with repetition. These results mirror findings in nature.

In future work, we plan to test our model in a more complex domain problem. We also plan to explore additional forms of inter-agent variation such as response probability and response duration. Activation probability models the scenario in which an agent fails to perform a task despite its activation threshold for that task being satisfied. Duration of task performance models agent stamina or focus. With four forms of inter-agent variability implemented, we will explore which combinations are most complementary.

Acknowledgements

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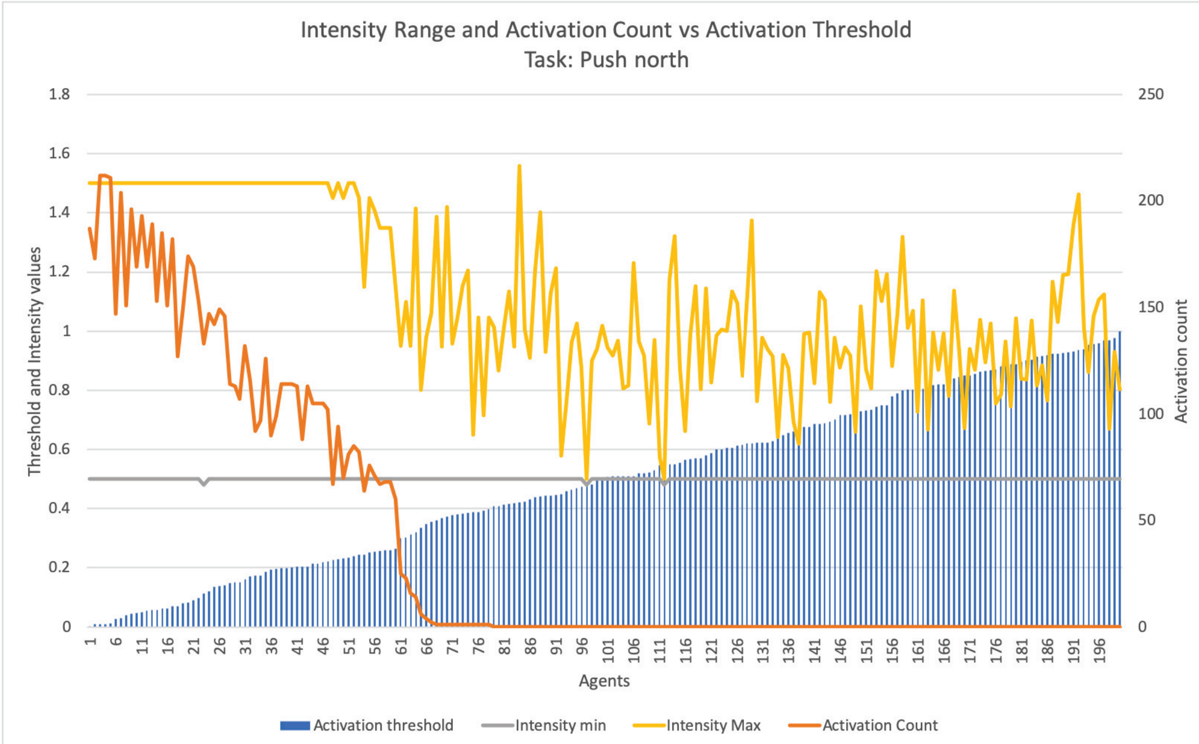

Figure 5: Intensity range, activation count, and activation threshold values for all agents from one run on a random target path. Maximum value for activation count is the number of time steps since agents choose one task per time step. The task represented is push north. This illustrates that most of the work is done by a relatively small number of agents with high intensity multipliers.

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