A Study of Marginal Performance Properties in Robotic Groups*

Avi Rosenfeld, Gal A Kaminka, and Sarit Kraus
Department of Computer Science
Bar Ilan University, Israel
{rosenfa, galk, sarit}@cs.biu.ac.il

1. Introduction

To date, only limited work has been performed on studying how performance scales with the addition of robots to groups. Our work focuses on studying this issue within one domain, robotic foraging. Foraging has been extensively studied, and is formally defined as consisting of locating target items from a search region *S*, and delivering them to a goal region *G* [3]. Previous work by Rybski et al. [5] demonstrated that groups of foraging robots do at times demonstrate marginal returns. As such, their productivity curves resembled logarithmic functions; the first several robots within their group added the most productivity per robot and each additional robot added successively less. In contrast, Fontan and Matarić's [6] foraging robots contained a certain group size, a point they call "critical mass", after which the net productivity of the group dropped. Similarly, Vaughan et al. [7] wrote that the rule of "too many cooks" applies to their groups and adding robots decreases performance after a certain group size.

Economists have studied the gains in productivity within groups. According to their Law of Marginal Returns, if one factor of production is increased while the others remain constant, the overall returns will relatively decrease after a certain point. This model contains no reference to a concept similar to a "critical mass" group size after which the added worker decreases the total productivity of the group. Our aim is to understand when the marginal returns predicted by the economic model would be consistently realized as work by [5] found they were, and when adding robots would decrease performance as [6] and [7] described.

2. Comparing Group Coordination Methods

We used a well tested robotic simulator, Teambots [2], to collect data about several existing coordination algorithms developed for the foraging domain. We created groups of robots that used the coordination methods of *aggression* [7], *dynamic Bucket Brigade* [4], and the use of a repulsion schema mechanism (*Noise*) [1]. We added several methods for comparison. Our Gothru group was allowed to pass through all obstacles and can only exist in simulation. At the other extreme, our *Stuck* group also contained no coordination behaviors but simulated a real robot and as such would become stuck when another robot blocked its path. *Repel Fix* resolved collisions by moving away from a teammate for a fixed period of time of 100 cycles. Our *Repel Rand* group moved backwards for a random interval uniform over 1 – 200. The *Timeout* method only reacted once a robot detected it had not sufficiently moved for 100 cycles. After this point, it attempted to become unstuck by moving in a random walk for 150 cycles.

Teambots [2] simulated the activity of groups of Nomad N150 robots. The field measured approximately 5 by 5 meters. There were a total of 40 such target pucks, 20 of which where stationary within the search area, and 20 moved randomly. Each trial measured how many pucks were delivered by groups of 1 – 30 robots within 9 minutes. For statistical significance, we averaged the results of 100 trials with the robots being placed at random initial positions for each run. Thus, this experiment simulated a total of 24,000 trials of 9 minute intervals for a total of 372,000 minutes of robotic activity.

According to the economic Law of Marginal Returns, marginal returns will be achieved when one or more items of production are held in fixed supply while the quantity of homogeneous labor increases. In this domain, the fixed number of pucks acted as this limiting factor of production. However, only the Gothru group demonstrated this quality over the full range of group sizes. All other groups contained a point where maximal productivity was reached. After the group size exceeded this point, productivity often dropped precipitously. Figure 1 graphically represents these results. Our X-axis represents the various group sizes ranging from 1 to 30 robots. The Y-axis depicts the corresponding average number of pucks the group collected.

We needed a mechanism for understanding why certain

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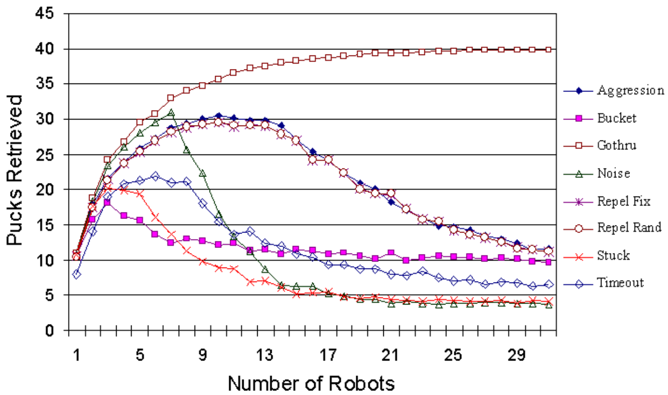

Figure 1. Foraging Productivity Results

coordination mechanisms were more effective than others. We posit that differences among robotic groups often arise from clashes over space. Specific to foraging, conflicts arose over which robot in the group had the right to go to the home base first. As the group size grew, this problem became more common. This caused the groups to deviate from the ideal marginal productivity, depicted by the Gothru group, by greater amounts. The length of time robots clash with their teammates because of joint resources, such as the home base location, serves as the basis for equating coordination models within any domain. Our *interference* metric facilitates this comparison.

3. Definition of Interference

We define interference as the length of time an agent is involved with, either physically or computationally, collisions, be them real or imaginary, from other robots and obstacles. Previously, Goldberg and Matarić [3] measured only robotic collisions as interference. While for some groups this definition may suffice, we found that many groups often engaged in collision resolution behaviors well beyond an actual collision. According to our definition, any time spent before a supposed collision in replanning and avoidance activities must also be recorded. Similarly, all post-collision resolution activity must be included as manifestations of interference. Thus, according to our definition, the Gothru group has zero interference because it never engages in any interference resolution behaviors and represents idealized group performance. All other groups register varying amounts of interference.

We found a very strong average negative correlation of -0.95 between the differences in groups' performance and their interference level over the entire range of 1 to 30 robots. For example, the Noise group most closely followed the idealized Gothru productivity graph for groups up until 7 robots, and registered significantly less interference than the other groups. However, this method didn't scale well beyond this point. When the group size became larger than seven, its interference levels grew exponentially and the group's performance quickly decayed. In contrast, the Aggression and repelling groups had significant levels of interference from the onset, but interference levels only grew linearly with respect to the group size. As a result, this group proved more effective with larger group sizes. Generally, groups were able to maintain marginal gains in productivity only when interference levels where relatively low.

4. Conclusion

We found that different coordination techniques affected the productivity graphs of foraging robotic groups during scale up. To determine the cause of the differences between coordination algorithms, we define a measure of interference that facilitates comparison, and found a high negative correlation between group interference and productivity. Effective coordination algorithms maintain marginal productivity over larger groups by reducing interference levels. However, if the new robot added too much interference into the system, it detracted from the group's productivity and marginal productivity gains would cease.

The spatial constrictions which cause interference in the foraging domain are common to many areas such as waste cleanup, area coverage in vacuuming, search and rescue domains, and planning collision-free trajectories in restricted spaces. We believe our novel metric of interference will allow for a better understanding of robotic teams in these domains as well.

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