Self-Organized Clustering of Square Objects by Multiple Robots

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Abstract. Object clustering is a widely studied task in which self-organized robots form piles from dispersed objects. Although central clusters are usually desired, workspace boundaries can cause perimeter cluster formation to dominate. This research demonstrates successful clustering of square boxes —an especially challenging instance since flat edges exacerbate adhesion to boundaries— using simpler robots than previous published research. Our solution consists of two novel behaviors, *Twisting* and *Digging*, which exploit the objects' geometry to pry boxes free from boundaries. Physical robot experiments illustrate that cooperation between twisters and diggers can succeed in forming a single central cluster. We empirically explored the significance of different divisions of labor by measuring the spatial distribution of robots and the system performance. Data from over 40 hours of physical robot experiments show that different divisions of labor have distinct features, *e.g.*, one is reliable while another is especially efficient.

1 Introduction

Object clustering involves gathering spatially distributed objects into a single central pile. This operation, akin to raking leaves, simplifies subsequent handling and is useful within a longer manipulation pipeline. The task is ideal for studying the role of physics and environmental interactions in producing complex collective behavior. This paper is concerned with clustering square objects, which is an important direction because (i) such objects have greater relevance for applications (specifically construction involving bricks), (ii) radically different packings result, which challenge existing geometry-based clustering theories, and (iii) sensitivity to environment boundaries, which may cause existing approaches to fail in forming central clusters, is exacerbated.

We introduce two simple behaviors *Twisting* and *Digging* that exploit objects' shape to pry boxes away from boundaries. A group of robots executing mixture of these two behaviors is able to repeatedly form central clusters. We examined the effect of different numbers of twisters and diggers on the system's performance, empirically determining the most reliable and most efficient divisions of labor. Data reported are from over 40 hours of experiments. The paper's primary contributions are:

- Assessment of Kazadi's cluster growth theory [4]: Experimental data verifies the theory, previously only validated with simulations of hypothetical robots.
- Division of labor: This is the first examination of the division of labor for clustering tasks; this paper illustrates that it can play an important role.

- New way to address boundary effects: This paper describes an open-loop motion to limit cluster formation on the boundaries. The motion does not depend on the robot disambiguating particular circumstances, but rather it is the context within which the actions are executed that produces the desired outcome. From a self-organization perspective, this is a particularly satisfying solution to the boundary problem since it depends primarily on the physics of the robot-environment interaction for its success.
- Illustrating that spatial distribution matters: While existing techniques for dealing with boundaries, (*e.g.*, using sophisticated rules for releasing objects [3]), our approach simply modifies the spatial distribution of robots. Thus far, analysis techniques (*e.g.*, [4, 5]) only consider spatially homogeneous distributions.

2 Motivation & Related Work

Multi-robot object clustering has been widely studied: Deneubourg et al. [1] presented an early distributed algorithm which achieved "sorting" with a local density sensor and no direct communication between agents. Inspired by biological models [6], Beckers et al. [2] carried out the first physical robot experiments and also demonstrated clustering without a density sensor. They gave an initial explanation for the emergence of clusters on the basis of the geometry of the piles. Martinoli [7] further quantified this geometric notion. Thereafter, Kazadi et al. [4] introduced a model which gives conditions for cluster formation to occur.

Holland and Melhuish [3] extended the clustering task to include spatial sorting. They conducted several experiments in which clusters formed at the edge of their arena, since flat boundaries have geometric properties similar to very large clusters. Their work is the most systematic empirical study of this boundary effect to date. A similar "preference" for cluster formation along boundaries has been noted within a biological system [8]. Some authors [1–3] explained clustering through *stigmergy* [9], a process wherein the environment, modified by agents' previous actions, affects subsequent task performance. More recent connections between robot clustering and biological models have been published [10].

Almost all previously published work in robotic clustering considers cylindrical pucks. Square objects have flat edges which exacerbate adhesion to boundary walls. It is particularly difficult for a cylindrical robot to move a box positioned against a wall into the center of the workspace. This is observable in the video posted by Vaughan's Autonomy Lab[1] in which 36 iRobot Creates successfully cluster square objects; most of the clusters form on the boundary.

Table 1 is a comparative summary of robots' capabilities and experimental environments in the most closely related literature. Our robots are much simpler than others, except for Vaughan's demo. They recognize the existence of an obstacle (via IR), but cannot ascertain its type. Interestingly, the rows in the table with the simplest robots either produced boundary clusters or have a special way of treating them, *e.g.*, Maris and Boeckhorst [11] define objects to be "lost" once they were pushed against a wall.

[1] We thank Vaughan's Autonomy Lab at SFU for posting this video as it inspired this paper. The video can be seen at `http://www.youtube.com/watch?v=b_kZmatqAaQ`

Work	Pucks/Seeds/Cubes/Boxes		Environment	
	Sensing	Manipulation	Sensing	Boundary & Effects
Beckers et al. [2]	◇ Detect circular pucks with force sensor in C-shaped scoop	◇ Push circular objects ◇ Control the number of carried pucks with a microswitch	◇ Two IR sensors for obstacle avoidance	◇ A square arena ◇ Side-steps the effect of boundary by using a deformable boundary
	Note: The robots can push pucks trapped on the boundary due to a deformable wall.			
Martinoli [5]	◇ Discriminate between circular seeds and obstacles with distinct IR sensor signatures	◇ Grasp, carry and release seeds	◇ Six IR proximity sensors for detecting obstacles	◇ A square arena ◇ Effect of the boundary ignored
	Note: The robots can recognize and access clusters geometrically.			
Holland & Melhuish [3]	◇ Detect circular pucks by sensing backward force on gripper	◇ Grip, retain, and release circular pucks with semicircular gripper	◇ Four IR proximity sensors for sensing the boundary	◇ An octagonal shaped arena with rigid boundary ◇ Use the probability of detecting a wall
	Note: Robots cannot discriminate between other robots and the boundary. The strategy of varying the wall probability introduces the false positive. The robots overcome the effect of boundary with sensors.			
Maris et al. [11]	◇ No sensing of the cubes	◇ Cubes pushed until obstacle detected	◇ Six IR proximity sensors for obstacle detection	◇ A square arena ◇ Consider pushed cubes against the boundary as "lost"
	Note: The robots manipulate cubes by only pushing behavior for clustering task. Robots pass over cubes on the boundary.			
Vaughan [unpubl.]	◇ Detect square boxes with bumpers	◇ Push and leave a box by a bumper's threshold	◇ No sensor for detecting objects except for boxes	◇ A rectangular arena ◇ Effect of the boundary ignored
	Note: Several clusters formed on the boundary.			
This paper	◇ Detect square boxes with bumpers	◇ Push and leave a box by a bumper's threshold	◇ A single IR proximity sensor for sensing the objects on the right side	◇ An octagonal shaped arena with rigid boundary ◇ Overcome the effect of boundary using motion strategies
	Note: No puck manipulator. Limited sensor information (1-bit IR sensor, 1-bit bumper). Boundary effect overcome without explicit sensing of it (self-organization).			

Table 1: A comparison of robot capabilities for clustering tasks.

3 Materials & Methods

We used iRobot Creates robots having only two sensors: a bumper and a proximity sensor In either case, the types of detected object (*e.g.,* obstacle, box, robot) cannot be distinguished. We consider 35cm×35cm square boxes as the objects to cluster; although a box has an insufficient mass to activate the bump sensor, two or more boxes together have adequate mass to depress the bumper. Similar to Melhuish and his group (*e.g.,* [3, 10]), we use an octagonal shaped workplace (4.5m×4.5m). Figure 1 (left) shows the initial configuration: boxes are uniformly spaced, and robots have fixed starting positions but with random orientations.

To analyze the cluster dynamics of a motion strategy, three trials, each lasting 90 minutes, were conducted for each experimental condition. Experiments used 5 robots and 20 boxes. All experiments were videotaped and annotated by observing frames every 5 seconds. A cluster is a group of more than three boxes, each touching at least one other. (Other papers sometimes permit a minor gap; we opted for this stricter condition as it is unambiguous). We distinguish between boundary and central clusters, and the goal being to produce only the latter. A boundary cluster is a group which has at least one box touching a wall.

Fig. 1: (left) initial configuration, (center) an example final configuration using the basic strategy, and (right) an example final configuration using the mixed strategy (2 Twisters and 3 Diggers). Video clips are available at http://students.cse.tamu.edu/jnk3355/experiments.html

4 The Basic Strategy

4.1 A baseline for comparison

Based on the controllers in [2, 3], we implemented the simple algorithm shown in Figure 2. The robots move straight but make a random turn when their bumpers are pressed. All operations only depend on local information.

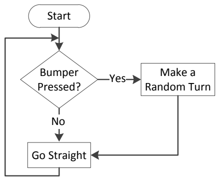


Fig. 2: Flowchart showing the basic behavior.

4.2 Resulting Cluster Dynamics in the Basic Strategy

Figure 1 (center) shows the final configuration of the first trial of the basic strategy. In all three runs, the robots produced clusters of square boxes, but most clusters formed on the boundary (*cf.* Experiment 2 in [2]). The results underscore the earlier statement: the boundary influences cluster formation since walls have the properties comparable to a large cluster. The workspace walls buttress partial structures and the motion required to dislodge boxes only occurs infrequently. A box on the boundary is unlikely to be moved to the center.

5 The Mixed Strategy

5.1 Prying boxes loose: two new motions

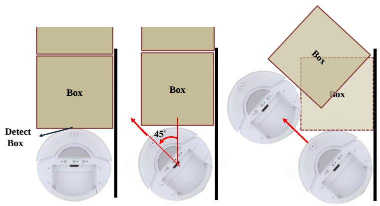


Fig. 3: Prying boxes away from the wall.

We propose two new behaviors to overcome the effect of the boundary and to increase the formation of a single central cluster of boxes. Our approach exploits the mechanics of square objects. As shown in Figure 3, striking the corner of a box can pry it loose from a tight packing. This reduces the area in contact with the wall and makes subsequent separation more likely when repeated. Using this prying motion, we introduce two complementary behaviors, *twisting* and *digging*. We call a robot executing the twisting behavior a *twister* and a robot performing digging a *digger*. A group comprising both types of robots is said to employ a *mixed strategy*. We stress the simplicity of both operations: only one IR proximity sensor is added to the basic strategy's requirements.

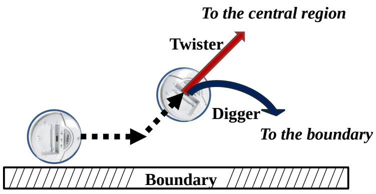


Fig. 4: Trajectories of the twisters and diggers after the prying motion.

Figure 4 shows trajectories of both behaviors on the boundary after a bump or time out (the latter, only for twisters). Diggers move along a curved arc to find a wall, while twisters go into the central region, potentially pushing a box. Intuitively, the twisters are more likely to convey objects, while the diggers form gaps between boxes and the boundary.

Twisting Behavior The prying motion shifts a box, and robots reaching the twisted box subsequently butt and bring it into the center, as shown in Figure 5a. To raise the probability of contact with boundary boxes, the robot operates in a wall following mode when its IR sensor detects an object on the robot's side. However, a robot will keep pushing it if one boundary box exists. Since it can be counter-productive to continue wall following, the robots only do so for 5 seconds, then perform a prying motion. The robot's motion in the central is the same as the basic strategy. Figure 5b shows the flowchart of the detailed algorithm.

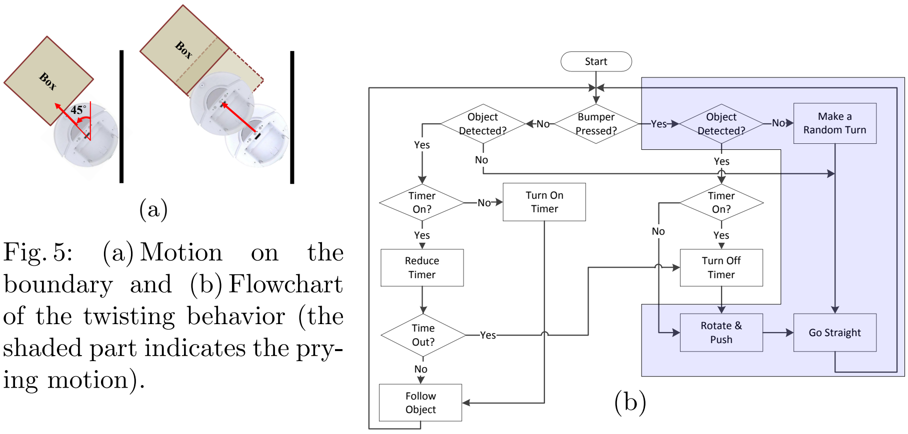
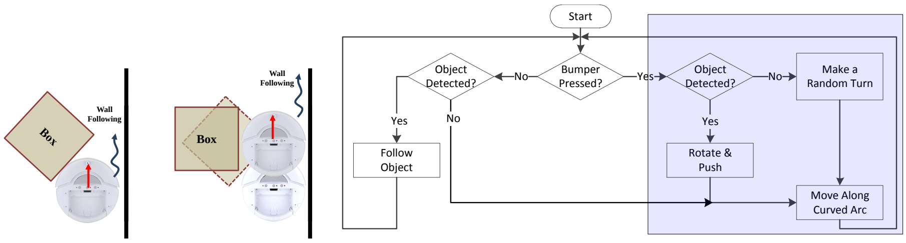


Fig. 5: (a) Motion on the boundary and (b) Flowchart of the twisting behavior (the shaded part indicates the prying motion).

Digging Behavior The digging behavior was developed to improve overall performance, by increasing the chance to detecting a wall, and further separate twisted boxes from walls, ultimately aiding in the prevention of boundary cluster growth. Unlike twisters, the robot remains in wall-following mode when its IR sensor detects an object. Also, the robot tries to find a boundary with the movement in a curved path instead of a straight trajectory. Apart from these two exceptions, the digging robots perform the same as the prying motion as twisters. The behavior is depicted in Figure 6.

5.2 Resulting Cluster Dynamics in the Mixed Strategy

We carried out experimental trials under the condition identical to the basic strategy case in order to verify the clustering performance of the mixed strategy. Five robots were used, two twisters and three diggers. Although twisting and digging are complementary, the division of labor affects the overall performance; we present the details in Section 6.



(a) (b)

Fig. 6: (a) Motion on the boundary and (b) Flowchart of the digging behavior.

Figure 1 (right) shows the final configuration of the first trial in the mixed strategy. Unlike to the basic strategy, a single large cluster emerged in the middle of the arena in all three trials. Figure 7 shows the average size of the biggest central clusters and their standard deviations through the time for the basic and mixed strategies. The results verify that our proposed motion strategy can successfully overcome the boundary effect and collect spatially distributed objects into a single pile at the designated position, the center of the workspace.

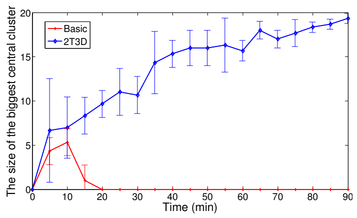


Fig. 7: A comparison of clustering performance. Vertical axis is the size of the largest central cluster (essentially the same performance metric employed by [2]). The horizontal axis is time measured in minutes.

6 Analysis of Division of Labor

The most significant difference between twisting and digging behaviors is the spatial distribution of robots. Figure 8 shows the averaged spatial distributions of robots for particular divisions of labor (these data were collected without boxes as a baseline). The numbers of robots for each case are normalized by area (via basic case numbers). As the ratio of diggers increases, boxes on the boundary are more likely to be separated from the wall. However, it does not guarantee that the separated objects will be brought into central clusters since diggers will remain along the wall after the prying operation. From this analysis, we consider how differences in spatial distribution might affect clustering progress.

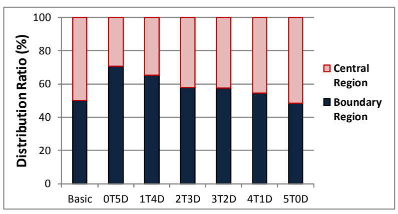


Fig. 8: Averaged spatial distribution of robots (central versus boundary regions) with respect to division of labor. Note: basic strategy robots are assumed to be uniformly distributed due to their random turn.

6.1 Clustering performances of differing Divisions of Labor

We conducted three trials for all possible combinations of the twister (T) and the digger (D). Only few trials succeeded in forming a single central cluster having all 20 boxes within 90 minutes. Despite single central clusters not being completely formed in all cases, it appeared as if the robots could achieve the goal if given more time. We are interested in the question of whether, given unlimited time, all combinations would form a single central cluster. This question is examined using Cluster Growth Theory in the next section.

Figure 9 shows the averaged size of the largest central clusters for each case. As a summary, showing means of the three trials hides a few interesting facts. For example, the 1T4D case appears to perform poorly compared to 2T3D. In fact, it was a very capable division of labor and once formed a complete central cluster in the shortest observed time of 25 minutes. However, 1T4D also failed in one of its trials. This illustrates that while 2T3D is to be preferred for reliable clustering, 1T4D may be preferred for efficient clustering. Figure 10 shows the box cluster dynamics for each of the three runs. The blue trial for 1T4D was extremely efficient, while the magenta trial had some number of boxes on the boundary. The reliability (and comparatively longer time) is visible in the 2T3D case as all the paths converge to the lower right corner.

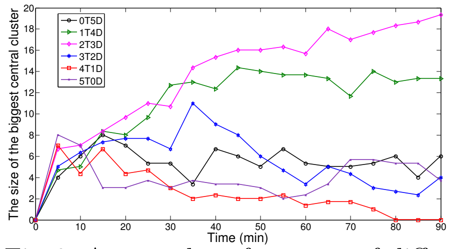


Fig. 9: Averaged performance of different Divisions of Labor.

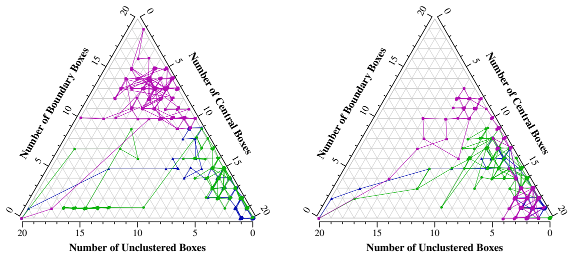


Fig. 10: Ternary plots detailing the cluster dynamics for each trial for two divisions of labor. (left) 1T4D, and (right) 2T3D.

6.2 Cluster Dynamics under differing Divisions of Labor

According to the theoretical dynamics of clustering systems, proposed by Kazadi et al. [4], a sufficient condition for the convergence of puck clustering systems is that the ratio of puck removal and puck deposit is monotonically decreasing. The cluster formation function was defined as below,

$$g(n) = \frac{\textit{Total number of box removal in cluster size, n}}{\textit{Total number of box deposit in cluster size, n}}. \tag{1}$$

The original analysis ignores the effect of the boundary, so we found it necessary separated the two qualitatively different cluster types. To identify the effect of differing divisions of labor, we examine $g(n)$ for the central boxes here. The slope of $g(n)$ affects the cluster accretive tendency. From now on, we write $g(n;t;d)$, adding the number of twisters, t, and the number of diggers, d as parameters. Through the experimental results, we obtained the curves of $g(n;t;d)$ for different t and d values. Except for the 0T5D case, all values of $g(n;t;d)$ are monotonically decreasing and are located below 1. On the basis of Kazadi et al.'s result, this would prove that each division of labor guarantees forming a single central cluster if sufficient time is allowed. The case of 0T5D can be explained by the spatial distribution of the robots: the diggers effectively generate gaps between boxes and boundaries, but the objects are rarely brought into the central region.

7 Conclusion

This paper described a multi-robot system in which agents employ simple local interaction rules to gather square objects into a single pile in the center of their workspace. As an existence proof, the work has two important aspects: First, we employ less capable robots than previous work. Secondly, the objects are square, making them more challenging to cluster and more functional than previous cases. We examined cluster growth properties through theoretical model of clustering of Kazadi et al. [4]. The presented data are the first empirically determined cluster formation functions for physical robots we are aware of.

Through physical experiments, we demonstrated that the combination of two complementary behaviors, twisting and digging, allows robots to overcome the influence of the boundary. Our approach uses mechanical interactions with boxes on the perimeter, and emphasizes action rather than sensing. It is closer to the spirit underlying the self-organized clustering process itself than previous approaches to lessen formation of boundary clusters. This work also focuses on managing the spatial distribution of robots rather than specialized manipulation of the objects. In this regard, it is a departure from the focus within the literature, which assumes a uniform distribution of robots. It suggests that one way to direct such self-organized systems might be to influence where they spend their time.

References

1. Deneubourg, J., Goss, S., Franks, N., Sendova-Franks, A., Detrain, C., Chrétien, L.: The dynamics of collective sorting robot-like ants and ant-like robots. In: Proc. of Simulation of Adaptive Behavior (SAB). (1991) 356–363
2. Beckers, R., Holland, O., Deneubourg, J.: From Local Actions to Global Tasks: Stigmergy and Collective Robotics. In: Proc. of Artificial Life IV. (1994) 181–189
3. Holland, O., Melhuish, C.: Stigmergy, self-organization, and sorting in collective robotics. Artif. Life **5** (1999) 173–202
4. Kazadi, S., Abdul-Khaliq, A., Goodman, R.: On the convergence of puck clustering systems. Robotics and Autonomous Systems **38** (2002) 93–117
5. Martinoli, A., Ijspeert, A.J., Mondada, F.: Understanding collective aggregation mechanisms: From probabilistic modelling to experiments with real robots. Robotics and Autonomous Systems **29** (1999) 51–63
6. Franks, N., Sendova-Franks, A.: Brood sorting by ants: distributing the workload over the work-surface. Behavioral Ecology and Sociobiology **30** (1992)
7. Martinoli, A.: Swarm Intelligence in Autonomous Collective Robotics from Tools to the Analysis and Synthesis of Distributed Control Strategies. PhD thesis, École Polytechnique Fédérale de Lausanne (1999)
8. Bonabeau, E., Theraulaz, G., Fourcassié, V., Deneubourg, J.L.: Phase-ordering kinetics of cemetery organization in ants. Phys. Rev. E **57** (1998) 4568–4571
9. Grassé, P.: La reconstruction du nid et les coordinations interindividuelles chezbellicositermes natalensis etcubitermes sp. la théorie de la stigmergie. Insectes sociaux **6** (1959) 41–80
10. Scholes, S.R., Sendova-Franks, A.B., Swift, S.T., Melhuish, C.: Ants can sort their brood without a gaseous template. Behav. Ecology & Sociobiology **59** (2005) 531
11. Maris, M., Boeckhorst, R.: Exploiting physical constraints: Heap formation through behavioral error in a group of robots. In: Proc. of Conference on Intelligent Robots and Systems (IROS). (1996) 1655–1660