Robot Spatial Distribution and Boundary Effects Matter in Puck Clustering

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Abstract

Puck Clustering, a particularly widely studied problem domain for self-organized multi-robot systems, involves gathering spatially distributed objects, called pucks, into piles within a planar workspace. Structures in the environment (partially formed clusters) encode information about where clusters should be formed, and their positions are involved in the mechanics of subsequent cluster formation. In this paper, we consider questions regarding the spatial distribution of robots and clusters, and their relation to the boundaries of the workspace. Prior theoretical analysis has assumed a uniform distribution of robots for gathering all objects into a single pile. Yet, in some instances, a disproportionate amount of time may be spent by robots on the boundary. Also, others have documented that the boundary can cause cluster growth itself. This paper considers the problem of clustering square boxes in the center of the workspace. The flat edges of these objects appear to exacerbate the affinity for cluster growth near boundaries. However, by exploiting the shape of our objects, we show that novel "Twisting" and "Digging" operations overcome this effect and enhance production of central clusters. We analyze the dynamics of boundary versus central puck clusters, and investigate how the spatial distribution of the robots changes along with the clustering process: showing stark differences between the standard mode of clustering and the mode we introduce here.

Introduction

The term stigmergy was originally coined by Grassé to explain his observations of the nest building behavior of wasps and how they introduce local environmental changes that then influence the subsequent construction behavior (Grassé, 1959). As a design principle, the concept places an emphasis on indirect communication between agents: each agent modifies and senses the shared environment locally rather than employing radio or audio communication channels. Starting with Beckers, Holland & Deneubourg (1994) several studies of minimalist multi-robot systems have been conducted in order to explore the utility of this idea for synthetic systems, and to assess the role it might play in natural systems.

The most common task domain for robotic study of these effects is self-organized object clustering. This involves several robots collecting spatially distributed objects and moving them into a few piles. This paper continues the tradition by conducting an experimental examination of a clustering task by simple mobile robots. We tackle the problem of clustering square objects, rather than the more common cylindrical ones. Additionally, our study specifically emphasizes the importance of forming clusters in the center of the workspace. We first consider the clustering behavior of a straightforward implementation of the standard algorithm clustering, but with the new object geometry. The algorithm consists of two behaviors, each of which exploits the non-cylindrical object geometry. We consider boundary effects that cause not only cluster growth itself, but an imbalanced amount of time spent by robots on the boundary. We propose two new operations, twisting and digging motions, in order to overcome the boundary effect and to improve production of central clusters. This paper will go over the operations in detail and show how the development and position of clusters changes the structure of the configuration for both central clusters and boundary clusters; this feedback effect where robots can move, and the dynamics of the clusters themselves.

Motivation & Related Work

The robotics literature contains several influential ant-inspired algorithms for object clustering and related tasks. Beckers *et al.* (1994) presented a series of object clustering experiments with multiple robots. Holland &

Melhuish (1999) later examined the use of stigmergy and self-organization in a homogeneous group of physical robots in spatial sorting, a generalization of the clustering task. Sorting includes an additional requirement that different object types be sensed and placed in positions that depend on the detected type. Kazadi, Abdul-Khaliq & Goodman (2002), along with providing a review of work until that date, introduce a theoretical analysis of clustering systems through a characteristic function that describes cluster growth properties. We examine empirically determined instances of this function below. More recently, Parker and Zhang (2006) examined a site preparation task in which their approach has several elements of the original clustering algorithms: simple robots employ a threshold-based sensing system in order to push several items. The force threshold is exceeded once piles of a sufficient size have been created. That work, and research in the multi-robot construction domain using square building-blocks (e.g., Jones & Mataric' (2004)) suggest that if such minimalist systems are to be used, a broader class of objects should be clustered.

This work was motivated by a video produced by Vaughan's Autonomy Lab at Simon Fraser University, which showed that iRobot Create robots executing their default demonstration behavior would cluster the square boxes they were shipped in (Autonomy Lab, 2007). Clusters were successfully created but, even superficially, the clusters formed in the video looked different from those described in the literature. The square shaped objects seemed to exacerbate boundary effects since many clusters were mostly located on the workspace perimeter.

Materials & Methods

Materials

We employed a minimalist multi-robot system: simple control algorithms, few sensors and no explicit communication suffice to produce cooperative box pushing and cluster formation. We conducted experiments using the iRobot Create platform which are equipped with two wheels operated via a differential drive mechanism and a passive caster. This permits the robot to move forward, or backward, perform turns while moving, and also to turn in place. The robot has left and right bumpers that are used to detect the presence of objects in front of the robot. The bumpers operate independently and are only depressed when the force against them exceeds a threshold. The robot has a single IR sensor on its right side, which is used for sensing the distance to the wall on that side of the robot and enables it to perform simple wall following. Unlike the majority of the existing work, the robots do not have specially shaped scoop, or shovel, for manipulating the objects used for clustering. We consider square boxes whose size is 35cm×35cm, similar to a robot's size (about 30cm in diameter), as the object for clustering. The boxes have the following crucial property: two boxes together have sufficient mass to depress the bumper although an individual box is inadequate to activate the sensor. Like much subsequent work by the Melhuish and his collaborators, we consider an octagonal shaped arena. In our experiments it is 4.5m ×4.5m; a square arena would result in square boxes getting stuck in the 90° corner. Figure 1 shows the initial configuration of boxes and robots used in our experiments.

Figure 1. Box separating progress by twisting mode

Motion Strategies

We first implemented a strategy based on examples in the literature, called the *basic mode*. After evaluating the performance of this approach (see the following section) we introduced a new approach we call the *mixed mode*, so named because it involves two complementary behaviors that the robots in the group execute concurrently. These two behaviors *twisting* and *digging* are described below. We stress that both are simple modes of operation, and since a single box is effectively invisible, both overcome partial sensor blindness through open-loop control strategies. These local rules depend on the geometry of the objects being clustered: manipulation and contact uses the shape and size of the items under consideration, configuration of the boxes depends on the packing, itself a function of the item geometry.

Basic Mode

Robots employ their bumpers in order to avoid any object that they encounter which they cannot push easily. The robot's bumpers only detect box clusters, other robots and walls. In the basic mode, the robot drives straight, and if anything depresses it, it will make a random turn. The logic is below:

Rule 1:
if (Left Bumper pressed or Right Bumper pressed) then
Make a random turn and go forward

Rule 2:
Go forward

Twisting Mode

When a robot operates in the twisting mode, it attempts to detach boxes from the wall following a series of motions. The algorithm in the twisting mode is detailed below.

Rule 1 :
if (Left Bumper pressed or Right Bumper pressed) then
  if (Timer is on) then
    Rotate and push the object
    Disable timer
  else
    Make a random turn and go forward

Rule 2 :
if (Wall is detected and Timer is off) then
  Enable timer
  Follow the wall

Rule 3:
  if (Timer is on) then
    Follow the wall
    Reduce timer
    if (Timer has timed out) then
      Rotate and push the object

The idea is that a single robot's twisting motion is able to strike a box at 45º (which it does for 3 seconds). The box is rotated through this motion. Other robots that subsequently contact the twisted box will, through repeated contacts, completely detach it from the wall. At best, two trials will affect this operation, which itself is sufficient to increase the likelihood of central clusters. Since the bumper will not be pressed if there is a single box at the boundary, the robot will simply keep pushing the box. In this case the box is pushed into a corner of the arena.

Figure 2. Box separating progress by twisting mode

Since it can be counter-productive to continue wall following, the robot uses a timer to follows the wall for a maximum of 5 seconds. The robots' action in the interior of the arena is the same as the basic mode. Figure 2 shows that that these modifications do indeed separate the boxes from the wall.

Digging Mode

Although the twisting mode alone was able to produce central clusters, the majority of the boxes remained close to the boundary. Thus, we developed a "digging mode" to improve separation of the boxes from the wall. The main purpose of this mode is to collect twisted boxes from the walls; it does this by having the robot steadily follow the wall. This method increases the probability that a robot will contact a box and separate the box from the wall. The robot finds a wall by moving in a curved path. The details are below.

Rule 1 :
if (Left Bumper pressed or Right Bumper pressed) then
  if (timer is on) then
    Rotate and push the object
    Disable timer
  else
    Make a random turn and go forward

Rule 2 :
if (Wall is detected and Timer is off) then
  Enable timer
  Follow the wall

Rule 3:
if (Timer is on) then
    Follow the wall
else
    Move along curved arc

After the twisting mode introduces a gap between the boxes and wall, a digging mode robot increases this separation from the wall. No timer is employed during wall following, increasing the probability that the robot will make contact with a box on the wall. If there is an object in front of the robot in digging mode, the robot moves identically to twisting mode.

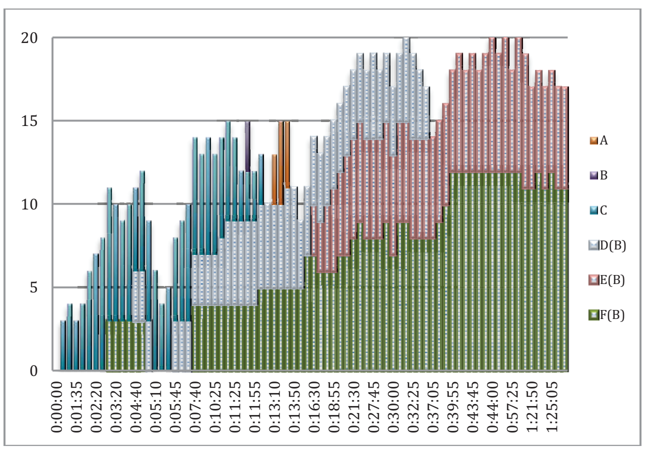
Experiments & Analysis

Execution & Resulting Cluster Dynamics

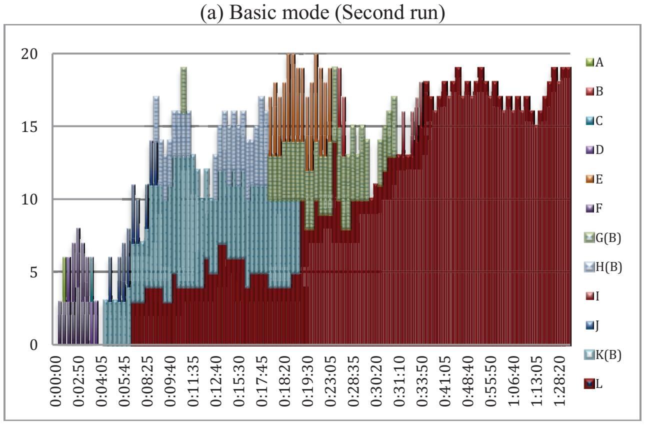
We conducted three 90 minute long trials with the both basic and mixed modes. The trials were videotaped and hand annotated by considering frames every 5 seconds. Figure 3 shows the development and changes in the number of boxes in each cluster over time for each mode. Boundary clusters are presented with dash bars in the graphs, and '(B)' is attached as their legend identifier. Solid bars indicate central clusters. In all cases, a cluster was defined as a group of more than three boxes, each being adjacent to at least one other. Boundary clusters are distinguished by having at least one box touching a boundary wall.

Employing the basic mode, the robots failed to gather all objects into a central cluster each time. Nor was a single complete cluster (having all the boxes) formed on the boundary in any of the trials. Notice, however, that several central clusters were formed initially. Continuous collisions with robots resulted in them being broken down within 15 minutes. By the end of the allotted time, no central cluster had formed, while several boundary clusters had emerged.

Unlike basic mode, all three runs of mixed mode ended with a single large cluster in the middle of the arena; no clusters remained on the boundary. Figure 3 (b) shows the progression by which the central cluster is created and finally becomes the only one. Note that like the trials of basic mode, boundary and central clusters were created along the way. However, boxes in the boundary clusters were separated by mixed mode robots, and delivered to the biggest central clusters. The times taken to reach the goal, building a central cluster with all 20 boxes, took *1:52:30*, *1:22:25*, and *1:48:25* for each experiment. The average time was *1:41:13* and can be considered as an expected time for collecting all boxes into a single pile given the experimental environment.



(a) Basic mode (Second run)



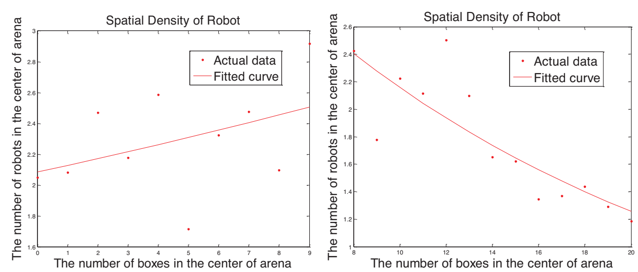
(b) Mixed mode (Third run)

Figure 3. Cluster dynamics in basic and mixed mode

Robot Spatial Distribution

Next, we consider the question of spatial distribution of the robots: specifically, the assumption of uniform (dilute-limit) distribution of robots. We divided the octagonal arena into center and boundary regions and measured the robots' spatial distribution. The boundary line between regions was drawn 70cm from the boundary, which approximately the same as the width of sum of width of a robot and a box, and ratio of center to boundary areas is 52:48. As already notes, the boundary can cause cluster growth itself; this is what we term the 'boundary-effect.' Square objects appear to exacerbate this effect.

Figure 4 shows the spatial density of robots for basic and mixed modes in the central region of the arena. The X-axis is the number of boxes in the central region. The Y-axis shows the density of robots in the central regions: this a normalized quantity calculated by taking the total number of robots within the central area and scaling it with respect to the area left unoccupied by boxes.



(a) Basic mode (b) Mixed mode

Figure 4. Spatial density of robots in the center of arena

In Figure 4(a), the range of value of fitted curve with spatial distribution of robots is approximately between 2.1 and 2.5. The result means 50% robots are positioned in the central region and the others are in the boundary region. It shows that the assumption that robots are distributed uniformly in basic mode is true. In mixed mode, on the other hand, a disproportionate amount of time is spent by robots on the boundary, especially for robots performing the digging motion. Figure 4(b) shows the mixed mode which, on the other hand, shows a relationship between number of central boxes and proportionate of robots on the boundary. We can interpret this in two ways. The first way is robot-centric: we can say that the disproportionate amount of time being spent by robots on the boundary (and this is especially true for robots performing the digging motion) breaks up those boundary clusters more frequently and results in a single central cluster. A second way is object-centric: with the formation of tight clusters in the central region, robots encounter multiple boxes each time they strike the cluster, causing immediate obstacle avoidance them repels them back to the boundary. Within this object focused point of view, the dynamical process which gives a tight packing in the center rather than boundary, affects the mean time between collisions, altering the robots behavior. Ultimately, the correct interpretation is something between these two extremes: both cluster shape and lifetime influence the position and trajectories of the robots, and robots influence the clusters. These data do show that the spatial density of robots can be an important factor that should be considered in clustering tasks, and that Kazadi *et al.*'s (2002) assumption of uniform distribution of robots for gathering all objects into a single pile can be violated in practice. Indeed, the strategy employed in order to enhance production of central clusters affects the spatial distribution of robots.

Analysis of Object Cluster Dynamics

Kazadi *et al.* (2002) present a theoretical analysis of clustering systems by analyzing conditions under which cluster formation occurs. They introduce the *cluster formation function*,

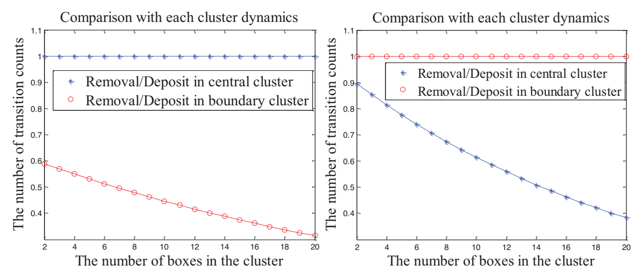
$$g(n) = \frac{Total\ number\ of\ box\ removal\ in\ cluster\ size, n}{Total\ number\ of\ box\ deposit\ in\ cluster\ size, n}$$

, which describes the ratio of the rates of object attrition and accretion for a given cluster size.

We studied cluster dynamics by determining the tendency of a cluster of a given size to grow or shrink and, by employing regression, have empirically determined the cluster formation functions. We combined observations of clusters with n boxes from across all the trials and we estimated the accrual and dissipation rates by recording each time cluster changes size by gaining or losing a box. We observed that to be most useful the analysis should consider central and boundary clusters separately; the original theoretical analysis ignores boundary conditions.

Kazadi *et al.*'s key result is that a sufficient condition for the growth of the largest cluster is that the ratio of puck removal and puck deposit is monotonically decreasing. To summarize here: for a given cluster size n, $g(n) < 1$ means that the cluster has an accretive tendency because the number of boxes deposited is larger than the number removed; $g(n) > 1$ means that the cluster has an attritional tendency since removals exceed deposits; and $g(n) = 1$ denotes a steady-state. Figure 5 shows the ratio of the rate of attrition to rate of accretion for a given cluster size across our trials. The solid line is the best fit of an exponential curve to the raw data. In the basic mode, the number of boxes removed in central clusters is the same as the number of boxes deposit in the central clusters because the all clusters are ultimately distributed on the boundary. On the other hand, the curve of boundary removal has higher offset and decreases more sharply than boundary deposits. This reflects the fact that clusters located on the boundary have a tendency to grow since the number of boxes removed is less than the number added. Figure 5 (a) is curve of function, $g(n)$, based on cluster size. Since most clusters in basic mode are created on the boundary, only the boundary curve is monotonically decreasing and less than one.

In the contrast to basic mode, the mixed mode system showed a tendency to produce clusters in the center of the arena. The curve of $g(n)$ in Figure 5 (b) expresses the clustering tendency: the larger clusters are, the greater their tendency to increase. Kazadi *et al.* (2002) study some hypothetical cluster formation functions. These data show that a distinction between clusters influenced by the boundary and those in free-space is useful in analyzing the system behavior. Moreover, their analysis of the predicted behavior between two clusters holds in the case of objects transferred between boundary and central cluster types (and vice-versa).



(a) Basic mode (b) Mixed mode

Figure 5. Clustering dynamics regarding cluster size

In addition, the lifetimes of all boundary and central clusters were recorded in seconds throughout the experiments. Compared to basic mode, boundary clusters had much shorter lifetimes in mixed mode, and central clusters had much longer lifetimes in mixed mode (Table 1). There are multiple aspects which contribute to this: robots spent more time on the boundary due to the wall following behavior; they were not only taking out boxes from the boundary either in twisting or digging mode, also blocking out-going boxes. Also, the longer lifetime of central cluster in mixed mode means a dominant cluster remains in the center of the arena for a long time.

Table 1. Lifetime of Clusters in Basic and Mixed modes

		Central Cluster		Boundary Cluster	
		Max	Mean	Max	Mean
Basic Mode (hour:min:sec)	1st	0:15:00	0:07:50	1:22:25	0:35:51
	2nd	0:11:35	0:04:07	1:22:20	0:43:45
	3rd	0:12:40	0:04:48	1:28:35	0:38:26
Mixed Mode (hour:min:sec)	1st	1:28:50	0:20:44	0:21:50	0:12:26
	2nd	1:29:15	0:11:01	0:15:20	0:08:28
	3rd	1:23:15	0:11:28	0:20:10	0:14:53

Conclusion

This paper studied the collective behavior of a multi-robot system in which “boundary-aware” robots employ simple local interaction rules in order to cluster square objects in the center of their workspace. The focus on square objects, which exacerbate the boundary effect, required that we assess and address the formation of boundary clusters. We introduce a novel controller we call “Mixed Mode” because it combines twisting and digging operations, both of which exploit the object geometry.

We demonstrated that the Mixed Mode controller can overcome the effects of boundary and induce reliable central cluster formation via physical robot experiments. The preceding analysis leads to the conclusion that our mixed mode is more efficient strategy in two ways: 1) The shorter lifetimes of boundary clusters reflect faster central cluster emergence. Since robots in mixed mode spend more time contacting boxes on the boundary, they prevent the production of large boundary clusters, and cause boxes to disperse into the center of the arena. 2) Empirically determined cluster formation functions also illustrate that mixed mode outperforms basic mode.

This paper shows the spatial density of robots can be an important factor that should be considered in clustering tasks, and that Kazadi *et al*.'s (2002) assumption of uniform distribution of robots for gathering all objects into a single pile can be violated in practice. Structures in an environment involve the mechanics of subsequent cluster formation and the distribution of robots. The position of robots in basic mode is less sensitive to a change of environments, but robots in mixed mode actually reflect environmental changes (more objects in the center, fewer robots in the center). This latter aspect may contribute to the successful movement of all the objects to the workspace center.

It has been pointed out that small variation in the environment, physical robots and controllers can have an impact on clustering performance, and that predicting this can be non-trivial. The preceding work can be viewed as a successful attempt to obtain a desired engineering outcome from the multi-robot system by exploiting the small domain-specific changes unique to our (square object and bounded space) scenario.

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