

# Object Transportation by Granular Convection Using Swarm Robots

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**Abstract** We propose a novel method for object transport using granular convection, in which the granular material is a robot swarm consisting of small robots with minimal sensors. Granular convection is commonly observed in the “Brazil Nut Effect”. In this work, we consider the transported object to be passive, however, and not actuated like the surrounding granular material. We show that the passive object can be transported to a given destination in spite of the fact that each robot does not know the location of the object being transported nor the location of the destination. Each robot moves based solely on a weak repulsive force from the destination and stochastic perturbations. We first show fundamental characteristics of a system with no communication between robots. We observe that very high or very low robot densities are detrimental to object transport. We then show that heterogeneous swarms increase performance. We propose two types of heterogeneous swarm systems: a swarm in which robots switch states probabilistically, and a swarm in which state propagates using local communication. The signal propagation system shows the best performance in terms of success rate and accuracy in a wide range of densities.

## 1. Introduction

Object transportation is a fundamental task in robotics and frequently arises in various situations from micro to macro scale. Our main interest focuses on micro swarm robotic systems in which the agents have minimal sensing requirements,

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have minimal communication abilities, and can manipulate objects only by pushing them. In this paper, we propose a series of distributed algorithms that are based on granular convection [1], also known as the “Brazil Nut Effect,” and a constant external field.

Granular convection is commonly observed in granola boxes in which the larger items tend to aggregate at the surface after the box has been shaken. This is interesting, as these objects seemingly defy gravity when traveling to the top of the box instead of sinking to the bottom, and has potential applications in manipulating objects at the nano- and micro-scales.

This paper studies the Brazil Nut Effect and its potential applications in robotic object transportation. Instead of gravity and external actuation (by shaking), our system is driven by self-propelled robots, which can be steered by the application of an external field. Depending on the capabilities of the robots, this external field can range from gravitational or magnetic fields to infrared or chemical gradients.

Such robots could be manufactured at very low cost and/or miniaturized and have applications from garbage collection at sea to transporting micro-scale objects in a self-assembly scenario. Currently, object manipulation at this scale is accomplished by application of external fields, e.g., magnetic forces [2]; specially designed environmental templates [3]; manipulation via micro-tweezers [4]; or by enclosing a swarm of agents, e.g., magneto-tactic bacteria [5], inside the object.

### ***1.1 Related work***

Object manipulation using a swarm of robots is a canonical problem also known as “box-pushing task” [6, 7, 8, 9, 10]. In these works, robots rely on sensors to detect when the box is reached and on communication to coordinate pushing direction. Some robotic researchers have also tried to apply protozoa for object manipulation [11, 12].

The work described in this paper addresses a subset of the box-pushing domain as it allows to push cylindrical objects, but no robot explicitly recognizes its behavior as object handling. No robot knows where the destination of the object is, nor where the object itself is. This allows the robots to be very simple, low-power, and inexpensive.

The key mechanism here is granular convection, which has been leveraged in a robot context for segregation and pattern formation [13, 14]. There is also a larger body of work on the physics underlying granular convection on transport and segregation processes [15, 16, 17]. The object undergoes a biased random walk, similar to bacterial chemotaxis [18, 29].

## 1.2 Contribution of this paper

We propose a novel method for object transportation in small-size, large scale distributed swarm robotic systems. The object, which is completely passive, has a given starting point and is required to reach a specific destination. We study this problem using a simple kinematic model that takes into account the robots' limited sensors and functions. Each robot does not know the location of the destination explicitly, but instead moves randomly in a closed environment.

We first discuss fundamental properties of the homogeneous system, i.e., all robots are identical, with no explicit communication. We then propose a heterogeneous system composed of robots that change their direction with two different probabilities. Finally, we introduce a heterogeneous system that uses local communication to adjust the fraction of robots that change their direction with higher probability. We show that heterogeneous robotic swarms can improve the success rate of object transportation, and that local communication can further improve performance.

## 2. Dynamical System Model

Let each robot move using the following dynamics:

$$m d\vec{v}_i / dt = \alpha \vec{F}_1(p) + \beta \vec{F}_2 - \gamma \vec{v}_i \quad (1)$$

where  $m$ ,  $\vec{v}_i$  denote robot's mass and the velocity of the  $i$ -th robot, respectively.  $\vec{F}_1(p)$  denotes a unit vector and its orientation changes randomly in the range of  $(-\pi, \pi)$  according to the probability  $p$ .  $\vec{F}_2$  denotes repulsive unit vector from the destination. It is calculated as

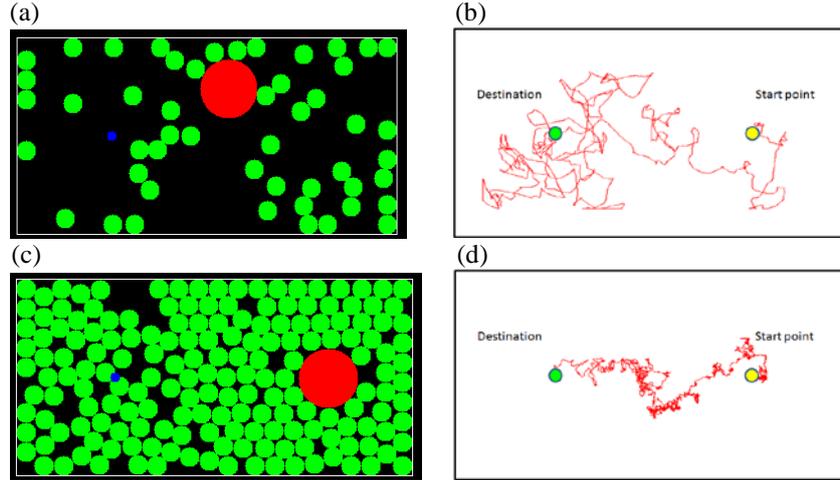
$$\vec{F}_2 = (\vec{r}_i - \vec{r}_d) / |\vec{r}_i - \vec{r}_d| \quad (2)$$

where  $\vec{r}_i$ ,  $\vec{r}_d$  denote the position of the  $i$ -th robot and the position of the destination, respectively.  $\gamma$  is a resistive force. For simplicity, we simulate the friction of the robots by this term. Simulation conditions are shown in Table 1.

**Table 1.** Simulation conditions.

Field size:	4.0 x 2.0
Boundary:	with walls
Robot's diameter:	0.2
Object's diameter:	0.6
Robot density:	$\rho$ (fraction of environment occupied by robots)
Resistive force:	$\gamma$ (fixed at 5.0)
Initial position of robots:	random
Initial position of object:	(1.0, 0.0)
Destination:	(-1.0, 0.0)
Simulation time:	equivalent to 10800 sec (= 3 hours) per a trial
Simulation frequency:	100 trials in each condition

Fig. 1(a) and (c) show snapshots of the simulation. Green, Red, and Blue circles indicate the robots, object, and destination, respectively. Fig. 1(b) and (d) show a typical example of trajectories of the object. The fluctuation becomes small as the density increases (lower row).



**Fig. 1.** Snapshots of simulation and the object trajectory. (a) and (b) are the case of  $N=50$  ( $\rho \sim 0.21$ ), and (c) and (d) are the case of  $N=180$  ( $\rho \sim 0.75$ ).

### 3. Robots with static characteristics

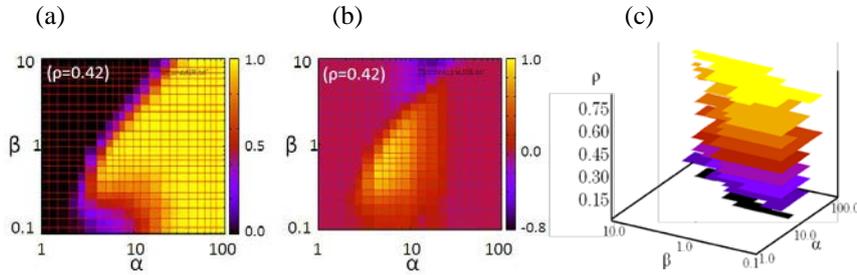
In this section, we describe the behavior of the system in the case where all robots behave identically. This corresponds to the Brazil Nut Effect, except for the fact that the object itself is not subject to actuation.

As defined in eq. (1), all robots move according to a “random force” of strength  $\alpha$  and a “repulsive force from the destination” of strength  $\beta$ . Fig. 2(a) indicates the relation between  $\alpha$ ,  $\beta$  and the success rate in case where the robots occupy 42% of the area in the environment, i.e.,  $\rho = 0.42$ . The success rate is defined as the fraction of trials in which the object is carried to within 20 pixels of the destination by the end of the trial. We observe that when  $\alpha < 0.2$ , transportation consistently fails and the success rate increases as  $\alpha$  becomes large.

When the repulsive force is dominant, i.e.,  $\beta$  is high, no transportation occurs because the robots drive away from the destination without performing random side movements that eventually propel the object toward the destination. When the random force is dominant, i.e., high values of  $\alpha$ , transportation to the destination occurs only by chance because their behavior is equivalent to Brownian motion of

the object. A green line in Fig. 2(a) indicates  $\beta=0$ , i.e., the success rate by Brownian motion. Fig. 2(b) shows the success rate after discounting the success rate due to pure Brownian motion, i.e., after subtracting the green line from Fig. 2(a).

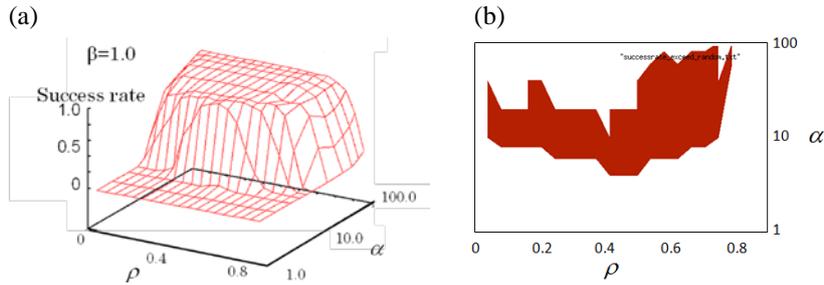
In order to clarify the effectiveness of the proposed method, we focus on the region where the success rate exceeds the result of Brownian motion. The effectiveness depends on the density of robots  $\rho$ , and Fig. 2(c) indicates the region where the success rate by the proposed method exceeds that of Brownian motion on the  $\alpha$ - $\beta$  plane. The effective region in this plane is relatively small under the condition of low density such as  $\rho < 0.2$  or high density such as  $\rho > 0.7$ , but it works well in a range of  $\alpha=\{10, 50\}$  and  $\beta=\{0.2, 5\}$ .



**Fig. 2.** (a) Success rate with  $\alpha$  (random force) and  $\beta$  (repulsive force from the destination) in case of  $\rho = 0.42$ . (b) Success rate after discounting success due to pure Brownian motion. (c) Region where the success rate by the proposed method exceeds the success rate of Brownian motion on the  $\alpha$ - $\beta$  plane for various robot densities  $\rho$ .

Fig. 3 shows the relationship between the success rate and the density of the robots. As shown in Fig. 2(b), the system shows better performance in a wide range of densities around  $\beta = 1.0$ . Fig. 3 shows the success rate is high for a wide range of  $\rho$  in the region  $\alpha > 10$ .

From these results, we can empirically conclude that the system shows reasonable performance around  $\alpha = 10 \sim 50$  and  $\beta \sim 1.0$ . For the remainder of this paper, we fix  $\alpha = 20.0$  and  $\beta = 1.0$  as typical values for the homogeneous system.



**Fig. 3.** (a) Success rate on the  $\alpha$ - $\rho$  plane. (b) Region where the success rate by the proposed motion exceeds that of Brownian motion on the  $\alpha$ - $\rho$  plane. Here,  $\beta$  is fixed as 1.0.

Next, we explore to the relation between  $p$ , the probability that the robots change direction, and the system performance. The smaller  $p$  is, the longer a robot maintains the direction imposed by the repulsive force. Simulation results in all previous experiments have been obtained with  $p=0.01$ . Fig. 4 shows the success rate as a function of  $p$ . Empirically,  $p=0.1$  is better than  $p=0.01$  for high densities but worse in low density. Low values for  $p$ , such as  $p=0.001$ , never perform well. (Low values for  $p$  induce a similar effect as low values for  $\alpha$ ).

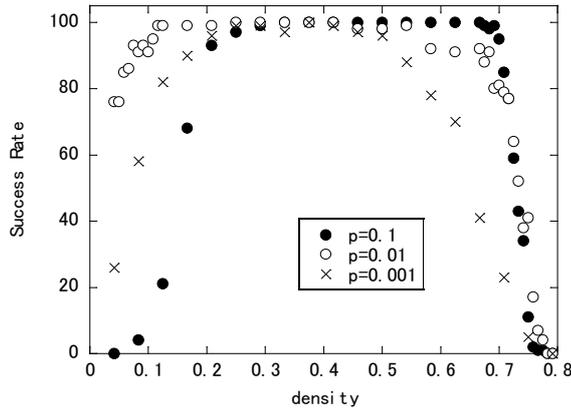


Fig. 4. Success rate as a function of density at different  $p$ .

#### 4. Extension to Heterogeneous System

When all robots are identical (homogeneous system) and the environment is finite, the density of robots gradually increases with growing distance from the destination as they are driven away from the destination due to the repulsive force. We have shown that the performance of object transportation decreases as density increases above 0.5. We are therefore interested in decreasing robot density in the vicinity of the object. We hypothesize that a heterogeneous swarm, in which some robots exhibit density-lowering behavior, can increase performance of object transportation. To this end, we propose two types of simple dynamics, and evaluate their performance. Each system consists of two types of robots, which dynamics differ by the values of  $p$ , namely  $p = 0.01$  and  $0.1$ , that is, some robots change their direction more often than others.

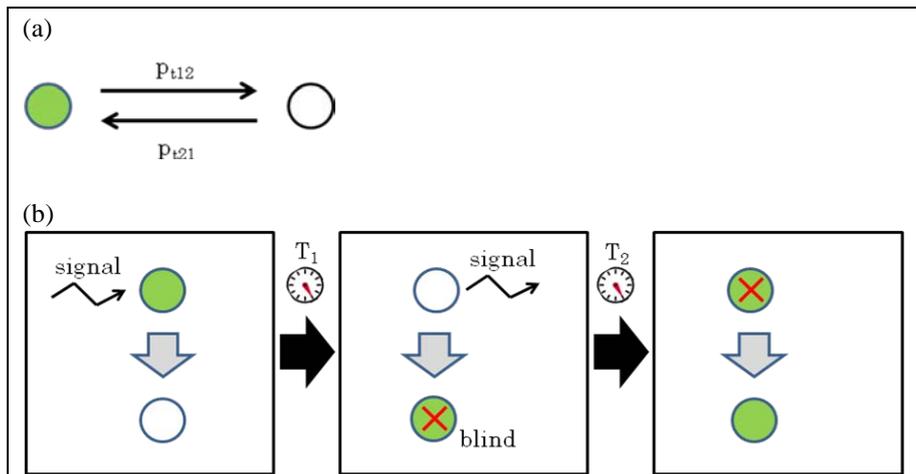
##### 1) Probabilistic model

Each robot changes its type asynchronously. The change obeys the transition probabilities,  $p_{12}$  and  $p_{21}$  (Fig. 5(a)).

2) *Signal propagation model*

In order to decrease the density around the object, we attempt to propagate “waves” of different behaviors through the swarm. To this end, we assume the robots have a simple communication protocol in which they can transmit and detect simple signals. The destination is continually emitting signals to all robots within a fixed radius. The robots use the following algorithm, depicted in Fig. 5(b):

- Initially, all robots are in state 1.
- If a robot receives a signal, it changes to state 2 and remains in state 2 for time  $T_1$ .
- After time  $T_1$ , the robot transmits a signal to all other robots within radius  $R$ , changes to state 3 for time  $T_2$ . In state 3, the robot is “blind” to additional signals.
- After time  $T_2$ , the robot reverts to state 1



**Fig. 5.** Schematics of dynamic heterogeneous system. Robots in state 1 are shown as green circles, robots in state 2 are shown as blue circles; and robots in state 3 are shown with a red X. (a) Robots in state 1 change to state 2 with probability  $p_{12}$ ; robots in state 2 change to state 1 with probability  $p_{21}$  (b) Robots receive a signal from either the destination or from a neighboring robot inducing it to change state, emit a signal, and revert to the original state after a refractory period.

### 4.1 Results

Using preliminary experimental results, we chose for  $p_{12}$  and  $p_{21}$  in the probabilistic model to be  $1.0 \times 10^{-4}$  and  $2.0 \times 10^{-4}$ , and  $T_1$  and  $T_2$  in signal propagation model as 100 sec and 500 sec, respectively.

The success rates of the two heterogeneous systems with respect to the homogeneous system for various densities are plotted in Fig. 6. Data is only reported for high density scenarios because there is little difference in the case of low density.

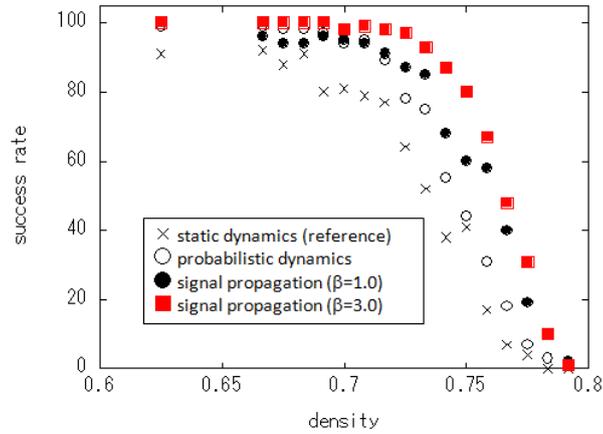
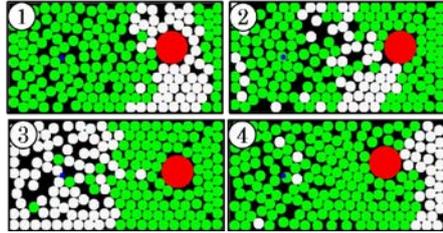


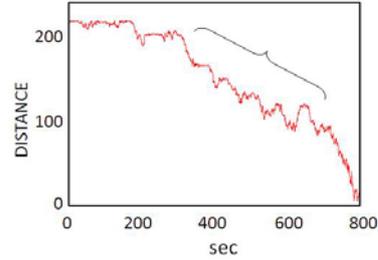
Fig. 6. Success rate of each model

We observe that the heterogeneous system in which robots switch types probabilistically slightly, but consistently, improves success rate when compared to the baseline performance of the homogeneous systems that has been tuned based on the empirical results from Section 3.

Fig. 7 shows a snapshot of an experiment with the signal propagation model. As the signal propagates, the cluster of the robots with  $p=0.01$  propagates from the destination to the boundary. This behavior is similar to peristaltic motion, and the object is transported showing pulsing motion (Fig. 8), i.e., tends to move back and forth. Using this approach further increases success rate over probabilistic dynamics and homogeneous system (Fig. 6).



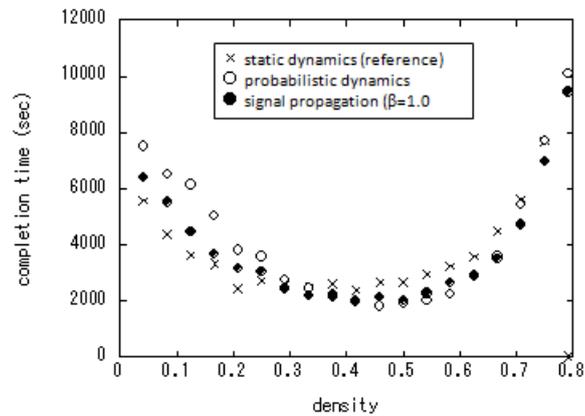
**Fig. 7.** Snapshot of signal propagation dynamics



**Fig. 8.** Distance from the destination by signal propagation dynamics in case of  $\rho=0.75$ . Pulsing motion appears in this behavior in the area indicated.

For simplicity, we choose  $\beta=1.0$  for both states, but if we introduce  $\beta$  in state 1 as 3.0 instead of 1.0, the success rate in this region is improved more as shown by the red rectangles in Fig. 8.

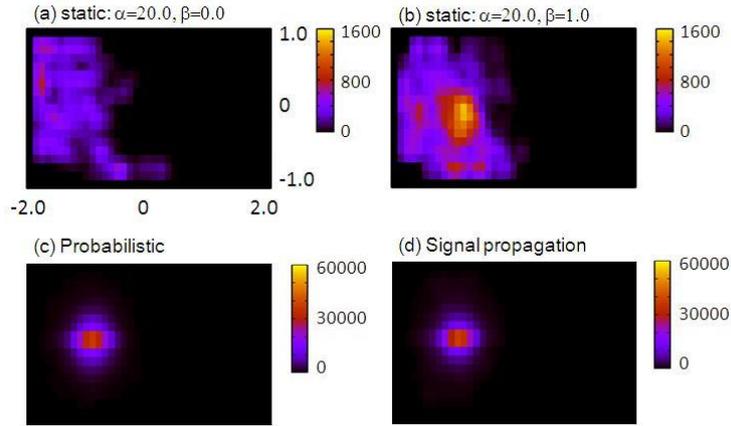
Next, we study the actual completion time, which corresponds to the speed or the efficiency of object transportation. Fig. 9 shows the average completion time of each of the dynamics for different densities. Here the completion time is defined as the first time the object reaches the destination. There is a tendency that the time becomes longer in low and high density region and is minimum around  $\rho=0.4\sim 0.5$ .



**Fig. 9.** Completion time of each dynamics.

It is also important to evaluate how long the system keeps the object in the vicinity of the destination once the object has reached the destination. A simple way of evaluation is to measure sojourn time around the destination. The experimental field is divided into  $40 \times 20$  cells, and we recorded the total sojourn time in each region (Fig. 10). The count starts when the object once reached destination. Fig.

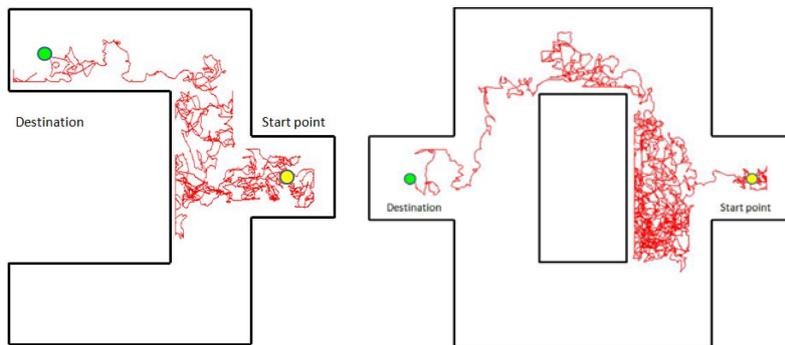
10 shows the accumulation of the result of 100 trials. The unit of color bar is “sec.” In the homogenous system, the distribution of the object position over multiple experiments is wide. In the heterogeneous systems, however, the distribution becomes narrow, and the distribution of the signal propagation dynamics is narrower than that of the probabilistic dynamics.



**Fig. 10.** Sojourn time of object position in case of  $\rho=0.63$ . (a) static system with  $\beta=0$ . (b) static system with  $\beta=1.0$ . (c) probabilistic dynamics (d) signal propagation dynamics.

## 4.2 Complex environments

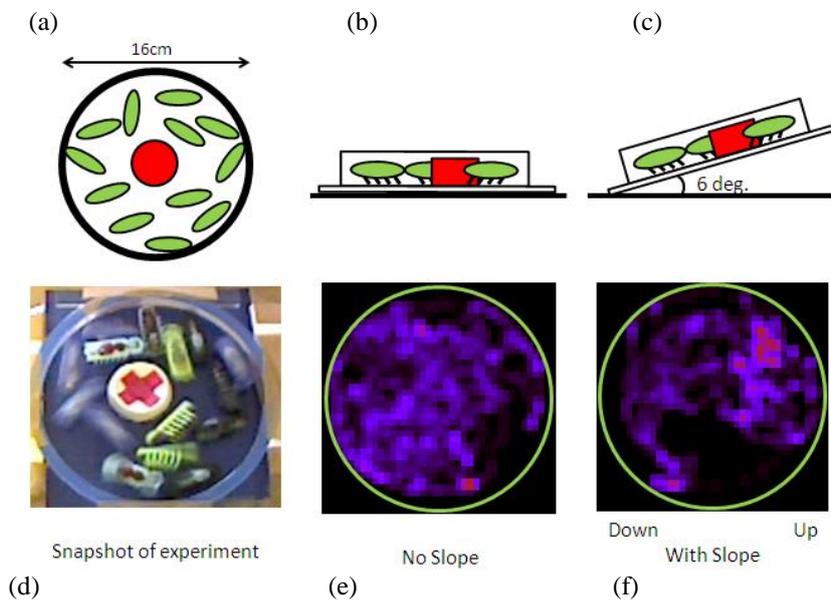
We are also interested whether the proposed object transportation mechanism works in more complex environments. Fig. 11 shows two sample environments of many we tried. These experiments confirm that the proposed approach generalizes to environments with more complex geometries.



**Fig. 11.** Object transportation in complex environment. Red line indicates the trajectory of the object. Yellow circle and green circle indicate the starting point and the destination, respectively.

### 4.3 Preliminary experimental validation

We performed a simple experiment to validate our approach for homogenous robot systems with the toy robot “Hex-bug”, which is driven by a vibration motor. The repulsive force is realized by the slope of the field. As shown in Fig. 12, which depicts the distribution of the object in the environment, the robots are capable of moving the objects consistently against the slope. The difference between Fig. 12(e) and Fig. 12(f) indicates that the object was transported to the right, or upper, side of the environment.



**Fig. 12.** Experiment by simple toy robots. (a) Cartoon of overhead view of the experiment. The red circle represents the object to be transported and the green ovals represent the Hex-bugs. (b) Cartoon of experimental control, in which the environment was horizontal. (c) Cartoon of experiment, in which the environment was tilted at  $6^\circ$  from horizontal, imparting a force on the Hex-bugs. (d) Photograph of the experiment. The object to be transported is marked with a red cross. (e) Heat map of the position of the object for the control. (f) Heat map of the position of the object for the experiment.

## 5. Discussion

Results suggest that granular convection has the potential to allow for controlled object transportation. Whereas all our experiments rely on a constant external force, finer control can potentially be achieved by manipulating the external field and robots with appropriate sensor for magnetic, electric, or chemical fields.

Parameters, particularly the ratio between randomness and directed motion, have been chosen ad-hoc in this paper and are functions of the specific simulation environment including the simulated friction, and sizes of robots and object. While this ad-hoc method is potentially applicable to real systems, in future work we are interested in grounding these parameters in first principles.

## 6. Conclusion

We propose a novel method for object transportation inspired by the Brazil Nut Effect, in which the robots have minimal sensors. Regardless of the simple dynamics of the robots based on random force and weak repulsive force from the destination, the object can be transported to the destination. Based on the observation that high density is detrimental to object transportation, we propose a heterogeneous system that is geared to lower the density in the vicinity of the object. Whereas a simple heterogeneous system in which some robots change direction slower than others improves performance, best results are achieved by using local communication to direct density-reducing behavior toward the object. In future work, we wish to confirm these results with a large number of very simple robots that are actuated by vibration and have the ability to communicate locally. We are also interested in analytically showing how density affects performance of object transportation.

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