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A Hardware and Software Testbed for Underactuated Self-Assembling Robots

EXTENDED ABSTRACT

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***Abstract*— We present the implementation and characterization of an affordable testbed for underactuated multi-agent, self-assembling systems. There has been recent interest into the control of nano- and micro-scale active particle systems, but these systems are often difficult to manufacture and observe, hindering control research. Our testbed offers an accessible way to experiment with different design and control approaches. The testbed is composed of an off-the-shelf rolling *weaselball* toy and a 3D printed external hub that modifies the agent's dynamics. The software toolbox includes simulations and code for data extraction and analysis of the weaselballs. The advantage of our testbed for studying distributed robotic systems is that these robots can be made quickly and cheaply, are relatively small, and do not require complex or expensive environments. The software in our toolbox includes a high fidelity Gazebo simulation, and Python code for analyzing trajectories from both simulation and overhead video of the system. Using this toolbox, we present useful computed properties of the system with regards to object clustering.**

I. INTRODUCTION

Cell scaffolds, immune systems, drifting jellyfish: many natural systems achieve organized behavior by harnessing seemingly random movement through mechanical or chemical interactions, breaking symmetries enough to create useful dynamics. We are particularly inspired by *active particles*, self-propelling micro- or nano-particles that are recently of great interest in materials science, micro-machining, and for medical and environmental applications [1] [2].

In robotics, mechanical agent-agent and agent-environment interactions are beginning to be explored [3], [4], sometimes termed embodied computation [5]. Low-cost multi-agent test beds are being actively developed, such as the Robotarium [6]. Our system is similar to other macro-scale testbeds that use fluid, air or electromagnetics to propel minimal self-assembling or swarming agents [7], [8], [9]. However, these systems require relatively expensive infrastructure, while our agents are self-propelled.

The Motion Strategy Lab has worked with *weaselballs* for years as a model of minimally controllable agents. In the multi-agent setting, they have been used to develop equilibrium density control algorithms based on environment geometry and discrete sensing and control [10], [11]. We extend this work by creating a hardware platform and related software library that lay the foundation toward developing control algorithms for tasks such as self-assembly and collective manipulation.

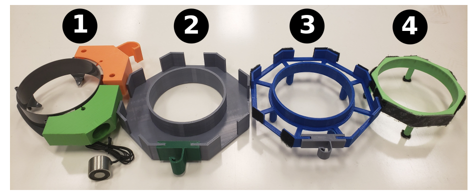

Fig. 1: Past iterations (1,2,3) and current hub design (4). Current design allows for fast (meters/min) motion and two stacked hubs can house electronics, sensors, and actuators.

II. PLATFORM DESCRIPTION

A. Hardware

The hub was designed to enable self-assembly of a collection of weaselballs. Earlier designs emphasized attaching sensors and mechanical attachments. However, the initial iterations were quite heavy; with heavy hubs, the motion of the weaselball is constrained and the agents move only a few centimeters a minute. Our current design is lighter and less complex; single agents may move a meter in 15 seconds.

The enclosure consists of whiteboard flooring, to minimize friction, and brick walls, though cardboard or other common materials may also be used for walls. All CAD models for hardware designs, and software described in Section II-B, are available on Github[1].

B. Software

We have implemented a Gazebo simulation of our platform for flexible and scalable data collection. Helpfully, Taylor and Drumwright [12] developed and validated a publically available Gazebo model of a weaselball. We created a hub model, utility scripts for generating multi-agent assemblies, and implemented AWS integration. We also have a Python+openCV toolbox for extracting trajectories from overhead video data of the physical robots and analyzing video and simulator trajectories. From trajectory data, we can compute quantities such as time to collision, displacement, velocity, and frequency of synchronization.

III. CHARACTERIZATION AND VALIDATION

Compliance with Environment: We observed that the agents tend to spend more time interacting with the environment than in the free space, simulating similar behavior at the micro scale [1]. Fig. 2 shows the distributions of position and orientation of a single simulated octagonal agent moving

[1] `https://github.com/alexandroid000/self-assembly`

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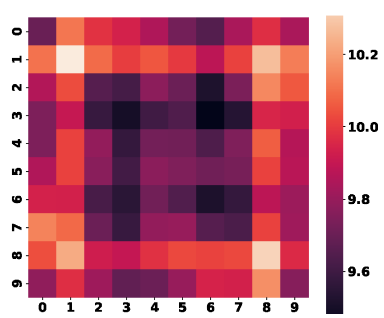
in a square environment (about 30 minutes of data, taken until distribution converged). The orientation data shows compliant effects consistent with agent and environment geometry. A large subset of possible agent movements near the boundary will keep the agent on the boundary, while movements in the free space do not favor any particular position or orientation, opening up discussion as to how environment design can influence collective dynamics.

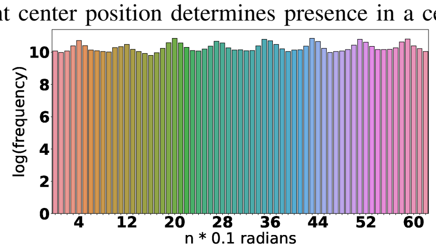
Toward Collective Manipulation: Here we show that the agents are capable of manipulating objects in a way consistent with the literature on self-organized clustering [3]. We placed two lightweight rectangular cardboard boxes in parallel in the center of the enclosure. Four agents were then allowed to move freely in the enclosure and collide with the boxes. When the boxes start further apart, 60% of the time the robots moved between the boxes, pushing the boxes to the environment boundary without clustering. However, when boxes are initially closer, they always clustered within a few minutes. Table I shows data for average time for first contact between the boxes and for full compliant alignment.

Box's Distance to Center	Average Time Until First Contact (seconds)	Average Time Until Flush (seconds)	Average Difference Between First Contact and Flush (seconds)
1 Inch	4	15.5	11.5
5 Inch	47.6	94.3	46.7
9 Inch	407	441.4	33.9
9 Inch Timeouts Excluded	118	203.5	84.8

TABLE I: Average time for obstacle clustering over 10 runs of each scenario. Final row excludes runs that did not cluster within 10 minutes.



(a) Log frequency of presence of agent in a discretized square environment. Discretization cell length and agent diameter are both approximately 0.1m, and agent center position determines presence in a cell.



(b) Relative frequencies of hub orientation. The eight distinct peaks are due to the octagonal shape of the hub aligning with square environment walls.

Fig. 2: Motion Characteristics of Simulated Single Hub

Effects of Assembly Size and Geometry: One observation is that weaselballs have a slight counterclockwise chirality, apparent in the asymmetric rotation of larger assemblies.

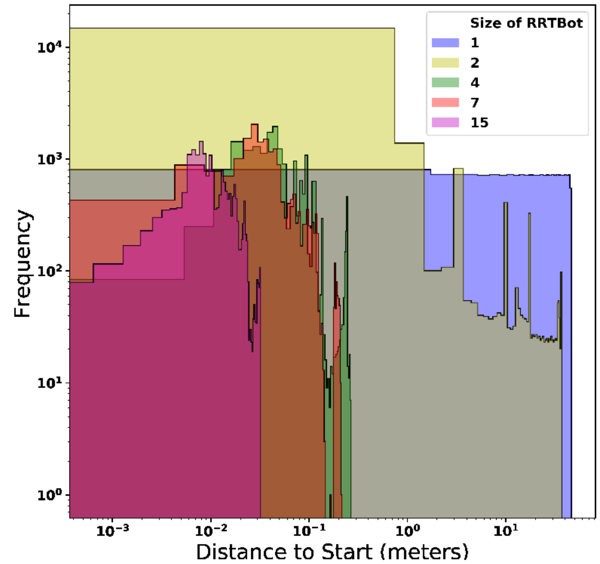


Fig. 3: Distribution of Euclidean distance of robot center from initial location for different assembly sizes. Data collected over two minute runs in simulation. Random assemblies of a given size (RRTbots) were generated by growing a random tree of connected hubs.

Second, larger assemblies tend to be more stationary (see Fig. 3). Third, there are instances of synchronization in weaselball assemblies. In both real-world assemblies and simulations, when the weaselball motions aligned, the assembly was more likely to continue its current motion until an external force was applied. This synchronization is more common in structures of 3 to 5 weaselballs; these assemblies seem to balance the trade-off between the probability of synchronization among majority of weaselballs and the strength of inter-agent forces. These characteristics are promising for the design of minimal, distributed control systems, perhaps ones that work by "doping" the multi-agent system with a few fully-controllable robots.

IV. Conclusion and Future Work

We are currently implementing controllable attachment, using electro-permanent magnets [13] and minimal on-board sensing and computation. We plan to tune interactions, assembly and manipulation through geometric design of agents such as in [17] and [18]. We are also interested in exploring switching global controls such as in [19], which can be emulated through tray tilting. We are working to extend the analysis of boundary effects, such as those in Fig. 2, by modelling boundary interactions as a scattering effect and extending related work on scattering control laws [14] [15] and robophysics [16]. Finally, we are developing minimal state representations and filters that scale well with the number of agents and environment complexity. Inspired by recent developments in ergodic control [20], we envision a system where the density and velocity of robots is tunable at the distribution level. This would allow control of differential "pressure" and collective manipulation through purely statistical mechanical interactions.

ACKNOWLEDGMENT

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