Decentralized Control of Distributed Manipulators: An Information Diffusion Approach

Extended Abstract

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ABSTRACT

This paper introduces a self-organizing decentralized controller employing an information diffusion mechanism to govern the behavior of surface-based distributed manipulators. These systems utilize independently controlled actuators arranged in a grid for precise positioning and orientation of objects. The proposed approach is demonstrated in a simulated virtual environment with a generic distributed manipulator. The system's self-organization capabilities are evaluated through experiments involving objects of varying sizes and shapes. The results show the robustness, fault tolerance, and performance of the system. The approach's high level of abstraction makes it versatile for different actuation principles and sensing devices, focusing on the essential information and module capabilities needed for the task. Code available at [5].

KEYWORDS

Decentralized Controller, Modular Robotic, Self-organization

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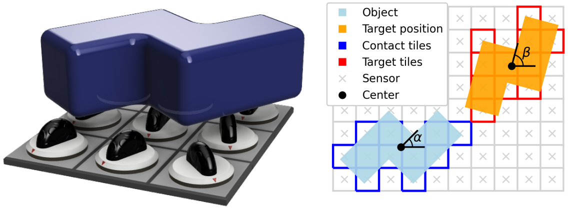
1 INTRODUCTION

Distributed manipulation systems consist of a grid of similar or identical independent actuators, combined with a control strategy that coordinates their movements to induce motion on objects resting on its surface (Fig. 1a). The purpose is to achieve precise positioning of planar objects. There are various forms of manipulation surfaces, and their actuation mechanisms have been extensively studied [3, 7, 12, 17, 18]. Controllers for these systems usually rely on generating a static vector field [4, 10, 11, 18]. However, this approach often requires restrictive assumptions concerning the symmetries and shapes of the objects, even the most robust of these control approaches fail to handle objects of specific shapes and sizes [2, 12, 17]. Moreover, these systems commonly adopt centralized control architectures [18] which constrains the scalability, as a single computer may struggle with numerous actuators [2] but also compromises the overall robustness due to dependency on a single control unit. To address these limitations, this paper proposes information diffusion as a decentralized control system for distributed manipulation. Through local communication, neighboring actuators coordinate their movements for precise positioning of planar objects. By eliminating centralized control, the approach enhances scalability and robustness.



(a) Example of a wheel-based distributed manipulator. **(b) Representation of the environment.**

Figure 1: Distributed manipulator and environment.

The central idea is that individuals capture and spread relevant environmental information, make decisions based on behavior rules, and apply a local force on the object to be manipulated. Despite the behavior rules simplicity, the interactions between the agents produce self-organization and enhance the system's capabilities, resulting in coordinated movement of the object. The approach is inspired by natural systems and draws on concepts from cellular automata, reaction-diffusion, and amorphous computing, leveraging information gradients in self-organizing systems [1, 6, 8, 9, 15, 16, 19].

2 METHOD

The methodology is evaluated within a two-dimensional simulated model based on previously developed modular manipulators created for experimental purposes [11, 13, 14] shown in Fig. 1b. This system consists of a grid of square modules, referred to as **tiles**, able to communicate with connected neighbors. An **object**, characterized by its **center** and **orientation** (α), is placed on top of the tiles. The objective of the system is to move the object from an initial position to a predetermined final position and orientation (β) referred to as the **target**.

All the tiles in the system are equally capable and governed by the same logic. Each of them possesses a **sensor** that allows it to detect the presence of an object above. A tile with its sensor detecting an object is referred to as a **contact tile** and is represented in Fig.1b with blue outlines. Tiles can induce a linear movement on

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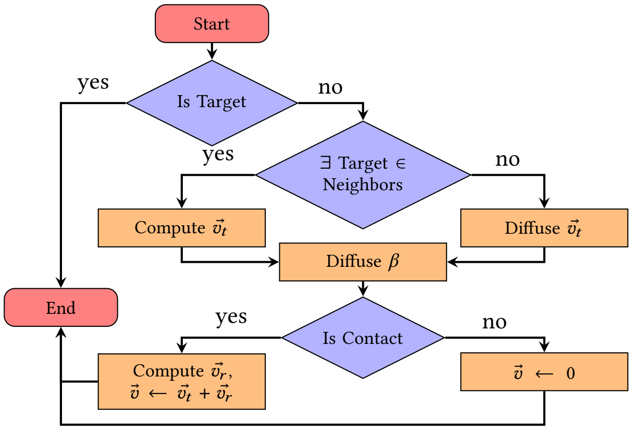


Figure 2: Behavior rules of the tile.

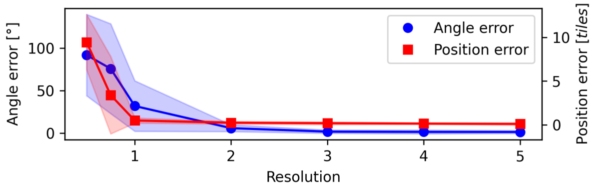
the object if they are in contact with it, and can be designated as **target tiles** if the object in its final desired position contains the center of the tile within its boundaries. In this paper, we assume that the tiles know their position and can infer the object's geometric center and orientation. Similarly, if a tile is set as a target, it can identify the geometric center and orientation of the object at the desired final position.

Each tile can communicate with its four adjacent tiles (up, down, right, left) referred to as the **neighborhood**. The control loop of a tile consists of updating its **state** through local communication with its neighbors and local sensor information, the state of a tile contains information about its position, sensor value, vector movements, and the mentioned inferred properties of the object and target. Then the tile will diffuse its vector translation ($\vec{v_t}$), vector rotation ($\vec{v_r}$), and orientations, and use it to decide how to contribute to the vector field following its behavior rules.

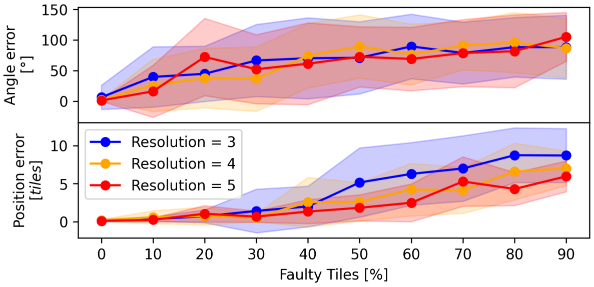
The mechanism of **information diffusion** in the system refers to how the values in the state of the tiles are spread between the individuals. The tile will contribute to the diffusion of information by adopting the new information processed out of the states of its neighborhood. The diffusion of information in a tile is given by averaging the information values of its neighborhood. **Behavior rules** refer to a logic path associated with a tile. These rules take as input the available information stored in the tile and generate a vector movement as output. The decision flow is shown in Fig. 2, where the diffusion of the values is given by the described mechanism, the vector translation points towards the average position of the target tiles among its neighborhood, and the vector rotation is computed to be perpendicular to the vector from the tile center to the object center and proportional to the orientation error ($\beta - \alpha$).

3 EXPERIMENTS

Two experiments were carried out to validate and study the potential and limitations of the proposed decentralized controller. The first one consisted of running the simulator for different object sizes, the performance of the controller is measured by the error between the final position of the object and the target position, with the positioning error calculated in relation to the length of the side of the tile. In this experiment, the term **resolution** refers to the relation between the size of the tile and the object. The second experiment measured the system's robustness against faulty agents. In each run, a certain amount of tiles were randomly chosen from the system with a uniform distribution and set to be faulty. A faulty tile does not contribute to the system's dynamics, nor is it registered by its neighbor tiles, rendering it functionally equivalent to an absent element within the system.



(a) Influence of resolution on performance.



(b) Influence of faulty agents on performance.

Figure 3: Experiments results.

In Fig. 3a, the system demonstrated strong orientation capabilities for resolutions exceeding three. However, a decline in performance was observed for objects with resolutions below this threshold, due to the risk of small objects not being detected by the sensors. On the other hand, the decentralized controller demonstrated effectiveness in translation for resolutions exceeding one. Fig. 3b illustrates that the system's orientation capabilities decline gradually as the percentage of faulty tiles increases, while the position error varies significantly after thirty percent.

4 CONCLUSIONS

This paper introduces a simple decentralized approach for controlling distributed manipulators which represents an alternative to existing centralized architectures with non-interacting agents. This approach has been demonstrated to exhibit self-organization and adaptation capabilities for planar manipulation tasks involving objects of varying shapes and sizes. Furthermore, it has been shown to be remarkably robust against failure.

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