Tessellation-Based Control Strategy for Multi-Robot Object Transportation in Unknown Environments

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***Abstract*—This paper introduces a novel control technique for a swarm of robots transporting one or more almost flat objects to a desired goal through an unknown environment. The proposed approach has three distinct parts. The first part of our work is about identifying the spatial property of the objects in the loading stations sequentially. The second part introduces a tessellation-based control strategy enforcing the agents to acquire the desired formation for every newly loaded object. In the final part, the swarm is required to carry the objects sequentially between the loading stations and finally to the desired destination in a fully decentralized way. The simulation result and the comparison study demonstrate our proposed approach's effectiveness for real-time object transport using swarms.**

I. Introduction

This research proposes a unique way to tackle the object transportation problem within a multi-robot system (MRS) to address the constraints in the current literature. Our primary goal is to increase the autonomy of the transportation process, reducing the necessity for human involvement. Our proposed method goes beyond the limitations of unit-loading structures[1],[2],[3] typically encountered in the literature. We intend to create a versatile and adaptive architecture to expand the traditional single-object-carrying problem to efficiently transport sequentially loaded multi-object items. This change will make the multi-robots traverse unfamiliar areas independently, locate acceptable items for transportation, and successfully coordinate their actions to transport the selected goods collectively[4]. This approach is simplistic enough to use it for real life problems. Our results outperform some of the current literature in the same field.

II. Tessellate-based Object Detection Algorithm

Let $\mathcal{L}$ be the set of loading stations and $\mathcal{O}$ the set of items to be loaded. Furthermore, we suppose that the i^{th} loading station ($L_i \in \mathcal{L}$) only has one object ($O_i \in \mathcal{O}$) to load, making $|\mathcal{L}| = |\mathcal{O}|$. The tessellates($\mathcal{T}_i$) generated for object O_i are further classified as A) *Permissible Tessellate*($\mathcal{T}_i^p$) or P-Tessellate and B) *Non-Permissible Tessellate*($\mathcal{T}_i^{np}$) or NP-Tessellate such $\mathcal{T} = \mathcal{T}_i^{np} \oplus \mathcal{T}_i^p$ that based on its overlap with the object O_i in the loading station. Since, the object to be carried needs to be balanced properly, all the agents must occupy the permissible tessellate ($\mathcal{T}_i^p$). Furthermore, let us assume the $|\mathcal{T}_i^p| \in \mathbb{Z}^+ \geq N$, where N is the number of robotic units in the swarm. 1 is the standard indicator function and $\Delta(A)$ stands for the area of the object A.

Algorithm 1 Permissible Tessellate Generation

for $O_i \in \mathcal{O}$ **do**
  Step 1: Compute centroid c_i^* of O_i
  Step 2: Generate set of circles $\mathcal{C}$ with center c_i^*, such that $\mathbb{1}_{\{\mathcal{C}_i \cap O_i\}} = 1$
  Step 3: Choose $\mathcal{C}_i^*$ such that $\min_{\mathcal{C}}(\Delta(\mathcal{C}))$ = $\mathcal{C}_i^*$
  Step 4: Inscribe set of squares $\mathcal{S}$ such that $\mathbb{1}_{\{\mathcal{C}_i^* \cap \mathcal{S}\}} = 1$
  Step 5: Choose square $\mathcal{S}_i^*$ such that $\mathcal{S}_i^* = \max_{\mathcal{S}_i} \Delta(\mathcal{S}_i \cap O_i)$
  Step 6: Generate Tessellates($\mathcal{T}_i$) on $\mathcal{S}_i^*$
  if $T_i \cap O_i \geq 0.5$ **then**
    Output: Permissible GREEN
  else
    Output: Non-Permissible RED
  end if
end for=0

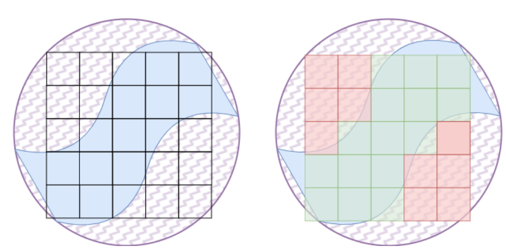

Fig. 1. The blue object ($O_i \in \mathcal{O}$) is placed inside a produced circle($\mathcal{C}_i^*$, forming square tessellates. The tessellates that overlap with the object(GREEN) are the permitted positions for the agents, and the non-overlapping tessellates (RED) are not.

III. Dynamics of the Robotic Systems

Consider a group of N robotic agents operating in a 2D space. Their objective is to carry an object towards a predefined target $T \in \mathbb{R}^2$. The motion dynamics of the i-th agent, positioned at $p^i \in \mathbb{R}^2$, are governed by the following equation [5]:

$$\dot{p^i} = -k_c \cdot (p^i - \Omega^i) + k_r \sum_{j=1, j\neq i}^{N} \left[\exp\left(-\frac{\|p^{ij}\|}{r_s^2} \right) \cdot (p^i - p^j) \right] \tag{1}$$

Here, $\Omega^i \in \mathbb{R}^2$ represents an arbitrary point towards which the i-th agent needs to approach. The term k_c is the convergence gain, $\|p^{ij}\|$ is the Euclidean distance between agents i and j, r_s is the repulsion region, and k_r is the repulsion gain to prevent inter-agent collisions. By following the control law in Equation 1, each agent will move towards Ω^i while avoiding collisions with neighboring agents.

IV. Optimal P-Tessellate Selection by the Agents

Once we get the permissible tessellates $\mathcal{T}_p$, we need to optimally place the agents such that the object to be carried is balanced. In order to do that, we propose the following algorithm. The threshold ϵ is problem-specific. Refer to Fig. 2 for a visual analysis,

Algorithm 2 Optimal P-Tessellate Selection by the agents

1: **for** $O_i \in \mathcal{O}$ **do**
2: **Step 1:** Symmetrically divide $\mathcal{C}_i^*$ in $2k$ regions, namely $R_j \forall j \in \{1, 2k\}$
3: **Step 2:** Omit regions $R_j^e = R_j$ where $|\mathrm{T}_p \cap R_j| \leq \epsilon$
4: **if** N = $|\mathcal{T}_p \cap (R_j - R_j^{e\,C})|$ **then**
5: Assign $\frac{N}{k}$ agents to the permissible regions $R_j \cap R_j^{e\,C}$.
6: **GOTO Step 8**
7: **else**
REPEAT Step 1 for for the remaining R_j regions
8: **end if**
9: **end for**=0

V. Object Transport through occluded environment

The simulation results show the effectiveness of the suggested control strategy in an occluded environment with multiple short passageways, as shown in Figure 3. As seen in Figure 2, once the formation is complete, an item is placed on top of the agents. The next challenge is to carry the thing to a certain destination while avoiding obstacles[5]. The control technique effectively navigates the agents through the restricted passages while avoiding collisions with obstructions. The centralized controller enables safe object delivery by directing robots to maintain formation and adapt trajectories to avoid obstacles. The simulation results show that the suggested control algorithm for loading and transportation is successful in obtaining the required formation and completing the goal of item transportation in a difficult obstructed environment [6].

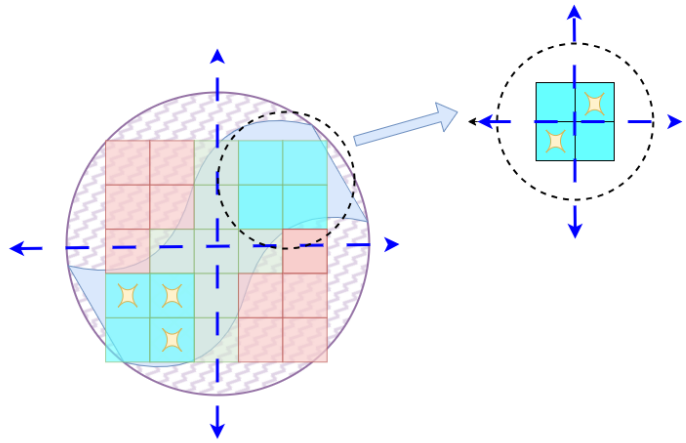

Fig. 2. The Proposed iterative algorithm assigns the optimal locations for N = 5 agents in the above figure. The blue regions are the desired $R_j \cap R_j^{e\,C}$ we get after Step 2. Similar approach should hold true for any N provided $\mathcal{T}_p \geq N$. The Blue arrows points to the second iteration, where we follow Step 1 for a smaller region.

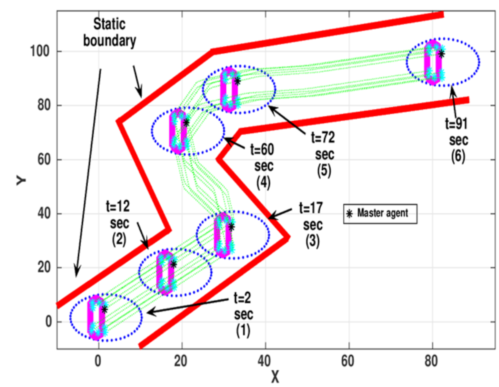

Fig. 3. Following the decentralized policy defined in (1), the simulation shows the effectiveness of our proposed approach in object transportation. We have taken 9 agents in this simulation and the normalized time for the agents to reach its final destination was about 51 seconds.

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