Orientation Control of Large Objects Using Multi-Arm Robotic Systems with Suction-Based End Effectors

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***Abstract*— This paper addresses the challenge of manipulating very large objects using multi-arm robotic systems equipped with suction-based end effectors. Large object manipulation presents significant challenges across various industries including manufacturing, construction, and aerospace, where traditional methods often lack precision, flexibility, or safety. We propose a novel gait-inspired control strategy that enables multiple robotic arms to coordinate their movements to reorient large objects that exceed the workspace of individual manipulators. The approach involves alternating between stepping phases, where individual robots reposition their contact points, and dragging phases, where all robots simultaneously apply forces to reorient the object. We validate our approach in a physics-based simulation environment using four UR5e robotic arms to manipulate rectangular prism objects, demonstrating successful reorientation of objects up to 5×5×1 meters with roll and pitch rotations of up to 100 degrees. The proposed method provides a framework for precise orientation control of large objects while addressing the challenges of workspace limitations, stability maintenance, and coordinated control.**

I. INTRODUCTION

The manipulation of very large objects presents significant challenges across numerous industrial sectors including manufacturing, construction, logistics, and aerospace. Traditional approaches rely on heavy machinery, cranes, or human workers, which frequently suffer from limitations in precision, adaptability, safety, or economic feasibility. As industries continue to evolve and automate, there is an increasing demand for more sophisticated and adaptable solutions capable of handling large objects with greater precision and reliability.

Robotic manipulation systems have demonstrated considerable success with small to medium-sized objects, but extending these capabilities to very large objects introduces unique challenges. These include managing scale and weight constraints, controlling complex dynamics, ensuring stability throughout manipulation processes, distributing forces appropriately, navigating workspace limitations, obtaining accurate sensing information, and designing suitable end effectors. The complexity increases exponentially when manipulating objects that exceed the payload capacity of individual robotic arms, necessitating multi-arm coordination [21].

Suction-based end effectors have emerged as a promising approach for handling large objects due to their adaptability to varied surface geometries, ability to distribute forces across contact areas, non-invasive gripping mechanisms, and scalable design [9]. Recent advancements in suction technology have produced more efficient, adaptable vacuum grippers that don't require external air supply and can be combined with other gripping mechanisms to create hybrid end effectors [30]. Such systems can conform to complex object surfaces while maintaining strong gripping forces, making them ideal for manipulating large objects with varied geometries [18].

However, these advantages come with inherent challenges in maintaining consistent suction forces, implementing coordinated control across multiple points of contact, ensuring compatibility with diverse surface materials, and balancing dynamic loads during motion. The complexity further increases when attempting to coordinate multiple suction-based end effectors across separate robotic arms [22]. Advanced solutions that combine suction with tactile sensing and force control are emerging [24], but remain limited in their ability to handle large-scale reorientation tasks.

This paper addresses the specific problem of orientation control for very large objects using a coordinated multi-arm robotic system equipped with suction-based end effectors. We present a novel control framework that enables precise and stable reorientation of large payloads through synchronized operation of multiple robotic manipulators using a gait-inspired approach. This approach allows for continuous manipulation while respecting workspace constraints.

The need for multi-arm manipulation solutions has grown significantly in recent years, driven by applications in warehouse automation, manufacturing assembly, and space robotics [**?**]. While dual-arm manipulation has received considerable attention [6], extending these techniques to systems with more than two arms introduces additional coordination challenges, especially when manipulating large, complex objects. Previous research has explored various strategies for multi-arm coordination, including leader-follower approaches [1], impedance control methods [33], and hybrid position/force control [27], but these have not fully addressed the challenges specific to large object reorientation.

The primary contributions of this paper are:

- A gait-inspired control strategy for reorienting large objects using multiple robotic arms with suction-based end effectors
- A path planning algorithm that finds optimal trajectories on the object surface while respecting workspace constraints
- A coordination mechanism that ensures stable orientation control throughout the manipulation process

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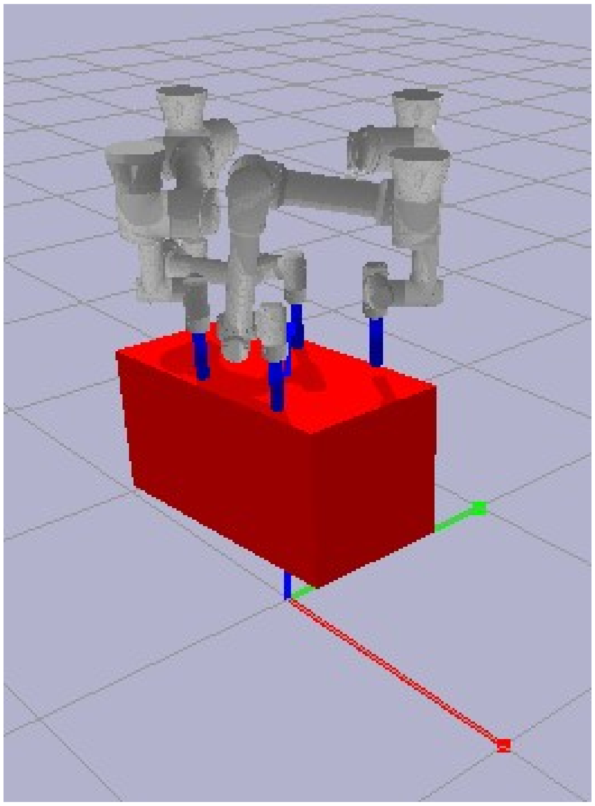


Fig. 1: Overview of the multi-arm robotic system with suction-based end effectors manipulating a rectangular prism object. Four UR5e robotic arms are arranged in an inverted configuration around the central object, allowing for coordinated manipulation of objects larger than any individual robot's workspace.

- Experimental validation in a physics-based simulation environment

II. RELATED WORK

A. Multi-Robot Manipulation Systems

Research in multi-robot manipulation has evolved significantly over the past three decades. Early seminal work by Koga and Latombe (1994) established fundamental principles for coordinated motion planning with multiple manipulators [14]. Their approach addressed the geometric and kinematic challenges of cooperative manipulation but was limited to quasi-static scenarios with perfect models.

More recent contributions have expanded these foundations to incorporate dynamics and uncertainty. Caccavale and Uchiyama (2016) presented comprehensive frameworks for controlling multiple manipulators handling a common object, focusing on force distribution and internal stress management [5]. Their work demonstrated that proper load distribution is critical for preventing object damage and maintaining stable grasps, though their methods relied heavily on accurate object models and precise robot positioning.

In the context of aerial manipulation, Mellinger et al. (2013) demonstrated cooperative transportation using multiple quadrotors, highlighting the importance of synchronized control across distributed systems [19]. Their approach successfully managed dynamic coupling between robots but was limited to relatively lightweight objects and simple trajectory following rather than complex reorientation tasks.

McEvoy et al. (2021) advanced the field further with their work on real-time adaptive multi-robot manufacturing, demonstrating how multiple manipulators can coordinate to handle objects larger than any individual robot's workspace [17]. Their approach incorporated online trajectory optimization but was primarily focused on additive manufacturing applications rather than object reorientation.

The RoboTurk project introduced a multi-user data collection platform that allows multiple remote users to simultaneously teleoperate a set of robotic arms for multi-arm tasks, demonstrating the potential of imitation learning for coordinating complex manipulations [**?**]. Ögren et al. (2012) surveyed dual-arm manipulation techniques, noting the increased complexity compared to single-arm systems and highlighting the need for advanced system integration and high-level planning approaches [21].

B. Object Reorientation and Surface-Based Manipulation

Object reorientation represents a specific subset of manipulation tasks with its own unique challenges. Traditional approaches to object reorientation with robotic systems can be broadly categorized into regrasping techniques, continuous sliding methods, and in-hand manipulation strategies.

The work by Chavan-Dafle and Rodriguez (2018) on motion cones established a mathematical framework for understanding the mechanics of controlled sliding during manipulation [7]. Their approach enabled planned reorientation through carefully controlled contact transitions but was primarily demonstrated on smaller objects with single manipulators.

Of particular relevance to our approach is the work by Stouraitis et al. (2020) on dyadic collaborative manipulation, which explored how robots can coordinate with humans to reorient large objects through a series of discrete moves [28]. Their research demonstrated the potential of sequential manipulation actions but did not address the specific challenges of suction-based end effectors or fully autonomous operation.

Wang et al. (2022) explored surface-based manipulation strategies using multiple contact points, demonstrating how coordinated motion across a surface can achieve complex object reconfigurations [31]. Their work provides valuable insights into contact-rich manipulation but did not specifically address the unique dynamics of very large objects or suction-based gripping.

Berenson et al. (2011) developed a framework for pose-constrained manipulation planning using Task Space Regions (TSRs), which allows for planning coordinated multi-arm motions while respecting workspace constraints [4]. This approach is valuable for planning trajectories in cluttered environments but does not address the specific challenges of maintaining stable contact with large objects during reorientation.

Recent work by Huang et al. (2023) has explored implicit contact diffusion for sequential contact reasoning, demonstrating improved performance in complex manipulation tasks involving multiple contact points [13]. Similarly, Zhong et al. (2023) developed a system for producing diverse plausible pose estimates from contact and free space data, which is valuable for planning robust manipulation strategies under uncertainty [34].

C. Suction-Based Manipulation

Suction-based end effectors have gained popularity in industrial applications due to their versatility and adaptability. Early work by Kolluru et al. (1998) explored the fundamentals of suction cup design and control for robotic applications, establishing basic principles for vacuum-based manipulation [15]. Their research highlighted the potential of suction grippers but was limited to simple pick-and-place operations rather than complex reorientations.

More recently, Pham and Yen (2003) investigated the mechanics of suction cup adhesion on various surfaces, providing valuable insights into the factors affecting grip stability [23]. Their work demonstrated that surface properties significantly impact suction effectiveness but did not address the coordination challenges present in multi-point suction systems.

In the context of large object handling, Gafer et al. (2020) demonstrated a multi-suction gripper system for industrial applications, showing improved payload capacity through distributed suction points [12]. However, their approach focused primarily on lifting operations rather than precise orientation control, and they did not address the dynamic challenges of object reorientation.

The integration of suction technology with other gripping mechanisms has led to the development of hybrid end effectors that combine the benefits of both approaches. Correll (2022) discussed how the optimal gripper must become "as hard or as soft as possible," suggesting that combining technologies like suction with mechanical gripping can provide enhanced manipulation capabilities [9]. Similarly, recent research has explored the development of magnetically switchable soft suction grippers that can transition between soft and rigid states to handle both delicate and heavy objects [26].

The robotics industry has seen significant advances in suction-based end effectors, including the development of systems that don't require external air supply, the integration of force and torque sensing, and the combination of suction with computer vision and machine learning technologies [2], [10]. These developments have expanded the capabilities of suction-based grippers but have primarily focused on single-arm applications rather than coordinated multi-arm systems.

D. Gait-Based Approaches in Robotics

While traditional gait analysis focuses on legged locomotion, the concept of cyclic, coordinated movement patterns has been adapted to various robotic applications. Bai and Wen (2019) demonstrated how gait-inspired motion patterns could enable small robots to manipulate objects larger than themselves through coordinated pushing and dragging operations [3]. Their work demonstrated the potential of sequenced contact-based manipulation but with direct pushing rather than suction-based attachment.

In manufacturing contexts, Sun et al. (2021) explored rhythmic manipulation patterns for assembly tasks, showing how cyclic motion primitives could simplify complex manipulation planning [29]. Their approach emphasized the benefits of repetitive motion sequences but primarily addressed small-scale precise assembly rather than large object orientation control.

The concept of robot "walking" on surfaces has been explored by Yim et al. (2018) for inspection tasks on large structures, demonstrating how suction-based attachment could enable navigation across varied surfaces [32]. Their research focused on locomotion rather than manipulation but provides valuable insights into reliable suction-based attachment for non-horizontal surfaces.

Bio-inspired approaches have also influenced gripper design, with researchers developing systems that mimic the grasping abilities of animals and humans. Maxwell (2019) pioneered a multi-DOF two-finger robot gripper designed to handle larger objects and execute in-hand rolling and twisting, employing a tendon-driven mechanism similar to those found in biological systems [16]. Similarly, bioinspiration has led to the development of various innovative gripper designs, including those that combine rigid and soft elements to adapt to different manipulation tasks [24].

E. Limitations of Current Approaches

Despite significant advances in robotic manipulation, several important limitations persist in current approaches to large object orientation control:

- Most existing approaches fail to adequately address how to manipulate objects significantly larger than the workspace of the individual manipulators, limiting their practical applicability.
- Existing multi-arm control strategies often rely on centralized planning with perfect information, making them vulnerable to communication delays and single points of failure.
- Most approaches simplify the problem by assuming quasi-static conditions, neglecting the complex dynamics that emerge during reorientation of large masses.
- Current methods typically assume perfect and continuous contact, which is unrealistic for suction-based systems that may experience partial or complete suction loss during operation.
- Many demonstrated techniques work effectively for objects within a limited size range but fail to address the challenges that emerge when scaling to very large objects.
- Few approaches enable truly continuous manipulation of large objects while respecting the kinematic limitations of fixed-base manipulators.

- Limited research exists on determining optimal paths through orientation space for large objects under the constraints of surface-based manipulation.

Recent work in space robotics has attempted to address some of these limitations, with researchers developing specialized techniques for on-orbit manipulation of large objects using multi-arm systems [22]. These approaches include the Extended Multiple Impedance Control (MIC) method for dual-arm control of passive objects in space [33] and disturbance-based impedance controllers that provide desired impedance behavior while applying motion using joint torque controllers [11]. However, these techniques have primarily focused on space applications and have not been extensively tested in terrestrial environments with larger numbers of manipulators.

III. PROPOSED APPROACH

To address these limitations, we propose a novel control framework specifically designed for orientation control of large objects using multiple robotic arms with suction-based end effectors. Our approach leverages a gait-inspired strategy that enables continuous manipulation while respecting workspace constraints through coordinated stepping and dragging motions.

A. System Overview

The core of our approach is an offline trajectory generation algorithm that produces open-loop trajectories for four 6-DOF robotic arms equipped with suction cup-based end effectors. These trajectories enable the system to progressively change the orientation of a very large object through a series of coordinated actions reminiscent of walking gaits. Our algorithm finds trajectories that follow the shortest path from initial to desired orientation, optimizing efficiency while ensuring stability throughout the manipulation process.

The physical setup consists of:

- Four UR5e robotic arms arranged in a circular pattern around a central object
- The robots are mounted in an inverted (upside-down) configuration to maximize workspace
- Suction-based end effectors with a 2cm diameter for non-invasive gripping of the object surface
- A rectangular prism target object positioned at the center of the workspace

The implementation uses the PyBullet physics engine to simulate the robotic manipulation with custom URDF models for the inverted configuration.

B. Control Strategy

The control strategy involves two primary phases that alternate in a cyclic pattern:

- **Stepping phase**: Individual robotic arms sequentially detach from the object surface, reposition to a new contact location, and reattach. This phase enables the system to progressively "walk" across the object surface, maintaining control while adapting to workspace limitations.

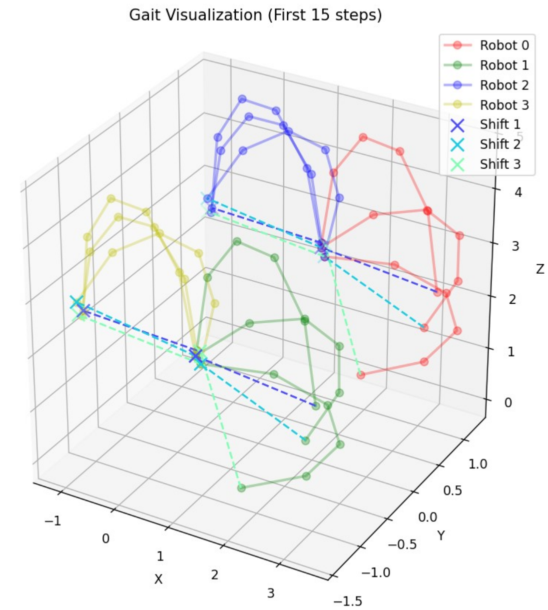


Fig. 2: Visualization of the gait cycle. Individual robot stepping phases are shown with colored lines (each color representing a different robot), while shift phases are indicated by X markers connected with dashed lines. The plot illustrates the alternating pattern of individual robot steps followed by coordinated shifts used to reorient the object.

- **Dragging phase**: All attached robotic arms coordinate to apply forces and torques that incrementally reorient the object while keeping it within the collective workspace of the system. This phase produces the actual orientation change while maintaining stable control of the object.

By alternating between these phases in a carefully orchestrated sequence, the system can achieve complex reorientation tasks that would be impossible with fixed grasping points or traditional manipulation approaches.

IV. ALGORITHM DETAILS

Our approach for orientation control of large objects using multiple robotic arms with suction-based end effectors relies on a gait-inspired control strategy. This section describes the key algorithmic components that enable coordinated manipulation while respecting workspace constraints.

A. Surface Representation

The foundation of our approach is a discrete representation of the object's surface as a navigable graph structure. Given the object's dimensions, orientation, and center position, we generate a uniform grid of points on each face of the rectangular prism. For each point, we calculate its 3D position and surface normal vector in the global coordinate frame using:

$$p_{global} = R \cdot p_{local} + c \quad (1)$$

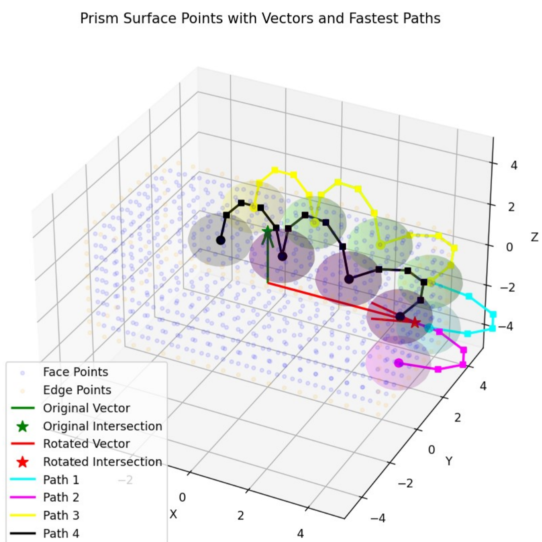


Fig. 3: Surface discretization and trajectory planning. The object surface is discretized into a grid of points, with face points shown in blue and edge points in orange. The planned robot trajectories are shown in different colors, with the optimal paths from initial to target positions highlighted. The green and red stars represent the intersection points for initial and target orientations, respectively.

where p_{global} is the point position in global coordinates, p_{local} is the position in local object coordinates, R is the rotation matrix derived from the object's orientation, and c is the object's center position.

Each point is classified as either a "face" point or an "edge" point based on its location. Edge points are identified when a point lies at the intersection of two or more faces. We then establish connections between adjacent points to create a graph structure for path planning. To ensure efficient spatial queries during subsequent processing, we construct a KD-tree from the point positions. This data structure enables rapid nearest-neighbor searches when selecting contact points and planning paths.

The resolution parameter controls the density of the surface discretization, with typical values around 0.05m providing a good balance between computational efficiency and path accuracy. This surface representation, illustrated in Fig. 3, forms the foundation for all subsequent planning operations, enabling robots to navigate along the object surface while avoiding problematic regions.

B. Contact Point Selection

With the surface representation established, we next need to select optimal contact points for the robotic end effectors. This process involves finding surface points that provide stable grasping locations for both the initial and target object orientations.

For a given orientation, we project a vector from the object's center in the direction specified by the orientation angles. The orientation vector v is calculated as:

$$v = R \cdot [0, 0, 1]^T \tag{2}$$

where R is the rotation matrix derived from the orientation angles. We then determine where this vector intersects the object's surface using a ray-box intersection algorithm. Around this intersection point, we select four contact points arranged in a square pattern.

These contact points must satisfy several constraints to ensure stable manipulation:

- Maintain a minimum clearance radius from edge points (typically 0.01m) to ensure reliable suction
- Maintain a minimum distance from each other (approximately twice the clearance radius) to prevent collisions between end effectors
- Maintain a minimum distance from the intersection point (typically 0.2m) to provide leverage for applying torques

The contact point selection algorithm uses the KD-tree to efficiently search for surface points that satisfy these constraints. If suitable points cannot be found at the exact desired locations, the algorithm relaxes the constraints progressively while ensuring a minimum distance from edges is always maintained.

This process is performed twice: once for the initial orientation and once for the target orientation, establishing both the starting and ending positions for the robot paths. The selection of appropriate contact points is crucial for ensuring stability throughout the manipulation process.

C. Path Planning

Once the contact points are established, we need to find optimal paths between corresponding initial and target points. We employ the A* algorithm adapted for navigation on the object's surface. The algorithm searches for the shortest path through the graph of surface points while avoiding edge regions.

For each pair of corresponding contact points, we define a cost function that combines the Euclidean distance between points with a penalty for proximity to edges:

$$f(n) = g(n) + h(n) + \alpha \cdot e(n) \tag{3}$$

where $g(n)$ is the cost to reach node n from the start, $h(n)$ is the heuristic estimate of the cost from n to the goal (Euclidean distance), $e(n)$ is an edge proximity penalty, and α is a weighting factor. This formulation guides the search toward paths that stay on face regions while minimizing travel distance.

To ensure appropriate spacing between waypoints along each path, we apply a discretization step that selects a subset of points from the raw A* path. Points are included in the discretized path if they:

- Are separated by at least twice the clearance radius from previously selected points
- Do not create a sphere (of radius equal to the clearance radius) that intersects with edge points

This discretization process reduces the number of waypoints while maintaining safe distances from edges and between robots. The start and end points are always included in the discretized path to ensure the robots reach their target positions.

D. Arc Generation for Smooth Transitions

To create smooth transitions when robots detach from and reattach to the surface, we add arc points between consecutive surface points. These arcs allow robots to lift off the surface, move to a new position, and return to the surface in a natural motion.

For each pair of consecutive points in a discretized path, we generate a semi-circular arc with the following parametric equation:

$$p(t) = p_{mid} + 0.5 \cdot v \cdot \cos(\pi(1-t)) + 0.5 \cdot \|v\| \cdot h \cdot d \cdot \sin(\pi(1-t)) \tag{4}$$

where $p(t)$ is the position at parameter $t \in [0, 1]$, p_{mid} is the midpoint between the two consecutive points, v is the vector from the start to end point, d is the unit direction vector for the arc (derived from the average of the surface normals at start and end points), and h is the arc height factor (typically set to 2).

The normal vectors at arc points are calculated by interpolating between the normals at the start and end points:

$$n(t) = n_{start} \cdot (1-t) + n_{end} \cdot t \tag{5}$$

This ensures smooth orientation changes as the robot moves along the arc. The arc height factor controls how high the robot lifts off the surface, with higher values providing more clearance but requiring larger motions. For our implementation, we typically generate 4 intermediate points along each arc, which provides sufficient smoothness while limiting computational complexity.

E. Gait Generation

The core of our approach is the gait generation algorithm that coordinates the movements of multiple robotic arms to reorient large objects. This algorithm creates a sequence of actions that alternate between individual robot steps and simultaneous shifts, forming a pattern reminiscent of a walking gait.

Our gait generation process begins by identifying key points along each robot's path, specifically the "original" surface points (excluding arc transition points). These points mark the locations where robots will make contact with the object surface. For each pair of consecutive original points, we create a sequence of steps and shifts. During a step action, one robot moves from its current position to the next position along its path while other robots remain stationary. This movement follows an arc trajectory above the object surface, with the robot detaching its suction gripper (suction off) during transit and reattaching (suction on) at the destination. The suction state sequence follows a pattern of [1] + [0] × n + [1], where n is the number of intermediate points along the path.

After each robot has completed its individual step, a shift action occurs where all robots simultaneously apply forces to reorient the object. During this shift phase, all robots maintain active suction (state = 1) to ensure stable control of the object. This alternating pattern of steps and shifts continues until the object reaches its target orientation.

A critical aspect of our algorithm is the transformation of the robot paths during the reorientation process. As the object rotates, the contact points on its surface move in 3D space. We calculate these new positions using:

$$p_{new} = R \cdot (p_{original} - p_{intersection}) + p_{intersection} - R \cdot s \tag{6}$$

where p_{new} is the new point position, $p_{original}$ is the original position, $p_{intersection}$ is the intersection point (the point where the orientation vector intersects the object), R is the rotation matrix derived from the orientation vector, and s is the shift vector that ensures the object remains within the robots' workspace.

For the orientation progression between the initial and target angles, we use an exponential interpolation function rather than linear interpolation. This approach creates smaller orientation steps at the beginning of the motion when the distal ends of the object are moving toward the robotic arms, and larger steps toward the end when there is safe clearance. The exponential interpolation is calculated as:

$$t_i = \frac{b_i^x - 1}{b_i - 1} \tag{7}$$

where b_i is the base parameter (typically set to 10 times the corresponding object dimension) and x ranges from 0 to 1. The resulting values t_i are used to interpolate between the initial and target orientation angles:

$$\theta_{roll} = \theta_{roll}^{initial} + t_1 \cdot (\theta_{roll}^{final} - \theta_{roll}^{initial}) \tag{8}$$

$$\theta_{pitch} = \theta_{pitch}^{initial} + t_2 \cdot (\theta_{pitch}^{final} - \theta_{pitch}^{initial}) \tag{9}$$

$$\theta_{yaw} = \theta_{yaw}^{initial} + t_1 \cdot (\theta_{yaw}^{final} - \theta_{yaw}^{initial}) \tag{10}$$

This exponential interpolation is particularly important for preventing collisions during the early stages of reorientation when the object geometry may bring its edges close to the robotic arms.

F. Robot Assignment

To optimize the assignment of robots to paths, we use the Hungarian algorithm, which solves the linear assignment problem in polynomial time. We construct a cost matrix C where each element C_{ij} represents the Euclidean distance between robot i's initial position and the starting point of path j:

$$C_{ij} = \|p_i^{robot} - p_j^{path\_start}\| \tag{11}$$

The Hungarian algorithm finds the assignment that minimizes the total distance traveled by all robots to reach their starting positions. This optimization is particularly important for large objects where inefficient assignments could result in configurations outside the robots' workspace or require unnecessarily large movements.

G. Command Generation

The final step in our algorithm is to convert the abstract gait into specific robot commands. Each command specifies the 3D position, orientation (as Euler angles), and suction state for each robot at each timestep.

For positions along the paths, we use the coordinates directly from the path planning stage. For orientations, we derive Euler angles from the surface normal vectors using:

$$\begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} \arctan 2(R_{23}, R_{33}) \\ \arcsin(-R_{13}) \\ \arctan 2(R_{12}, R_{11}) \end{bmatrix} \tag{12}$$

where R is the rotation matrix derived from the surface normal (ensuring the z-axis aligns with the normal), and R_{ij} represents the element at row i and column j of this matrix.

Our command generation ensures proper sequencing of actions to maintain stability throughout the manipulation process. During steps, only one robot moves while others remain stationary. During shifts, all robots move simultaneously to reorient the object. Suction states are coordinated such that at least three robots maintain active suction at all times, ensuring stable control of the object.

H. Implementation and Parameter Selection

The complete algorithm has several key parameters that affect performance:

- Surface resolution: Controls the density of points in the surface discretization. We typically use 0.05m, which balances computational complexity and path accuracy.
- Clearance radius: Defines the minimum distance from edges for stable suction. We use 0.01m based on the size of our suction cups.
- Number of arc points: Controls the smoothness of transitions. We use 4 points per arc for a balance between smoothness and computational efficiency.
- Minimum intersection distance: Ensures contact points are distributed around the intersection point. We use 0.2m to provide sufficient space between the robotic arm to properly step without collision.
- Arc height factor: Controls how high robots lift when stepping. We use a factor of 2, which provides sufficient clearance without excessive motion.
- Orientation progression factor: Controls the progression speed through orientation space. We set this to 10 times the object's largest dimension, creating a nonlinear progression that prevents collisions.

These parameters can be tuned based on the specific object geometry, robot capabilities, and task requirements. For this initial implementation, we constrain our approach to rectangular prism objects with flat surfaces suitable for suction-based attachment, with open-loop trajectory generation and without considering dynamics or robot kinematic limitations.

In summary, our algorithm presents a novel approach to the orientation control of large objects using multiple robotic arms. By discretizing the object surface, planning optimal paths, generating a coordinated gait sequence, and translating this into specific robot commands, we enable the manipulation of objects much larger than the workspace of any individual manipulator.

I. Scope and Limitations

For this initial implementation, we constrain our approach to rectangular prism objects with flat surfaces suitable for suction-based attachment. The current implementation also has the following limitations:

- Open-loop trajectory generation (no feedback control)
- Offline planning
- Kinematics only (no dynamics considerations)
- Objects have close to zero mass with large volumes
- No robot kinematics limitations were considered
- No collision avoidance was considered
- Only roll and pitch rotations of the object were considered

These simplifications provide a tractable starting point while still addressing the fundamental challenges of large object orientation control.

V. EXPERIMENTAL RESULTS

The proposed approach was implemented and tested in a PyBullet-based simulation environment using four UR5e robotic arms in an inverted configuration. The arms were arranged in a circular pattern with a radius of 0.6m around a central rectangular prism object. Each arm was equipped with a suction-based end effector with a diameter of 2cm.

A. Reorientation Capabilities

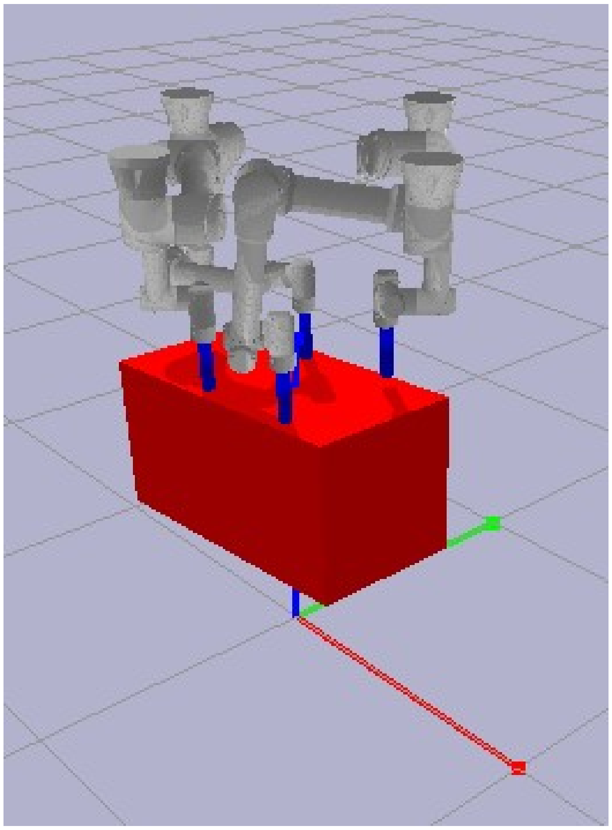
The system successfully demonstrated the following capabilities:

- Roll and pitch object re-orientation up to 100 degrees
- Manipulation of rectangular prism objects up to 5×5×1 meters. Given that the UR5e robotic arm has an individual reach of 0.85m, the showcase that this approach can handle objects about five times the reach of the robotic arms used.
- Stable control throughout the manipulation process

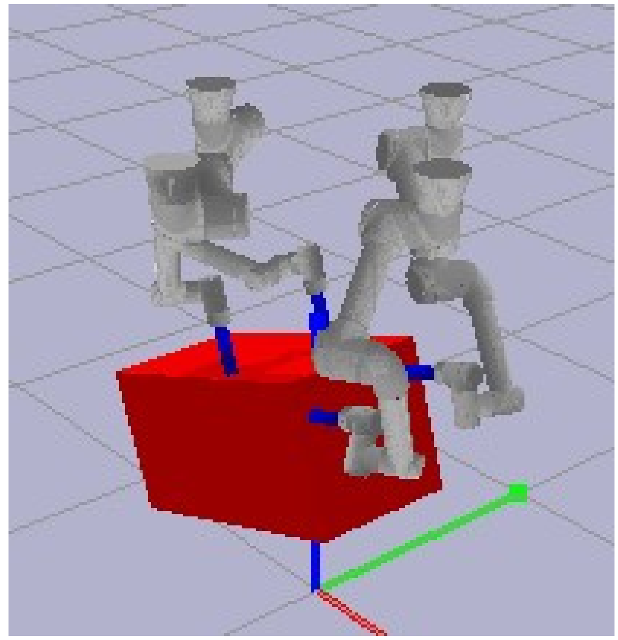
B. Limitations

The approach also showed several limitations:

- Unable to achieve yaw rotations of the object
- Certain combinations of roll and pitch angles were not achievable due to kinematic limitations of the UR5e arms
- Optimal scenario was one degree of freedom re-orientation at a time (e.g., re-orientation on just the pitch or roll axis)



(a) Initial configuration



(b) First intermediate orientation (30° pitch)

Fig. 4: Initial and first intermediate configuration of the robotic manipulation system. (a) Four UR5e robotic arms in an inverted configuration arranged around a rectangular prism object in its initial horizontal orientation. (b) The system after the first series of gait cycles, achieving approximately 30 degrees of pitch rotation.

C. Visual Progression of Reorientation

Figs. 4 and 5 show the progression of the object reorientation task in our simulation environment. The system starts with the rectangular prism in a horizontal orientation (Fig. 4a) with all four robots attached to the upper surface. Through a series of coordinated gait cycles, the system progressively rotates the object to 30° (Fig. 4b), then 60° (Fig. 5a), and finally to the target 90° pitch orientation (Fig. 5b).

This visual sequence demonstrates how our gait-inspired approach enables the manipulation of an object that is significantly larger than the workspace of any individual robot. By repositioning contact points through the stepping phases and applying coordinated forces during the shifting phases, the system maintains stable control throughout the reorientation process.

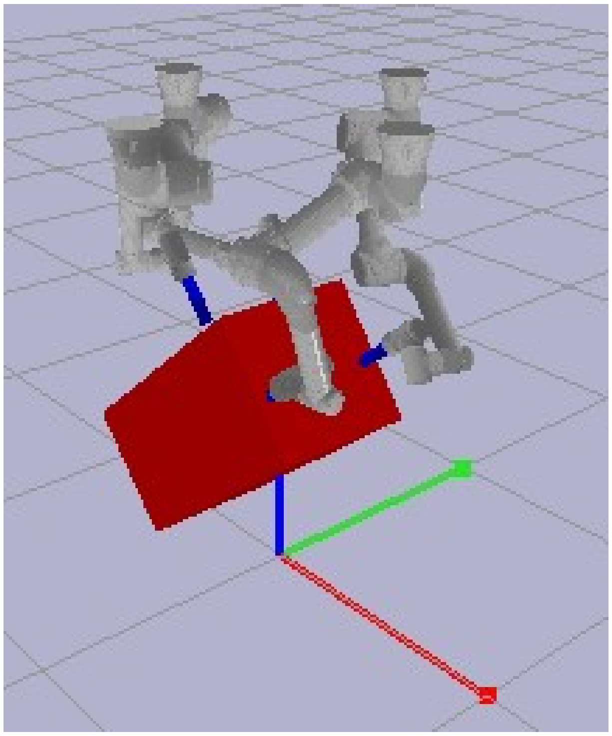
VI. Discussion

The gait-inspired approach presented in this paper offers several key advantages over existing methods:

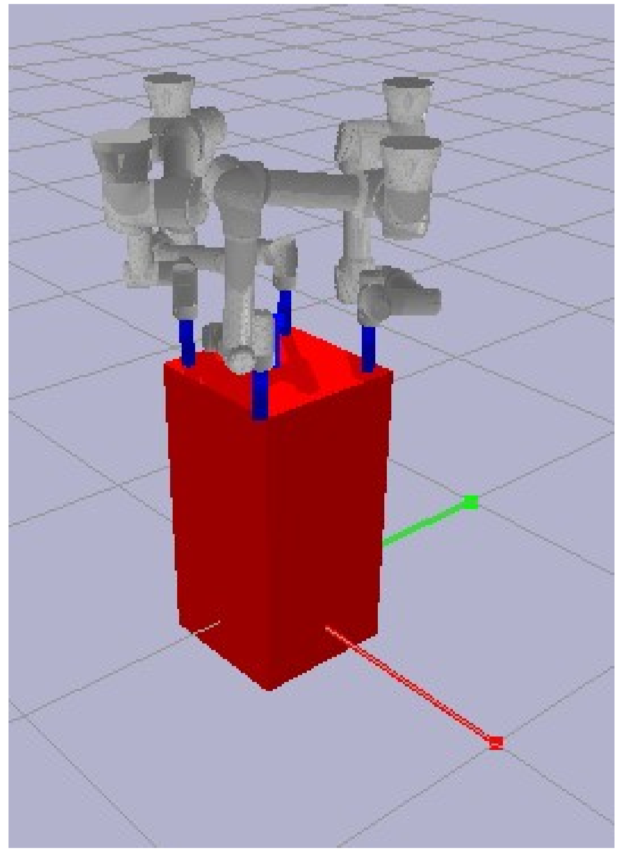
- By progressively repositioning contact points, the system can effectively manipulate objects much larger than the workspace of any individual manipulator.
- The approach enables strategic placement of contact points to optimize force distribution and stability throughout the manipulation process.
- The sequential nature of the stepping phase allows the system to maintain control even if individual suction cups temporarily fail or lose effectiveness.
- The approach can be scaled to different numbers of manipulators and object sizes by adjusting the gait parameters and coordination patterns.
- Our planning algorithm determines the shortest path through orientation space from initial to desired configuration, minimizing the number of required gait cycles and overall manipulation time.

Our work builds upon and extends previous research in several ways. While dual-arm manipulation has been extensively studied [21], our approach scales to systems with more than two arms, enabling more complex manipulation tasks. Unlike traditional centralized control approaches that require perfect models, our method can adapt to workspace limitations through its stepping and shifting phases.

The exponential orientation progression technique we introduced provides a novel solution to the challenge of collision avoidance during reorientation. By intelligently varying the step size based on the object's geometry and the risk



(a) Second intermediate orientation (60° pitch)



(b) Final orientation (90° pitch)

Fig. 5: Second intermediate and final configuration of the robotic manipulation system. (a) The system after further gait cycles, achieving approximately 60 degrees of pitch rotation. (b) The final orientation after completing all gait cycles, showing the object fully rotated to 90 degrees pitch. This demonstrates the capability of our approach to reorient large objects despite the limited workspace of individual robots.

of collision, we achieve smoother transitions than linear interpolation approaches used in prior work [5], [28].

The combination of suction-based end effectors with coordinated gait patterns represents a new direction in large object manipulation. Previous research on suction grippers has primarily focused on single-arm applications [9], [30] or specialized hybrid grippers [24], but has not fully explored their potential for multi-arm coordination in large object reorientation.

However, there are several areas where further work is needed:

- Incorporating robot kinematic constraints into the planning process
- Extending the approach to handle yaw rotations
- Implementing feedback control to handle uncertainties and disturbances
- Developing multi-goal approaches for complex reorientation tasks, where we set intermediate goals between the initial and final desired orientation
- Testing with alternative robot arm configurations better suited for this type of task

Future research could also explore the integration of advanced sensing technologies, such as tactile sensors and force/torque sensors, to enhance the system's ability to adapt to unexpected changes in the environment [2]. Additionally, the application of machine learning techniques, as demonstrated in recent work on robotic manipulation [10], [25], could enable more robust and adaptive control strategies for handling a wider variety of object geometries and material properties.

The concepts developed in this paper could also be extended to other domains, such as space robotics, where multi-arm systems are increasingly being used for on-orbit servicing and debris removal [22], [20]. The combination of our gait-inspired approach with specialized space manipulation techniques could lead to more capable systems for handling large objects in microgravity environments.

VII. CONCLUSION

This paper presented a novel approach for orientation control of large objects using multiple robotic arms with suction-based end effectors. The gait-inspired control strategy enables the manipulation of objects significantly larger than the workspace of individual manipulators by coordinating the movements of multiple robots in a walking-like pattern.

The experimental results demonstrated successful reorientation of large rectangular prism objects with roll and pitch rotations of up to 100 degrees. The approach effectively addresses the challenges of workspace limitations, stability maintenance, and coordinated control in multi-arm manipulation systems.

Future work will focus on extending the approach to more complex object geometries, incorporating obstacle avoidance, implementing feedback control, and addressing the limitations identified in the experimental evaluation. The ultimate goal is to develop a robust and flexible system capable of manipulating various large objects in real-world industrial settings.

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