Model-Free Large-Scale Cloth Spreading With Mobile Manipulation: Initial Feasibility Study

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Abstract— **Cloth manipulation is common in domestic and service tasks, and most studies use fixed-base manipulators to manipulate objects whose sizes are relatively small with respect to the manipulators' workspace, such as towels, shirts, and rags. In contrast, manipulation of large-scale cloth, such as bed making and tablecloth spreading, poses additional challenges of reachability and manipulation control. To address them, this paper presents a novel framework to spread large-scale cloth, with a single-arm mobile manipulator that can solve the reachability issue, for an initial feasibility study. On the manipulation control side, without modelling highly deformable cloth, a vision-based manipulation control scheme is applied and based on an online-update Jacobian matrix mapping from selected feature points to the end-effector motion. To coordinate the control of the manipulator and mobile platform, Behavior Trees (BTs) are used because of their modularity. Finally, experiments are conducted, including validation of the model-free manipulation control for cloth spreading in different conditions and the large-scale cloth spreading framework. The experimental results demonstrate the large-scale cloth spreading task feasibility with a single-arm mobile manipulator and the model-free deformation controller.**

I. INTRODUCTION

Cloth manipulation is critical because it is basic for many downstream applications such as household service [1], elderly care [2], and surgery scenarios [3]. Cloth manipulation tasks are challenging since the cloth is highly deformable and difficult to be modelled accurately. In this work, we consider one of the common cloth manipulation tasks, spreading *large-scale cloth* over a supporting surface, by using model-free manipulation control and a single-arm mobile manipulator. For large-scale cloth, its size is larger than the workspace of the manipulator's end-effector. This means that a fixed-base manipulator may not be able to finish cloth manipulation tasks such as a spreading task (see Fig. 1). Unlike [4], we will not fix any sides of the cloth; in other words, the cloth can move freely on the supporting surface. This case demands more efforts to manipulate the cloth given only a single grasping point. For example, pulling the cloth along a fixed direction as in [4] may make a part of the large-scale cloth out of the supporting surface, which may fail the task.

The main contributions of this work are

1) Proposing a model-free large-scale cloth spreading framework based on behavior trees that allows us to manipulate cloth with a mobile manipulator;

2) Demonstrating the effectiveness of the control algorithm and proposed framework experimentally, thus validating the feasibility of using mobile manipulation for large-scale model-free cloth spreading.

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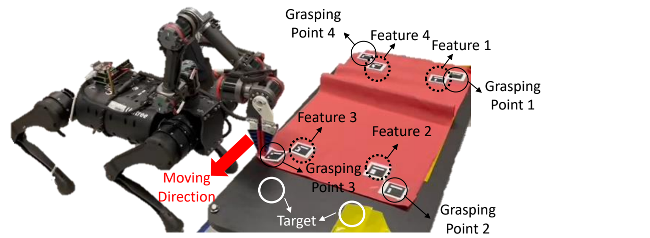

Fig. 1. A single-arm mobile manipulator is spreading cloth with Grasping Point 3. Obviously, the end-effector cannot reach Grasping Point 1 if the mobile platform does not move. To reduce unnecessary movement, it is also expected to manipulate the features as many as possible towards the target in one standing position. For example, instead of manipulating corners (features) one by one, Feature 2 and 3 can be manipulated to the target (white circles) together. Overall, for large-scale cloth spreading, a mobile platform is necessary to be included and the manipulation control should be able to cover multiple features if possible. All features and grasping points are selected around the corners to focus on the feasibility study.

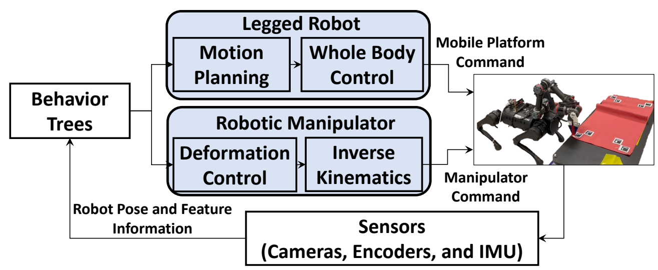

Fig. 2. Schematics of the proposed model-free large-scale cloth spreading framework.

II. MODEL-FREE LARGE-SCALE CLOTH SPREADING FRAMEWORK

A. Overview

We propose a behavior-tree-based framework for cloth spreading, as shown in Fig. 2, which consists of two main parts: a mobile platform and a robotic manipulator. Two parts are coordinated by a behavior tree. One is the legged robot (Unitree A1), allowing us to reach any feasible space. Another is the six Degrees of Freedom (DoFs) robotic arm (INNFOS GLUON). A two-finger gripper is attached to the arm. This framework is also applicable to other mobile platforms such as wheeled robots and legged-wheeled robots.

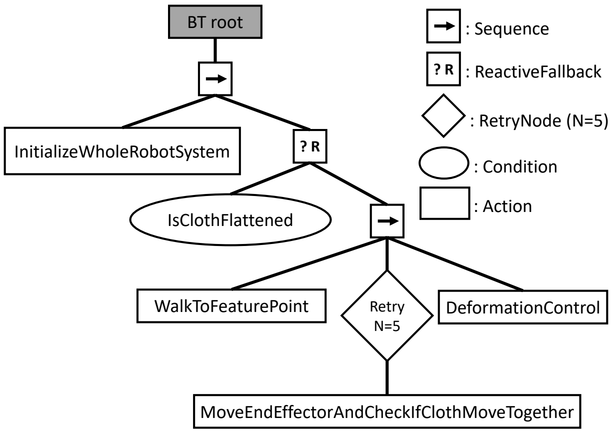

Fig. 3. Behavior tree of the proposed model-free large-scale cloth spreading framework.

B. Behavior Tree (BT)

Compared with one-way FSMs, BTs are able to alleviate the limitations on modularity, re-usability, and reactivity. Following the terms in [5], a standard BT has one root node, and the execution starts from this node. Signals (ticks) are then sent to a leaf node. After the leaf node executes, the status is sent to its parent. This mechanism makes BTs different from FSMs. Fig. 3 shows the BT design for the proposed model-free large-scale cloth spreading framework.

C. Model-Free Deformation Control

Following [6], we describe the deformation in a model-free paradigm. Specifically, to manipulate the deformable cloth, k feature points are selected on the cloth. The i-th feature point is denoted as

$$\boldsymbol{s}_i = [x_i, y_i, z_i]^T, \tag{1}$$

and $\boldsymbol{s}_i$ is assumed to be measurable. For a compact notation, the feature point vector can be denoted as

$$\boldsymbol{s} = [\boldsymbol{s}_1^T, \boldsymbol{s}_2^T, ..., \boldsymbol{s}_k^T]^T \in \mathbb{R}^{3k}. \tag{2}$$

Assumption 1: When manipulating the deformable cloth, we assume each feature point can be locally described by a smooth function, $\boldsymbol{s}_i = \boldsymbol{g}_i(\boldsymbol{x})$. Then, the relationship between the feature point vector and the end-effector position is $\boldsymbol{s} = \boldsymbol{g}(\boldsymbol{x})$, where $\boldsymbol{g} = [\boldsymbol{g}_1^T, ..., \boldsymbol{g}_k^T]^T$. Note that $\boldsymbol{g}$ is unknown.

Based on these feature points, an m-DoF deformation task $\boldsymbol{y}$ can be defined as $\boldsymbol{y} = \boldsymbol{r}(\boldsymbol{s})$. The task can be designed explicitly, as mentioned in [6]. To implement the task, a velocity controller of the end-effector can be designed as

$$\boldsymbol{u} = \boldsymbol{J}^{\dagger}\boldsymbol{K}(\boldsymbol{y}^* - \boldsymbol{y}), \quad \boldsymbol{J}(\boldsymbol{x}) := \frac{\partial \boldsymbol{r}(\boldsymbol{s})}{\partial \boldsymbol{s}} \frac{\partial \boldsymbol{g}(\boldsymbol{x})}{\partial \boldsymbol{x}}, \tag{3}$$

where $\boldsymbol{K} > 0$ and $(\cdot)^{\dagger}$ denotes a left pseudoinverse operation if $m > p$ or a right pseudoinverse operation if $m < p$. $\boldsymbol{J}(\boldsymbol{x})$ is called as *Deformation Jacobian Matrix*, and it maps the end-effector motion to the evolution of the defined task. The Jacobian will be updated online by using the Broyden rule.

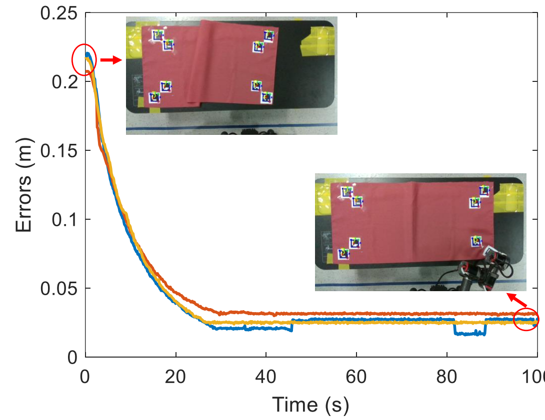

Fig. 4. Errors of feature position in cloth deformation condition 1 (3 trials).

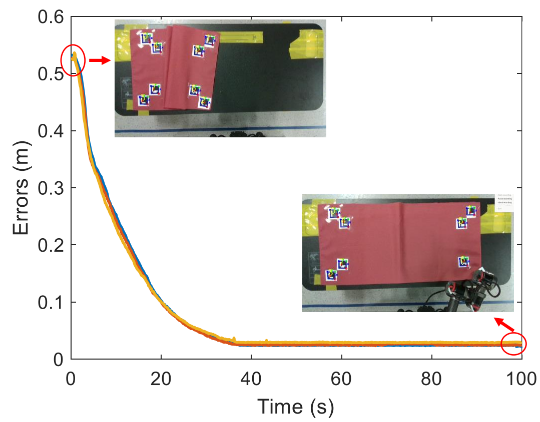

Fig. 5. Errors of feature position in cloth deformation condition 2 (3 trials).

III. Initial Experimental Results

A. Experimental Setup

To study the task feasibility, without loss of generality, we use a legged manipulator to manipulate a piece of cloth (35 cm $\times$ 72 cm) within a horizontal plane. We assume the cloth's shape is rectangle-like, but our method is not limited by the shape. The cloth was initially put on a table with a height of 0.28 m. As shown in Fig. 1, four feature points (ArUco markers) close to each corner were selected. An overhead camera (Intel® RealSense™ depth camera D435) was used to detect and locate each feature point, and the depth information was ignored here. A motion capture system (Vicon) was used to locate the legged robot and the overhead camera. In the validation of the deformation controller, all positions were expressed in the body frame of the legged robot, while all were expressed in the Vicon frame in the validation of the framework.

B. Validation of Model-Free Deformation Control

Two cloth deformation conditions were shown. The error is defined as $||\boldsymbol{s}_{dsr} - \boldsymbol{s}||$, where $\boldsymbol{s}_{dsr} \in \mathbb{R}^8$ is the desired position for four features. In the first condition (Fig. 4), three trials are displayed and all of them converged to the error of less than 0.032 m after around 28 s. The final cloth condition is almost fully flattened. Fig. 5 shows another

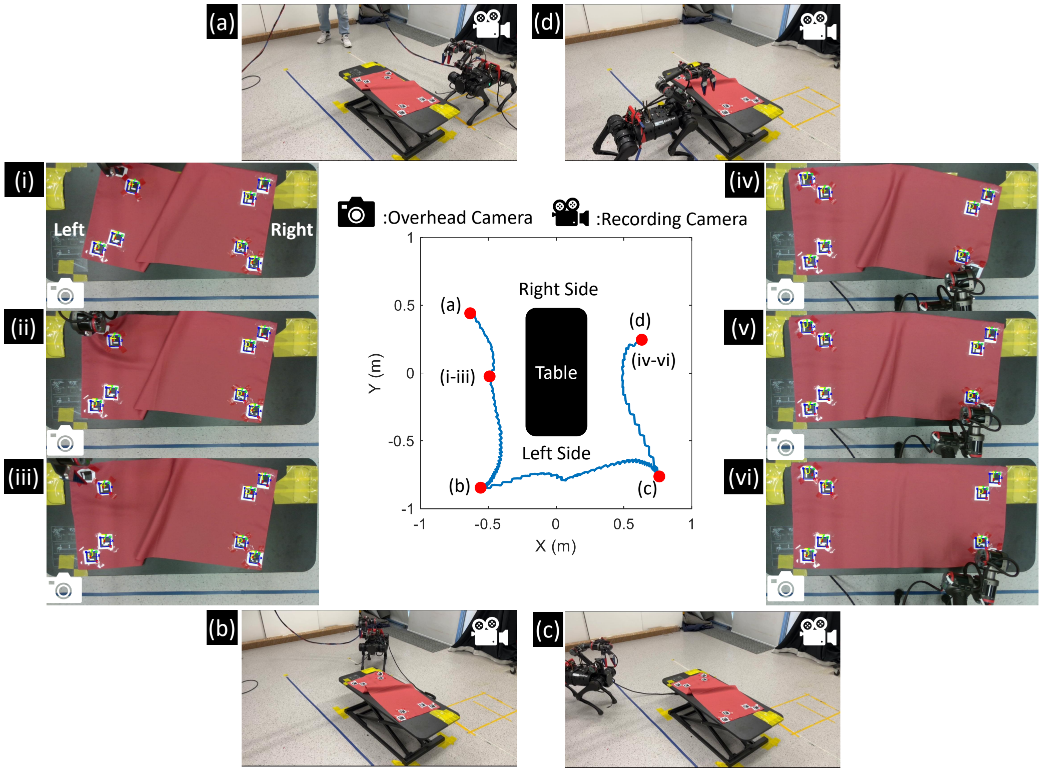

Fig. 6. Experiment of a large-scale cloth spreading task with the proposed framework.

initial deformation condition where the initial positions of Feature 2 and 3 were much farther from the target (initial error: 0.524 m). The model-free deformation controller still can make the error converge to the value of less than 0.030 m, but the manipulation duration became longer (36 s). From the results of the two conditions, a steady state error was found for each trial. This was mainly because the visual measurement noise would affect the feature localization and further inject disturbance into the Jacobian update process. To improve the control performance, a more precise and robust feature localization method is needed, which will be our future work.

C. Validation of Large-Scale Cloth Spreading Framework

To validate the proposed framework, we set the cloth condition that requires multiple operations at different standing positions. Running BTs helps to specify the grasping points and thus the trajectory of the mobile platform can be planned accordingly. As shown in Fig. 6, the mobile platform's trajectory is plotted (blue solid line). Fig. 6(a) shows its starting status. Once finishing the first manipulation (Figs. 6(i-iii)), it moved to the next location (Fig. 6(d)) following the predefined waypoints with a safe distance (see Figs. 6(b-c)). When manipulating the cloth at the first standing position, the cloth condition change is shown in Figs. 6(i-iii)). With the deformation control, the two feature points on the left side were manipulated to the predefined target. Figs. 6(iv-vi) show the cloth manipulation at the second standing position. After establishing the contact, the manipulator moved two feature points on the right side to the target. At the same time, the feature points on the left side were not affected and the cloth was fully spread finally.

The experimental results demonstrate the effectiveness of the proposed framework and the feasibility of spreading large-scale cloth in the sense of model free. Of course, the framework can be further improved. For example, the distance between the mobile platform and the table can be smaller for saving occupying space, via motion planning in narrow space (e.g., [7]). Besides, an optimal grasping point selection strategy can be designed to improve cloth manipulation efficiency and minimize the travelling path of the mobile platform.

IV. CONCLUSIONS

This paper presented a model-free large-scale cloth spreading framework based on BTs. The introduction of the mobile platform eliminates the limitation on the workspace. Without the need of modelling the cloth, a vision-based deformation control was applied to manipulate the cloth. Both the deformation control and cloth spreading framework have been verified experimentally. The results show the feasibility of spreading large-scale cloth using a single-arm mobile manipulator and a model-free control approach, paving the way to manipulating large-scale cloth with more complex conditions (e.g., highly crumpled conditions). In the future, extra components will be integrated into the current framework, such as onboard perception and action planning modules. Different cloth materials will be tested and the framework will be applied to more practical scenarios like in households.

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