

RESEARCH ARTICLE

Casting Manipulation With Unknown String via Motion Generation, Actual Manipulation, and Parameter Estimation

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ABSTRACT In this manuscript, we propose a motion strategy for manipulating strings with unknown properties. Our approach iteratively refines its motion generation based on parameters estimated from observed string behavior, without the need for real-time feedback. This strategy has been shown effective in achieving several motion objectives using uniform strings of similar lengths. In this research, we improve upon this strategy by addressing the challenges posed by varying string lengths and non-uniform strings. For this, we utilize a non-uniform string model and address various string properties to demonstrate the feasibility of our proposed motion strategy. Experiments conducted with different string types and lengths (between 300 to 610mm), including some with non-uniform mass distributions, demonstrate our method's effectiveness. Results show that our proposed method functions effectively with various kinds of strings, regardless of length and mass distribution, without requiring precise model parameters. Unique to this approach is its ability to adapt to various string characteristics through parameter estimation and motion generation, significantly reducing the need for real-world manipulation trials. Our findings illustrate the potential of our method for use in advanced robotic applications that require handling deformable objects.

INDEX TERMS Robotic manipulation, dexterous manipulation, unknown string, deformable objects.

I. INTRODUCTION

The manipulation of deformable objects is a crucial area of inquiry as such materials' inherent highly nonlinear characteristics greatly influence manipulation. Studies have been conducted on a variety of deformable materials, including fabrics, cables, and clothing [1]. Historically, cable insertion and knotting/untying operations have been the primary focus of string manipulation studies. However, these studies have been largely limited to small or slow-moving deformations. Recently, studies have tackled the dynamic manipulation of strings. String's weaving method, material, and memory effect of materials can greatly impact the deformation behavior of the strings during dynamic manipulation, making it a particularly difficult problem to solve. In this study,

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we aim to examine casting manipulation as a method for dynamic string manipulation. Casting manipulation involves robots using a string to extend their reach, by gripping the string and reaching its end towards distant targets.

II. RELATED WORKS

Previous work on casting manipulation includes the work by Suzuki et al., who fabricated a casting manipulator by attaching a cable to a single-degree-of-freedom linkage and modeled the cable as a multi-link system [2], [3]. Arisumi et al. constructed a device with an end-effector attached to a string to collect samples in craters on the Moon that robots cannot access [4]. Fagiolini et al. designed a casting manipulator that can reach 3D positions and presented a control scheme appropriate for the flight of the end-effector [5]. Recently, Lim et al. proposed a self-supervised learning framework Real2Sim2Real to realize casting manipulation

in a two-dimensional plane [6]. However, the casting manipulation was performed on a desk in the study [6], thus it was not influenced by the direction of gravity. In contrast, in [2] and [5], specialized casting manipulators were developed, making it difficult to apply motion planning to traditional robot arms. In this study, we assume that a robot arm performs manipulation by grasping a string on the ground. Then, we aim to accomplish the casting manipulation of a target object on a two-dimensional plane under the influence of gravity.

In general, in research on robot motion planning, it is crucial to minimize the gap between simulation and reality (sim2real). Sim2real achieves motion objectives by acquiring a motion policy in simulation, manipulating the target based on the policy, and then bridging the gap between simulation and reality. A typical approach to achieve this is to construct an accurate physical model and identify its parameters. Lang et al. modeled the deformation of a deformable object by a discrete Green's function matrix and estimated the model using a specialized facility (The Active Measurement Facility) [7]. Chen et al. developed a friction measurement device to accurately depict contact between a garment and an object on a computer [8]. Caldwell et al. represented the flexible loop as a chain of rigid links connected by a torsional spring and identified the stiffness characteristics of the model based on forces and displacements during manipulation by the robot [9]. While, in many cases, the gap between simulation and reality is very small for models estimated based on actual measurements, and the models can represent a wide range of nonlinear characteristics; it is not rare for special tests to be necessary to identify the model. Therefore, it is inappropriate for situations where the robot is to grasp a string and immediately manipulate it at home. Lee et al. proposed imitation learning based on force information when manipulating flexible objects [10]. Ma et al. attempted to detect key points and extract features using G-doom, a recurrent neural network [11]. Mate et al. proposed a task-agnostic algorithm based on deep learning that avoids explicitly modeling cloth behavior and does not require reward shaping for convergence [12].

In [13] and [14], quasi-static motion, dominant for strings and cloth, is used. Therefore, the nonlinear characteristics of the string do not affect its motion.

Dynamic manipulation for strings and cloth has also been explored in various studies. Jangir et al. utilized reinforcement learning to demonstrate the importance of velocity and trajectory in dynamic manipulation and investigated the effectiveness of different cloth state representations [15]. Nah et al. successfully identified the optimal action for manipulating a whip by encoding control based on dynamic primitives [16]. Yamakawa et al. demonstrated that the motion of a string follows the trajectory of the robot arm's tips only if the robot arm's tips move at a constant speed and high velocity, which can be utilized to realize dynamic manipulation of the string [17]. Several other works have realized dynamic manipulation [18], [19]; however,

these studies are limited in their applicability. These studies are applicable only to their targeted strings and motions, as they only consider them in simulations or introduce strict assumptions. In practice, the characteristics of strings can greatly vary depending on their weaving method and material. Therefore the aforementioned studies can only be applied to a limited small subset of strings.

In an effort to address these limitations, some studies have adjusted simulations from multiple string and robot arm motion samples to generate motions that take into account the characteristics of the string. For example, [6] used differential evolution to ensure that the trajectory of the string motion in the simulation matched the actual trajectory and utilized a tuned simulator to generate a large data set to bridge the gap between the simulation and reality. Similarly, Yang et al. trained their model using recurrent neural networks and synthetic data generated by simulation and implemented an efficient differential evolution algorithm for parameter identification. They showed that the performance was comparable to models trained on real-world data [20]. Chi et al. also employed a learning framework, Iterative Residual Policy, for dynamic manipulation of linear objects, optimizing manipulation by online prediction of the deformation of the flexible object when small changes are made to the previous manipulation [21].

III. CONTRIBUTION OF THIS PAPER

The authors have realized several motion objectives for strings with unknown properties by repeating motion generation, actual manipulation, and parameter estimation [22], [23], [24]. Specifically, our proposed method differs from previous research as it does not acquire training samples by manipulating the robot in the real world in advance, as in previous studies. Instead, the first manipulation uses a randomly configured model of the string to generate a motion that achieves the desired action. The robot arm then executes the generated motion and estimates the characteristics of the cord based on the resulting motion, significantly reducing the number of times manipulation is performed in the real world. We emphasize that our approach does not estimate true model parameters. The strong point of our approach is that it aggressively uses model redundancy and iterates motion generation and model parameter estimation like heuristic approaches. Through several iterations, model parameters that satisfy expressing the actual string movement will be estimated, and a motion that achieves motion objectives will be generated.

Our previous work has been limited to a few kinds of string lengths of approximately 300mm, which obscured the feasibility range of our proposed method. It also did not consider non-uniform mass distribution. The difference in mass distribution can lead to changes in deformation properties, making strict model identification complicated. Machine learning-based algorithms require a significant amount of learning data to address these issues. To overcome these challenges, we expanded our proposed method to

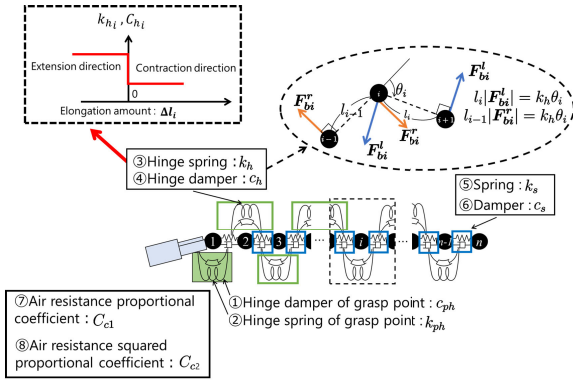


FIGURE 1. String model for motion generation.

include mass values as string model parameters, thus enhancing model redundancy. Conventional models, which assume uniform mass, cannot accurately represent the movement of non-uniform strings. By combining our proposed motion strategy (motion generation, actual manipulation, and parameter estimation) with the expanded string model, we can manipulate various kinds of strings. In this paper, we address strings ranging in length from 300mm to 610mm with non-uniform mass distribution. The results demonstrate that our proposed method was effective with all strings used in the experiments.

For these reasons, we believe that our research contributes to expanding the feasibility of the manipulation of deformable objects with unknown properties. In this work, we show the effectiveness of our proposed motion policy (iterative motion generation, actual manipulation, and parameter estimation).

IV. PROPOSED MOTION STRATEGY AND STRING MODEL

A. STRING MODEL

The string model used for motion generation and parameter estimation is depicted in Fig. 1. Table 1 enumerates the parameters. In addition to the 10 parameters shown, the mass of each point is also considered an unknown parameter. For k_h and c_h , different parameters were used depending on the direction of string tensile and compression. In this paper, the parameters for the tensile direction are denoted as k_{sh} , c_{sh} , and the parameters for the compression direction are k_h , c_h (See upper left of Fig. 1). The mass parameters differ only at the location where the weight is attached. We assumed that the location of the weight can be determined via a camera or other means. It is important to note that this model is not a true physical model. For example, when calculating the bending force, the equation of equilibrium is established at adjacent masses. For an object such as a string, which can be approximated as an n-dimensional serial link, motion is computed by adding the accelerations from the robot's grasping position to the tip. As mentioned, the proposed string model is not a true physical model, but it does satisfy the balance of forces. The proposed model is mainly employed to represent hair and strings in CG space due to its very low computational load.

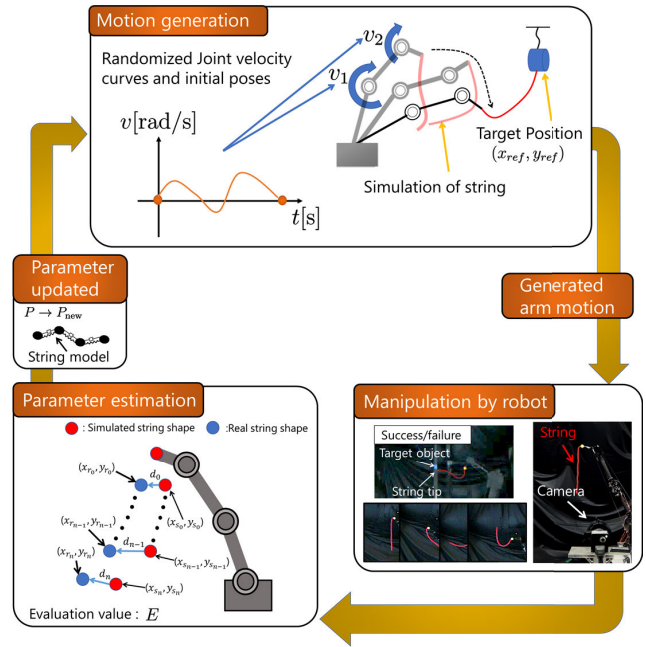


FIGURE 2. Proposed motion strategy.

B. OUR PROPOSED MOTION STRATEGY

Fig. 2 illustrates our proposed motion strategy. Our proposed method repeats the process of motion generation, actual manipulation, and parameter estimation. Initially, the user specifies the parameters of a random string and initiates motion generation. When a movement that satisfies the objectives of the manipulation is generated, the motion generation is terminated. Subsequently, the generated motion is executed by a robotic arm that grasps the string. The string movement is captured using a camera, and the coordinates of each quality point are recorded via image processing. Then, parameters are estimated such that the motion of the string model is consistent with the actual motion of the string. The estimated parameters are used to generate motion once more. This process is repeated until the motion objective is achieved. This research does not intend to obtain a strictly accurate model of the string. Rather, we estimate the combination of parameters that can express the specific string motion based on the specific string motion that occurs during actual manipulation. The estimated parameters may be redundant depending on the string motion, but if, for example, the string deforms significantly during bending, the parameters related to bending are estimated with high sensitivity, and their characteristics are reflected in the motion generation in the simulation.

V. MOTION GENERATION METHOD

A. FIRST MOTION GENERATION

Manipulation trajectory is generated through the generation of randomized velocity curves for each joint. As depicted in Fig. 3, the motion generation process begins with the utilization of a Bezier curve to generate a velocity curve

TABLE 1. String model parameters.

Force	Coefficient(String model parameters)	Explanation of parameter
F_s	k_s	Elastic force between the mass points
F_d	c_s	Damping force between the mass points
F_b	k_h (Compression direction), k_{sh} (Tensile direction)	Force caused by torsional spring moment between the three mass points
F_h	c_h (Compression direction), c_{sh} (Tensile direction)	Force caused by torsional damper moment between the three mass points
F_c	C_{c1}, C_{c2} (Squared term)	Air resistance at the mass point
F_g	-	Gravitational force
F_{ph}	k_{ph}	Torsional spring moment between the robot hand and grasped mass point
F_{phc}	c_{ph}	Force caused by torsional damper moment between the robot hand and grasped mass point

for each joint. The motion time denoted as T is randomly determined within a range of 0.2 to 1.2 seconds. The motion time is then divided by the number of control points N , in the Bezier curve, and the height of each control point is calculated using equation (1).

$$V_k = V_{k-1} + \alpha_k \Delta t, \quad \Delta t = t_k - t_{k-1}, \quad k = 1 \dots N \quad (1)$$

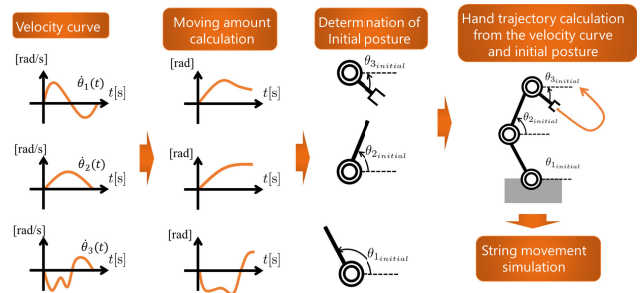
The resulting velocity curve is subsequently integrated to determine the amount of rotation for each joint. If the calculated rotation exceeds the robot joint's limit, the velocity curve is regenerated. If the rotation amount is within the robot's motion constraints, the initial angles of each joint are randomly determined within the movable range. By utilizing the robot's initial posture and the determined velocity curve, the paw trajectory is calculated, and a string movement simulation is performed to assess whether the desired objective has been achieved. If the objective is achieved, the motion generation is terminated, otherwise, the process returns to the initial step.

B. MOTION GENERATION OF THE SECOND AND SUBSEQUENT MANIPULATION

In the second and subsequent motion generation, the robot's initial posture is taken over from the posture obtained in the initial motion generation. The velocity curves for each joint are generated in a similar manner as in the first phase. The height of the control points in the Bezier curve, generated during the initial phase, are randomly altered within a range of ± 0.5 rad/s of their previous position, and the Bezier curve is regenerated based on these modified control points. This process is repeated until the desired motion is achieved. The reason for adopting this approach is that the proposed method utilizes parameters derived from the actual manipulation of the robot arm, thus the parameters are estimated to the specific motion of the string. Therefore, if the direction of the force applied to the string differs significantly, the estimated parameters may not be valid, as demonstrated in [22].

C. METHOD FOR GIVING A MOTION OBJECTIVE

In motion generation, the objective is defined as being achieved when the tips of the string hit the target object. The

**FIGURE 3.** Procedure of motion generation.

target object is positioned at (x_{ref}, y_{ref}) , and the robot arm employs the previously outlined motion generation method to determine whether the objective has been attained while the string is in motion.

VI. PARAMETER ESTIMATION

During manipulation, a camera captures the string's actual movement and the profile of each joint angle of the robot. These two sources of data are used for parameter estimation. The image of the string is extracted by centering on the grasping point of the robot arm. Each string model parameter is randomly selected. The actual motion of the robot arm is used to simulate the string motion. Specifically, the robot's movement is simulated in the simulator according to the profile of each joint obtained from the simulation. Then, based on the simulated robot's movement, the string model is simulated using Euler's method. The point positions of the string model obtained from the simulation are compared with the actual string movement image series, and the evaluation value E is calculated. This process is iteratively repeated while changing the parameters. After a specified number of iterations, the parameter with the lowest evaluation value is output as the estimated parameter. It should be noted that the evaluation value E assesses the difference between the actual positions of the string and those predicted by the simulator. Therefore, we select the parameters that result in the smallest difference, meaning the lowest evaluation value.

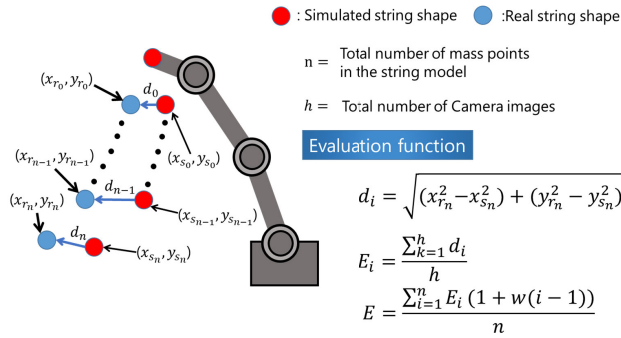


FIGURE 4. Calculation method for evaluation value E.

A. PARAMETER SELECTION METHOD

When determining the value of each parameter of the string model, the exponential form is utilized to randomly select it. This results in a wide range of parameters. In order to expedite parameter convergence, the parameter estimation range is gradually narrowed through the application of the following equation,

$$P_a = P_{min} \left(\frac{P_{max}}{P_{min}} \right)^{\chi_m}, \quad 0 \leq \chi_m \leq 1 \quad (2)$$

$$\chi_m = \chi_{best} + \frac{\chi_0}{M} \beta^m \cdot \text{RAND}(-1, 1) \quad (3)$$

where M is the number of actual string manipulations, let m be the number of parameter changes times and P_a denote a specific parameter. The maximum value P_{max} and minimum value P_{min} of the parameters are predetermined. The initial value χ_0 is selected when determining χ_m . The function $\text{RAND}(-1,1)$ means random numbers within the range of -1 to 1. The value of β is slightly less than 1, and is utilized to gradually constrict the search range during each iteration of the parameter update. The χ_{best} denotes the final estimated parameter value (exponent) from the previous manipulation. The properties of deformable objects can exhibit a wide range of characteristics, necessitating a broad search range for each parameter. Therefore, we divide the parameter search space logarithmically and specify χ_m to enable exploration across a vast space. As indicated by Equation (3), χ_m is selected around the χ_{best} , which may sometimes exceed the defined domain ($0 < \chi_m < 1$). In our method, if χ_m falls below 0, it is set to 0, and if it exceeds 1, it is set to 1.

B. EVALUATION VALUE E CALCULATION METHOD

Fig. 4 shows the method of Evaluation value calculation. The distance between the position of each mass point on the actual string (x_{r_i}, y_{r_i}) and the position on the simulation (x_{s_i}, y_{s_i}) is d_i , and the evaluated value E is calculated by comparing the actual position with the simulated position. The average value of d_i per image frame for a mass point i is E_i , and h is the total number of images taken. The farther away from the grasping position, the greater the motion of the mass point of the string. Therefore, we weight the image using the weight w toward the tip of the string. The overall matching ratio was calculated

String Type	String length [mm]	String appearance	Target position
1	300	Oil clay 10[g]	1
2	300		1
3	300		2
4	510		3
5	510	Plastic pipe	3
6	510	Plastic pipe	3
7	610		4

FIGURE 5. String used in experiment.

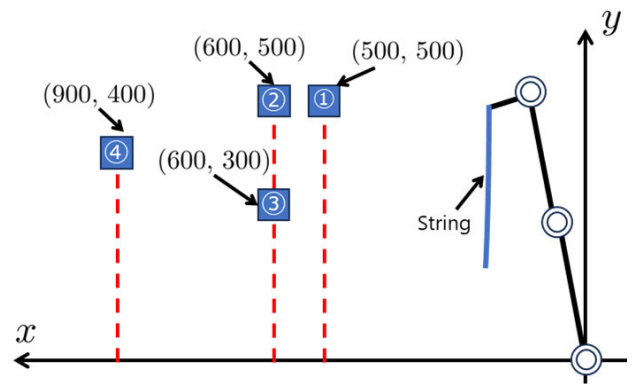


FIGURE 6. Target positions [mm].

using Equation (6).

$$d_i = \sqrt{(x_{r_i} - x_{s_i})^2 + (y_{r_i} - y_{s_i})^2} \quad (4)$$

$$E_i = \frac{\sum_{k=1}^h d_i}{h} \quad (5)$$

$$E = \frac{\sum_{i=1}^n E_i (1 + w(i - 1))}{n} \quad (6)$$

VII. CASTING MANIPULATION WITH NON-UNIFORM STRINGS

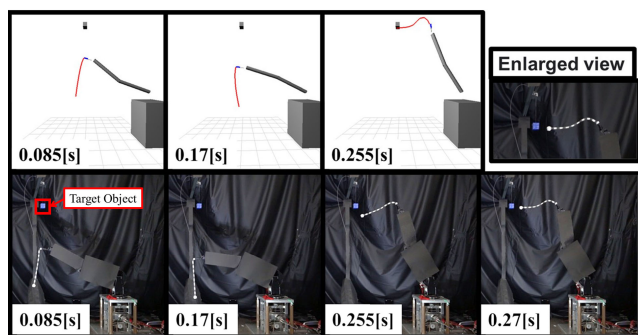
A. USED STRING AND THE TARGET POSITIONS IN THE EXPERIMENT

In order to evaluate the feasibility of the proposed method for non-uniform strings, seven different types of strings were used in the experiments.

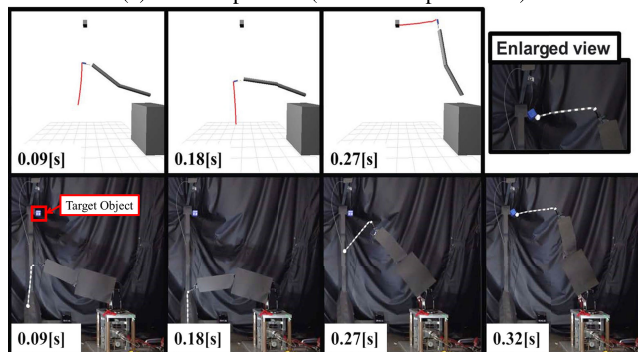
As depicted in Fig. 5, the strings used have different lengths (300, 510, and 610 mm) and were partially weighted with 10 [g] of oil clay. In particular, string types 6 and 7 were attached to the plastic pipe so that they exhibit different stiffnesses. The experiments were also conducted with five different target positions, as shown in Fig. 6. Table 2 presents the range of parameters employed in the estimation process, with the minimum value of each parameter being utilized to initiate the motion generation of the robot arm.

TABLE 2. Parameter ranges at casting manipulation with non-uniform string.

Each parameter	Minimum values	Maximum Values
k_s [N/m/kg]	1000	1000000
c_s [Ns/m/kg]	1.0	10.0
k_h [Nm/rad/kg]	0.001	10.0
c_h [Nms/rad/kg]	0.001	10.0
k_{sh} [Nm/rad/kg]	0.0001	1.0
c_{sh} [Nms/rad/kg]	0.0001	1.0
C_{e1} [Nm/s/kg]	0.000001	10.0
C_{e2} [Nm/s/kg]	0.000001	10.0
k_{ph} [Nms/rad/kg]	0.001	0.01
C_{ph} [Nms/rad/kg]	0.001	0.01



(a) 1st manipulation(with initial parameter)



(b) 2nd manipulation

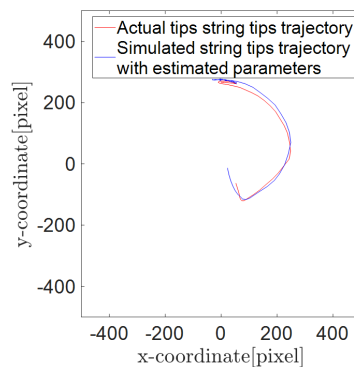
FIGURE 7. Manipulation with string type1 with target position $(x_{ref}, y_{red}) = (500, 500)mm$.

B. EXPERIMENTAL RESULTS OF NON-UNIFORM STRINGS

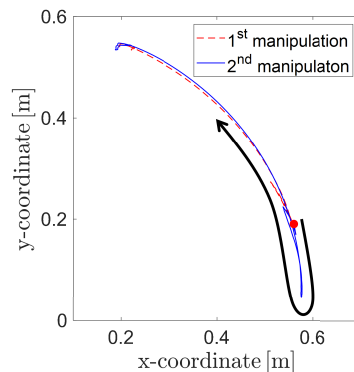
String type 1 (a string with 10 g of oil clay attached to the tip of the string) is taken as an example to illustrate the changes before and after parameter estimation (Fig. 7). When the initial parameters were used to generate the motion, the tips of the strings did not hit each other, as shown in Fig. 7a. However, after the estimation, the tip of the string reaches the target object, as shown in Fig. 7b. Fig. 8a shows a comparison between the motion of the tip of the string in the successful casting operation and the estimated tip motion of the string model. It can be seen that the motions of both are matches. This result shows that after parameter estimation, the string motion becomes consistent between simulation and reality. In addition, the robot arm tip trajectories before and after parameter estimation are shown in Fig. 8b. After

TABLE 3. Repetitions until achieving manipulation with the proposed method.

String type	Repetition times	String type	Repetition times
1	2	4	2
2	2	5	3
3	2	6	2
		7	2



(a) Simulated and actual string tips trajectory



(b) Robot arm tips trajectories

FIGURE 8. Robot arm and string trajectory with target position1.

parameter estimation, the trajectory of the robot arm is longer than before estimation. This is considered to be because the actual string does not expand or contract more than the initial parameters, and casting manipulation is realized by making the robot arm move more widely. This indicates that the trajectory was modified by reflecting the actual string characteristics to the motion generation via parameter estimation.

We investigate the manipulation feasibility toward other strings (2, 3, ..., 7). In particular, manipulation results with strings 5 and 7 are shown in Fig. 9 and Fig. 10, respectively. This shows that simulated and actual string movements become similar via parameter estimation in all string types. This result shows the proposed sim2real strategy (repeating to motion generation, actual manipulation, parameter estimation) is functioning within a string length range that is 300 to 610 mm. Table 3 shows the proposed

TABLE 4. Estimated mass weight.

String type	Attaching weight 1	Attaching weight 2	Others
1	$m_{10}=9.1$	-	1.0
2	$m_4 = 1.0$	1.0	11
3	$m_5=17$	-	4.3
4	$m_{13}=3.5$	$m_{15}=20$	1.0
5	$m_6=18$	$m_{12}=9.1, m_{13}=6.1$ (pipe part m_{12} and m_{13})	1.0
6	$m_{13}=1.9, m_{14}=4.0, m_{15}=4.8$ (pipe part m_{13}, m_{14} and m_{15})	-	1.0
7	$m_9=11$	-	1.0

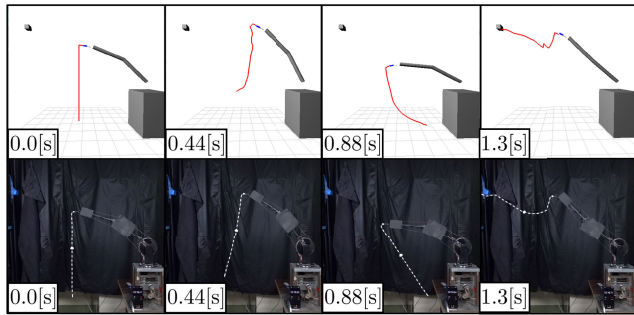


FIGURE 9. Manipulation with string type 5 (2 times repetition).

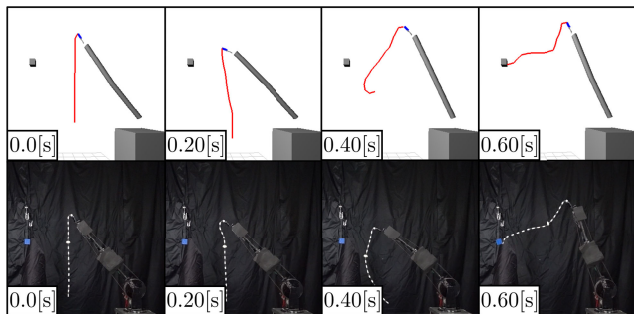


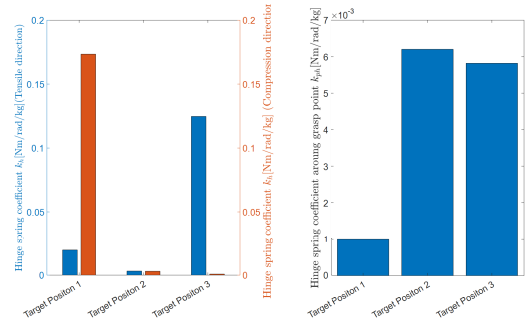
FIGURE 10. Manipulation with string type 7 (1 time repetition).

repetition times from the first manipulation to achievement manipulation. The proposed method can achieve casting manipulation with unknown strings without numerous trials and learning data. It should be noted that the repetition times of the proposed method vary depending on the complexity of the manipulation. Manipulation with complex string movement makes it difficult to estimate feasible string parameters, and thus may require more than several trials.

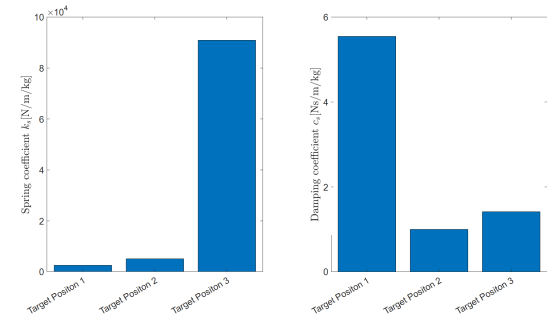
VIII. DISCUSSION ON PARAMETERS ESTIMATED FOR CASTING MANIPULATION AT EACH TARGET POSITION

A. DISCUSSION ABOUT ESTIMATED PARAMETERS

We examined the estimated string parameters through the following experiments. We used string type 1 to execute casting manipulation towards target positions 1, 2, and 3. Fig. 11 shows the estimated parameters at these three target points. The estimated parameters were different for each target point. This result indicates that the string parameters



(a) Estimated string parameter k_h (k_{sh}) and c_h (c_{sh})



(b) Estimated string parameter k_s and c_h

FIGURE 11. Estimated string parameter with each target position.

were estimated as feasible parameters for expressing this string movement. While the parameters are not unique, they suffice to generate robot arm motions considering the string properties.

B. DISCUSSION OF ESTIMATED MASS M_i PARAMETERS

Table 4 shows estimated mass parameter m_i with each string types. All strings' attached masses were 10g of oil clay. However, the estimated mass parameters were not the same. In String 5, very light plastic tubes were attached to m_{12} to m_{13} . The estimated values near them were $m_{11} = 9.1$ and $m_{12} = 6.1$, which were larger than those of the other parts. This discrepancy arises because the proposed method estimates parameters based on the actual motion of the string. This trend was also true for string 6. The effect of the plastic part with different stiffness was interpreted by the model as a segment that remains undeformed due to its estimated

mass. Consequently, since the equation of motion relies on the relationship between force, acceleration, and mass, variations in mass can seemingly alter the string's stiffness. Based on the above, we can argue that while the proposed method does not strictly model real-world objects; it does achieve the motion objective with a minimal number of trials by focusing on the actual movement of string observed during the motion process.

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