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Plucking Motions for Tea Harvesting Robots Using Probabilistic Movement Primitives*

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***Abstract*— This study proposes a harvesting robot capable of plucking tea leaves. In order to harvest high-quality tea, the robot is required to pluck the petiole of the leaf without cutting it using blades. To pluck the leaves, it is necessary to reproduce a complicated human hand motion of pulling while rotating. Furthermore, the rotation and pulling of the hand, and the time taken, vary greatly depending on conditions that include the maturity of the leaves, thickness of the petioles, and thickness and length of the branches. Therefore, it is necessary to determine the amount of translational and rotational movements, and the length of time of the motion, according to each situation. In this study, the complicated motion is reproduced by learning from demonstration. The condition is judged in terms of the stiffness of the branches, which is defined as the force received from the branches per unit length when the gripped leaf is slightly pulled up. Combining the learned motions probabilistically at a ratio determined by the branch stiffness, the appropriate motion is generated, even for situations where no motion is taught. We compared the motions generated by the proposed method with the motions taught by humans, and verified the effectiveness of the proposed method. It was confirmed by experiment that the proposed method can harvest high-quality tea.**

I. Introduction

The tea industry is one of the largest in the world [1]. However, in recent years, it has become difficult to secure a sufficient labor force due to a decline in the agricultural population and rising labor costs [2]. Tea cultivation has various phases such as manuring, irrigation, pruning, and plucking [1]. Plucking particularly requires intensive labor [3]. Most teas are hand-plucked because of the lack of advancement in automation [1]. Apart from being labor-intensive, hand plucking is tedious and monotonous [3]. Therefore, there is a growing need for automation, and automatic harvesting systems have been studied in many countries, such as Japan, England, France, India, and China [4]. In those systems, tea is usually harvested by cutting the top of the tree with blades. Harvesting by cutting, instead of plucking the leaves, can easily damage the stems and petioles, adversely affect the germination of new shoots [5], and accelerate the oxidation of harvested leaves [6]. Additionally, as the leaves are not harvested selectively, some of them may be old and broken [7]. Thus, conventional automated systems are rarely used because of their considerably lower quality compared with manual plucking [4].

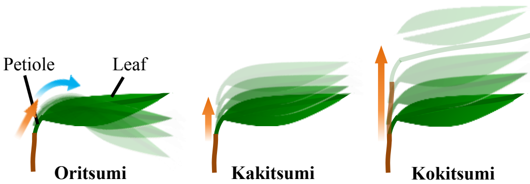

Fig. 1. Three plucking techniques. Our system is aimed at plucking with the Oritsumi technique to harvest high-quality tea.

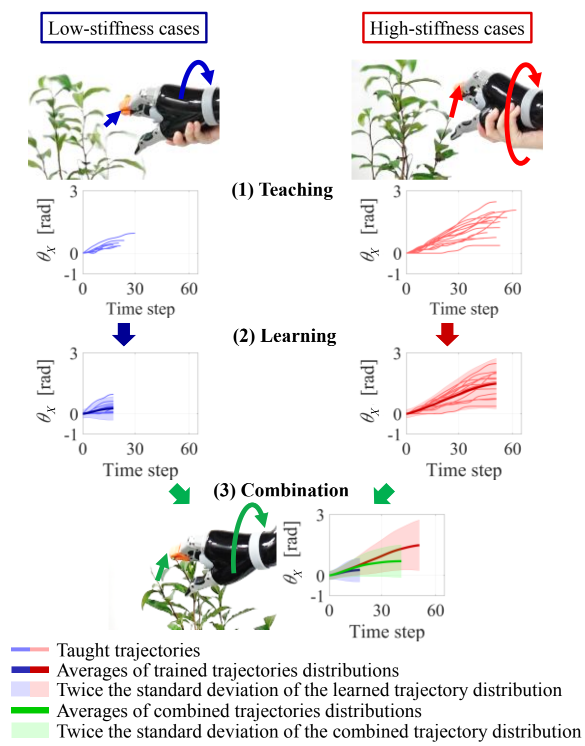

Fig. 2. Outline of proposed system. The proposed system has three steps. First, humans directly teach the robot the plucking motions for small and large values of branch stiffness. Second, the taught motions are learned for each case. Third, the motion that interpolates the two learned motions is generated by probabilistically combining them.

To address this problem, there is a need for automated systems that can harvest high-quality tea, similar to human hands. As shown in Fig. 1, there are three different methods of hand plucking: Oritsumi, Kakitsumi, and Kokitsumi [7]. Oritsumi is the method in which the petioles of the selected

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leaves are grasped with the thumb and forefinger and plucked one by one by pulling the hand while rotating. As the cut surface is the least damaged, it is possible to preserve the highest leaf quality. Kakitsumi is the method of grasping the petioles in the same way as Oritsumi and pulling upwards, without rotating, to pluck the leaves. Kokitsumi is the method of plucking by stripping, discarding stiff petioles, and harvesting only the leaves and the soft petioles. The quality is low due to the rough plucking. Chen et al. [2] proposed plucking using a parallel robot. They verified the accuracy of identification of the leaves to be plucked and the movement of end effector. However, details of the plucking motions were not described. Han et al. [4] proposed plucking with an actuator that moves in the *X*, *Y*, and *Z* directions. However, as the movement does not include rotation, it can be regarded as being similar to Kakitsumi. Therefore, the quality is considered to be lower than that of Oritsumi.

Accordingly, it is considered that high-quality tea plucking requires the reproduction of Oritsumi motions that involve rotating and pulling like a human hand. In addition, the ease of plucking leaves varies greatly depending on conditions that include the maturity of the leaves, thickness of the petioles, and thickness and length of the branches. Therefore, the rotation, upward pull, and motion time required from a robot hand depends on the situation. Therefore, the amount of rotational and translational movement and the time length of the motion need to be determined according to the situation. For example, in a situation where the leaf is mature and the petiole is thick, the leaf is difficult to pick. It is therefore necessary to generate a motion with a large rotational and translational displacement, and a long time length.

Research on robots used to harvest fruits by plucking has been progressing for crops other than tea. Yaguchi et al. [8] proposed a tomato harvesting robot with a mechanical hand that can rotate infinitely. Silwal et al. [9] proposed an apple harvesting robot that plucks apples by rotating and pulling them. In these studies, systems for recognizing fruits, removing them with a hand, and transporting them with a cart have already been proposed. However, most varieties of tomatoes and apples have a pedicel on top of the calyx, and they can be easily separated by applying a torque by rotating around the peduncle. However, since there is no pedicel in tea leaves, the complex movement of pulling while rotating the hand like a human is extremely important for plucking.

Complex motions are difficult for humans to program manually. For this reason, many studies on learning complex motions via Reinforcement Learning (RL) and Learning from Demonstration (LfD) are in progress [10][11][12][13]. RL is a method by which a learning agent achieves optimal behavior based on interactions with its environment and rewards feedback [14]. However, achieving the desired level of performance is data-intensive [14]. LfD is a method by which humans demonstrate and teach agents [13]. It is easier to reflect human actions and learn human-like behavior [15]. However, it is necessary to teach a higher number of motions, in order to generate motions corresponding to more situations. However, teaching requires time and effort and it is desirable to have as few taught motions as possible. Therefore, it is important to extend the motions learned in a particular situation to generate motions that are not learned [16]. Many studies have been performed to generate motions according to the situation faced by the robot. For example, Pervez et al. [16] had a robot learn a certain motion and respond to changes in the position of the objects. In other studies, a robot learns several different motions and selects the appropriate motion according to the task to be achieved or the user's intention [17][18]. However, these studies do not assume that the time length and displacement for a certain action are determined according to the situation.

In this study, we focus on the generation of the plucking motion. As shown in Fig. 2, the plucking motions are directly taught to the manipulator, learned, and combined according to the situation. The situation of leaves, petioles, and branches that affect the plucking motion was assumed to be reflected in the stiffness of the branches, and the plucking motion was generated according to this stiffness. The stiffness of the branches is defined as the force received from the branches per unit length when the gripped leaf is slightly pulled up. The greater the stiffness of the branches, the more difficult it is to pluck the leaves, and the longer the time length and displacement of the plucking motion. Therefore, humans directly taught the plucking motions appropriate for both small and large stiffness. Next, the taught motions in the low-stiffness and high-stiffness cases were learned with Probabilistic Movement Primitives (ProMPs). We then aimed to generate a motion with a time and displacement corresponding to the situation including instances wherein the stiffness of the branches was intermediate and the motions were not taught. The amount of motion was determined by probabilistically combining learned motions in the low-stiffness and high-stiffness cases. The composition ratio depends on the stiffness of the branches. In the combination for conventional ProMPs [19], the degree to which one motion is activated is adjusted. Therefore, there is no purpose to combine multiple motions with a particular ratio. In addition, as the time steps of the motions are all aligned and combined, the case with highly different time lengths of the motions is not considered. Therefore, in this study, the composition ratio was expressed by the activation functions of ProMPs. The time length of the motion, after combination, was determined from the relationship between the time length of the motion and the stiffness of the branches in the taught data. As a result, intermediate displacements and time lengths of the learned motion were generated. For cases wherein the stiffness was intermediate and the motions were not taught, it was still possible to generate the movement and time length appropriate for the situation while reproducing the human plucking motion. The contribution of this study is the method of generating the plucking motion, which can harvest tea of good quality, by reproducing the complicated motion of a human hand and the determination of translational and rotational displacements, and the time length of the motion, according to a situation. We applied LfD to the tea plucking motion. In addition, we propose a new method to judge the conditions, based on the stiffness of the branches, and combine two motions with significantly different time lengths in an appropriate ratio by extending ProMPs. The validity of the probabilistic combinations was confirmed by evaluating the similarity of our method with motions taught by humans. It was confirmed by experiments with an actual robot that good quality tea could be plucked and harvested by the motion generated by the proposed method.

II. Overview Of System

A. Work

Tea leaves plucked using Oritsumi are considered to be of the highest quality. In this study, it was assumed that the leaf to be harvested was recognized and the manipulator hand could grasp the vicinity of the petiole. By pulling the grasped leaf while rotating, it is plucked as if the petiole is broken. Each tea leaf has a different maturity. In addition, petiole thickness and branch length vary. Therefore, it is necessary to generate a plucking motion with an appropriate rotational and translational displacement and a time length corresponding to the leaf condition.

B. Robot

A harvesting robot of the mobile manipulator type was assumed. As shown in Fig. 3, Jaco² [20], manufactured by Kinova Robotics, was used as the manipulator. It is a six-degree-of-freedom manipulator with three fingers on the end effector. It was possible to input the positions and orientations of the hand. It was also possible to measure the position and orientations of the hand and the force applied to the hand.

Fig. 3 shows the coordinate system of the robot. Assuming that the petiole of the leaf grows upward, the robot holds the petiole of the leaf from the side. The origin of the coordinate system is the initial point held by the robot. As a result, as shown in Fig. 3, the pulling and rotation required for plucking using Oritsumi, are described by the Y, Z, θ_X displacements.

C. Proposed System Flow

The proposed system consists of three stages as shown in Fig. 4. The first step of the system was teaching. The manipulator measured the stiffness of the branches. Then, the human demonstrated the plucking motion. The next step was learning. The taught data were classified into low-stiffness and high-stiffness cases by an operator. After that, each of the data related to the low-stiffness cases and the high-stiffness cases were learnt. The last step was combination. The manipulator measured the stiffness of branches. Then, the length of time and the combination ratio of the motion to be generated were determined from the measured stiffness. Based on these, the motions related to the low-stiffness cases and the high-stiffness cases were combined. Finally, the leaves were plucked through the generated motions.

III. Teaching, Learning, and Combination of Motions

We demonstrated plucking motions to the manipulator several times in gravity compensation mode. A human taught the motions by moving the robot with his hand. As the human teaches the motions directly to the robot, it is possible to consider the physical characteristics of the robot during this process. Furthermore, it is easy for the humans to demonstrate the action skills that they are acquainted with. Therefore, the robots can be instructed intuitively.

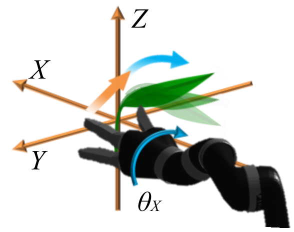

Fig. 3. A schematic of the coordinate system. The pulling and rotation of plucking are described by the Y, Z, θ_X displacements.

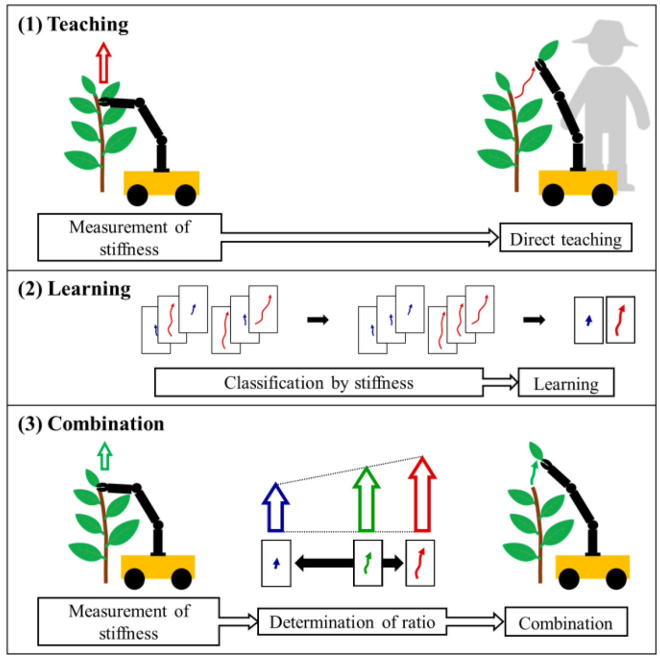

Fig. 4. Proposed system flow. The robot measured the stiffness of the branches, to judge the condition which affected the plucking motion.

We extended ProMPs [19][21] to learn and combine the taught motions probabilistically. ProMPs is a method of probabilistically expressing, learning, and generating motions in the form of a Gaussian distribution of trajectories. New motions are generated by conditioning, combination and blending of primitives. Especially, in combination, it is possible to consider variations of motions by calculating not only the means but also the variances of the primitives. However, it is essential to adjust the extent of activation of certain primitives, as the combinations of some primitives at a specified ratio are not effective. In addition, as the time steps of the primitives are all aligned and combined, the case with highly different time lengths of the motions is not considered. In this study, ProMPs were extended to combine two actions of different time lengths. Moreover, by combining these two primitives in the ratio of $1-\alpha : \alpha$, their intermediate motion is generated. Table I shows the nomenclature used in this section and subsequent sections of the paper.

A. Teaching

First, the manipulator measures the stiffness k. The stiffness of the branches is defined as the force received from the branches per unit length, when the grasped leaf was slightly pulled up. The robot gripped the leaf and measured the Z-direction force on the robot's hand. The robot moved the hand slightly up by approximately 1 cm and, with the branch pulled slightly, measured the Z-direction force applied on the robot's hand again. The force demonstrated a little variation, even when there was no movement of the hand. Therefore, the average value over several seconds was used as the measurement value. In order to realize efficient plucking, it is desirable to execute this measurement in a relatively short time, experimentally determined to be 1 second. The stiffness of branches is calculated in the following equation using the difference in the upward force applied to the hand before and after the movement $\Delta\overline{F_z}$, and the displacement ΔZ, of the hand in the vertical direction.

$$k = \frac{\Delta\overline{F_z}}{\Delta Z}\,. \tag{1}$$

Next, the human teaches the plucking motion of the grasped leaf directly to the manipulator. In this study, we measured the positions and orientations of the hand at 10 Hz during the instruction time. The measured time histories were learned as trajectories in ProMPs.

B. Learning

1) Method of Learning [17][19][21][22][23]

The number of time steps of each trajectory is expressed as T. We called it motion time. With the basis function matrix $\boldsymbol{\Phi}$ and the weight vector $\boldsymbol{\omega}$, the demonstrated trajectory $\boldsymbol{\tau}$ is represented by a linear model in the following form:

$$\boldsymbol{\tau} = \boldsymbol{\Phi}\boldsymbol{\omega} + \boldsymbol{\varepsilon}\,. \tag{2}$$

Trajectory noise ε is a Gaussian noise with a zero mean and a variance of σ^2. The basis function matrix $\boldsymbol{\Phi}$ is composed of M basis functions and scattered across time step t.

$$\boldsymbol{\Phi} = \begin{bmatrix} \Phi_1(1) & \Phi_2(1) & \cdots & \Phi_M(1) \\ \Phi_1(2) & \Phi_2(2) & \cdots & \Phi_M(2) \\ \vdots & \vdots & \ddots & \vdots \\ \Phi_1(T) & \Phi_2(T) & \cdots & \Phi_M(T) \end{bmatrix}. \tag{3}$$

In this study, we used the normalized Gaussian functions for the basis functions. The i th basis function is expressed as follows, using the center c_i and variance h of the Gaussian function.

$$\Phi_i(t) = \frac{b_i(t)}{\sum_{j=1}^{M} b_j(t)}\,, \tag{4}$$

$$b_i(t) = \exp\left(\frac{-(t-c_i)^2}{2h}\right). \tag{5}$$

TABLE I. Nomenclature.

Symbol	Parameter	Unit
F_z	Z-direction force on the end effector	N
k	The stiffness of the branches	N/m
$\boldsymbol{\tau}$	Trajectories	-
N	Number of trajectories	-
$\boldsymbol{\Phi}$	Basis function matrix	-
M	Number of basis functions	-
c_i	The i-th center of the Gaussian distribution as a basis function	-
h	Variance of Gaussian distribution as a basis function	-
$\boldsymbol{\omega}$	Weight vector	-
$\boldsymbol{\varepsilon}$	Observation noise	-
λ	Ridge regression normalization parameters	-
$\boldsymbol{\mu}$	Mean of Gaussian distribution	-
$\boldsymbol{\Sigma}$	Variance of Gaussian distribution	-
T	Number of time steps of each trajectory, i.e., motion time	-
α	ProMPs activation function	-

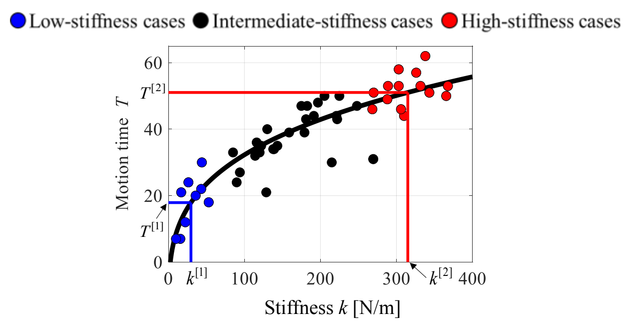

Fig. 5. Relation between stiffness k and motion time T in the taught data. The time length of a new motion is determined based on the relation.

We estimate the weights $\boldsymbol{\omega}$ using linear ridge regression with the ridge factor λ as follows:

$$\boldsymbol{\omega} = \left(\boldsymbol{\Phi}^T\boldsymbol{\Phi} + \lambda\boldsymbol{I}\right)^{-1}\boldsymbol{\Phi}^T\boldsymbol{\tau}\,. \tag{6}$$

The distribution $p(\boldsymbol{\omega})$ over the weight vector $\boldsymbol{\omega}$ is Gaussian with the mean $\boldsymbol{\mu}_{\boldsymbol{\omega}}$ and the variance $\boldsymbol{\Sigma}_{\boldsymbol{\omega}}$ calculated as follows:

$$p(\boldsymbol{\omega}) = N(\boldsymbol{\omega} \mid \boldsymbol{\mu}_{\omega}, \boldsymbol{\Sigma}_{\omega}). \tag{7}$$

The trajectory distribution $p(\boldsymbol{\tau})$ is computed by marginalizing out the weight vector $\boldsymbol{\omega}$ as follows:

$$p(\boldsymbol{\tau}) = \int p(\boldsymbol{\tau} \mid \boldsymbol{\omega})p(\boldsymbol{\omega})\,d\boldsymbol{\omega}\,. \tag{8}$$

When the distribution of the weight vector $p(\boldsymbol{\omega})$ is Gaussian, the distribution of the trajectory $p(\boldsymbol{\tau})$ is also Gaussian. Therefore, it is expressed using the mean and variance of the trajectory using the following equation. The distribution of this trajectory $p(\boldsymbol{\tau})$ is a probabilistic representation of the movement primitives, i.e., a ProMP.

$$p(\boldsymbol{\tau}) = N(\boldsymbol{\tau} \mid \boldsymbol{\mu}_{\tau}, \boldsymbol{\Sigma}_{\tau})\,. \tag{9}$$

2) Learning of Plucking Motions

First, the taught data are selected according to the stiffness of the branches. In this study, nine scenarios with low stiffness and fourteen with high stiffness of the branches were selected to be learnt.

Next, the data is spatially scaled. The difference of the positions and orientations of the hand during the leaf grasping process is important to pluck the leaves. Therefore, we employed the trajectories $\boldsymbol{\tau}'$ with all the initial values of the trajectories aligned to 0. The data is also scaled in time. Fig. 5 shows the relationship between the stiffness of the branches k and the motion time T in the taught data. Among robust regressions using linear functions, exponents, logarithms, unary power series, and binomial power series, the mean square error was minimized in the binomial power series model, so the relationship is approximated as follows:

$$T = \left[14.3 \times k^{0.275} - 18.6 \right]. \tag{10}$$

For the average values of stiffness $k^{[1]}$ and $k^{[2]}$, when the stiffness of the branches is low and high, respectively, the durations of the motion calculated based on (10) are $T^{[1]}$ and $T^{[2]}$. When the stiffness is low, the time steps are smaller than that of the other case. Therefore, assuming that the hand is stopped without changing the position and orientation after plucking, the end values of the time history are maintained and aligned with the time steps of the high-stiffness cases. After the spatial and temporal scaling, the data is learned, and the primitives are calculated and used for combination.

C. Combination

1) Method of Combination [19][21]

A new primitive generated by combining N primitives is expressed as follows using the activation function $\alpha^{[i]} \in [0,1]$ of the i-th primitive:

$$p_{new}(\boldsymbol{\tau}) \propto \prod_{i}^{N} p_i(\boldsymbol{\tau})^{\alpha^{[i]}}. \tag{11}$$

The resulting distribution $p_{new}(\boldsymbol{\tau})$ is again Gaussian with a variance $\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{*}$ and a mean $\boldsymbol{\mu}_{\boldsymbol{\tau}}^{*}$, which are calculated as follows:

$$\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{*} = \left(\sum_{i} \left(\frac{\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{[i]}}{\alpha_{\boldsymbol{\tau}}^{[i]}} \right)^{-1} \right)^{-1}, \tag{12}$$

$$\boldsymbol{\mu}_{\boldsymbol{\tau}}^{*} = \boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{*} \left(\sum_{i} \left(\frac{\boldsymbol{\Sigma}_{\boldsymbol{\tau}}^{[i]}}{\alpha_{\boldsymbol{\tau}}^{[i]}} \right)^{-1} \boldsymbol{\mu}_{\boldsymbol{\tau}}^{[i]} \right). \tag{13}$$

2) Combination of Plucking Motions

First, the time length of the motion is calculated. In ProMPs, the time lengths of the motions to be combined must be equal, and the time length of the motions after combination is equal to that of the motions before combination. Consequently, the time length of the combined motion cannot be considered unique to each situation. Therefore, the time length of the motion after combination T is calculated from the taught data, using (10) and the measured stiffness of the branches.

Next, the composition ratio is calculated. An intermediate motion between the low-stiffness and high-stiffness cases is generated by combining them with the ratio $1-\alpha : \alpha$. The motion corresponding to a situation of intermediate stiffness of the branches was therefore generated. However, it is necessary to determine the activation function of each ProMP. This implies that it is impossible to specify the combination ratio directly. Therefore, the combination ratio is presented, using the activation functions of the two primitives. The relationship between the activation functions of the primitives in the low-stiffness cases and the high-stiffness cases $\alpha^{[1]}$ and $\alpha^{[2]}$, respectively, is specified as follows:

$$\alpha^{[1]} = 1 - \alpha^{[2]}. \tag{14}$$

This ratio is defined as the inverse of the interior division ratio, when the motion time T is considered as the internal division point of the stiffness $k^{[1]}$ and $k^{[2]}$ in the low-stiffness cases and the high-stiffness cases, respectively. It generates a motion that interpolates two motions, i.e., the motion corresponding to low branch stiffness and that corresponding to high stiffness. The activation functions $\alpha^{[1]}$ and $\alpha^{[2]}$ of the primitives in these cases are calculated as follows:

$$\alpha^{[1]} = \frac{T^{[2]} - T}{T^{[2]} - T^{[1]}}, \tag{15}$$

$$\alpha^{[2]} = \frac{T - T^{[1]}}{T^{[2]} - T^{[1]}}. \tag{16}$$

IV. Validity Of Probabilistic Combination

To confirm the validity of the proposed method for generating motion through probabilistic combinations, we evaluated the similarity of our method with motions taught by humans. We calculated the similarity between motions the taught motions with an intermediate stiffness and the motions generated from the probabilistic combination which uses the means and variances of the proposed method. We compared these motions with those generated through non-probabilistic combination using only averages. The displacement required for plucking leaves, that is, the final displacement, is important. Therefore, the relationships between the time lengths of motions and the last displacements were compared between the probabilistic combination and the non-probabilistic combination. It was assumed that there was no influence of the observation noise.

Fig. 6 shows the relationship between the time length of the motion and the last displacement, and Table II shows the root mean squared error (RMSE). Since the proposed method had smaller errors, it can be seen that the proposed method had a higher degree of similarity with the motion taught by humans. Therefore, it can be concluded that the probabilistic combination of motions was better than the non-probabilistic combination.

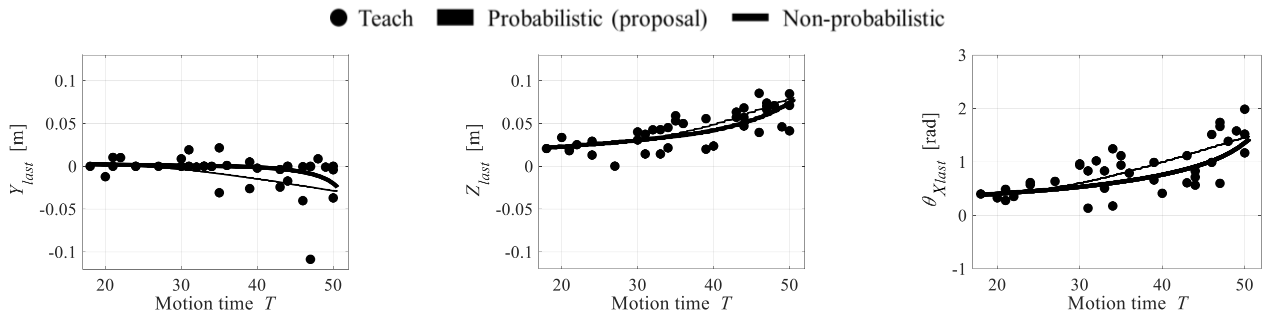

Fig. 6. Relation between motion time and last displacement. The final displacement is important to pluck leaves. Therefore, the relationship between the motion time and last displacement was compared.

V. Experiment

To confirm that the tea leaves can be actually plucked by Oritsumi with the motion generated by the proposed method, we experimented harvesting using the designed manipulator. The motion was reproduced by inputting the mean of the probabilistic distribution of the generated motion to the manipulator. For comparison, experiments were also performed with motion generated by non-probabilistic combination using only the mean, motion of the proposed method with only the Y and Z components, and motion with only the Z component. The four types of motion were expressed as probabilistic, non-probabilistic, $Y + Z$, and Z, respectively. The trial was performed 20 times for each of the four types of motion. As shown in Fig. 7, success was defined as the leaf being completely harvested, together with the petioles. Partial success was defined as only a part of the leaf being picked. The leaf not being harvested at all was defined as failure.

Figure 8 shows the experimental results of the four types of motion. The proposed method had the highest success rate and lowest failure rate among the four types of motion. In the case of non-probabilistic combination, there were more partial successes and fewer successes than the proposed method. As the Y displacement was larger than that in the proposed method, the gripped leaves were likely to slip due to movement in the Y direction, and were likely to be torn off at the point where they were gripped by the finger. There were several partial successes in the case of $Y + Z$. It is considered that the gripped leaves were slippery and were easily torn off at the gripping point because they were pulled diagonally upward without rotation. In the case of Z, there were several failures. This was because the gripped leaf was slippery and the extent of pulling was insufficient, as it was pulled directly upward, without rotation. In addition, plucking without rotation is equivalent to Kakitsumi. Therefore, even if the plucking was successful, there was considerable damage to the cut surface, which reduces the quality of the harvested leaves. Further, from the relationship between the measured stiffness and the results of the plucking shown in Fig. 9, it can be confirmed that when the measured stiffness was intermediate, an intermediate plucking motion was generated corresponding to the measured stiffness. Fig. 10 shows the trajectory of the motion generated in the trial of successful plucking. It can be confirmed that the intermediate time length and the amount of movement were determined corresponding to the situation of intermediate stiffness of the branches. Fig. 11 shows how the hand of the manipulator moved to pluck the leaf. It can be confirmed that the plucking motion by the proposed method can reproduce the motion of a human hand that simultaneously pulls and rotates, that is, the motion of Oritsumi.

From the results, it was confirmed that the motion generated by the proposed method can actually harvest tea leaves by Oritsumi. In addition, the quality of the harvested tea leaves and the success rate were higher than that of the other compared methods.

TABLE II. Similarity with motions taught by humans. The proposed method had smaller errors. Therefore, it can be said that it can generate motions similar to the motions taught by humans.

RMSE	R_Y [m]	R_Z [m]	R_{θ_z} [rad]
Probabilistic (proposal)	0.0168	0.0119	0.622
Non-probabilistic	0.0171	0.0120	0.747

Fig. 7. Differences in harvested tea leaves. An inappropriate motion resulted in only a part of the leaf being picked.

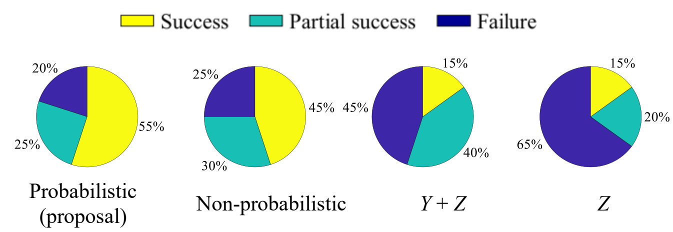

Fig. 8. Percentage of results. Probabilistic (proposal) had the highest success rate and lowest failure rate among the four types of motion.

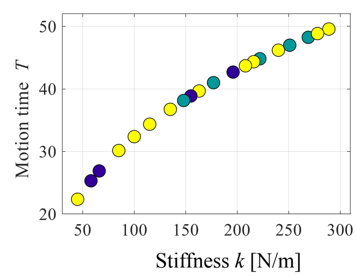

Fig. 9. Relation between stiffness k and results. When the measured stiffness was intermediate, an intermediate plucking motion was generated to pluck the leaf corresponding to the measured stiffness.

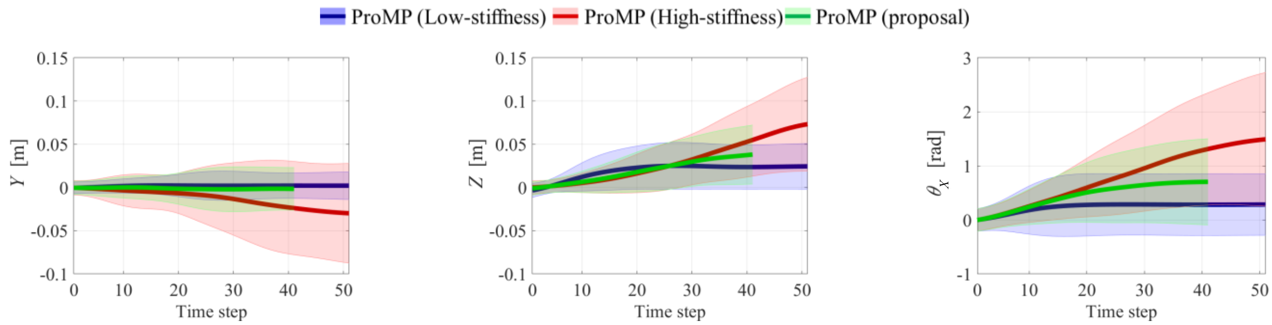

Fig. 10. ProMPs. Intermediate displacements and time lengths of the learned motions were generated.

Fig. 11. Plucking motion generated by the proposed method. The complex plucking motion, with pulling and rotation, was reproduced.

VI. Conclusion

In this study, we reproduced the complex movements of the hand-plucking operation that can harvest high-quality tea without cutting with blades, that is, the simultaneous pulling and rotation of a human hand. We proposed a method for generating tea-leaf-plucking motions according to the condition of the leaves, petioles, and branches. The stiffness of the branches was used to determine the leaf conditions, which affect the plucking action. The plucking motions were directly taught, probabilistically learned, and combined with ProMPs. The time length of motion was determined from the taught data on branch stiffness. The amount of motion was determined by calculating the combination ratio, expressed as activation functions of ProMPs, dependent on the stiffness of the branches. As a result, when a branch of intermediate stiffness was encountered, the motions for which were not taught, a plucking motion reproducing a human plucking motion was generated corresponding to the situation. The effectiveness of the proposed method was verified by evaluating the degree of its similarity with human-taught motions and experimenting with an actual robot.

In this study, we focused on the motion of the robot, but various issues remain to realize an economical tea-plucking robot. For example, movement in tea plantations, detection of leaves, determination of gripping position, and manipulation of gripping remain open problems. As a future issue regarding the motion, it is necessary to consider the observation noise and clearly compare the proposed method with the comparative method. In addition, as a future prospect, we aim to improve the success rate of plucking, by considering information other than the stiffness of the branches when judging the leaf conditions. Furthermore, we aim to apply the proposed method in fruit plucking in addition to tea leaf plucking.

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References

[1] S. Sharma, S. Sarangi, S. Pappula, "A framework for performance evaluation of plucking activity in tea", *IEEE Global Humanitarian Technology Conference (GHTC)*, pp. 14-21, 2016.

[2] J. Chen, Y. Chen, X. Jin, J. Che, F. Gao, N. Li, "Research on a Parallel Robot for Tea Flushes Plucking", *International Conference on Education, Management, Information and Medicine*, 2015.

[3] S. K. Jain, A. Jain, A. Goswami, R. Purohit, A. S. H. H. Vinjarapu, S. K. Gawre, "IoT based Smart Tea leaves Plucker with Two Revolute type Planar Manipulator", *IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*, pp. 1-6, 2018.

[4] Y. Han, H. Xiao, G. Qin, Z. Song, W. Ding, S. Mei, "Developing situations of tea plucking machine", *Engineering*, vol. 6, no. 6, pp. 268-273, 2014.

[5] P. O. Owuor, D. M. Kamau, E. O. Jondiko, "Responses of clonal tea to location of production and plucking intervals", *Food chemistry*, vol. 115, no. 1, pp. 290-296, 2009.

[6] Iruma City Museum ALIT, "TEA MUSEUM", http://www.alit.city.iruma.saitama.jp/07tea-museum/16tea-picking.html, (Japanese), (as of Nov 2019).

[7] World Green Tea association, "Quality of hand picked tea", http://www.o-cha.net/english/teacha/cultivation/handpicked.html, (as of Nov 2019).

[8] H. Yaguchi, K. Nagahama, T. Hasegawa, M. Inaba, "Development of an autonomous tomato harvesting robot with rotational plucking gripper", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 652-657, 2016.

[9] A. Silwal, J. R. Davidson, M. Mo. C. Karkee, Q. Zhang, K. Lewis, "Design, integration, and field evaluation of a robotic apple harvester", *Journal of Field Robotics*, vol. 34, no. 6, pp. 1140-1159, 2017.

[10] W. Montgomery, A. Ajay, C. Finn, P. Abbeel, S. Levine, "Reset-free guided policy search: Efficient deep reinforcement learning with stochastic initial states", *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3373-3380, 2017.

[11] A. Yahya, A. Li, M. Kalakrishnan, Y. Chebotar, S. Levine, "Collective robot reinforcement learning with distributed asynchronous guided policy search", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 79-86, 2017.

[12] J. Lee, "A survey of robot learning from demonstrations for human-robot collaboration", *arXiv preprint arXiv:*1710.08789, 2017.

[13] A. G. Billard, S. Calinon, R. Dillmann, "Learning from humans", *Springer handbook of robotics Springer, Cham*, pp. 1995-2014. 2016.

[14] T. Brys, A. Harutyunyan, H. B. Suay, S. Chernova, M. E. Taylor, A. Nowé, "Reinforcement learning from demonstration through shaping", *Twenty-Fourth International Joint Conference on Artificial Intelligence*, 2015.

[15] Z. Zhu, H. Hu, "Robot learning from demonstration in robotic assembly: A survey", *Robotics*, vol. 7, no. 17, 2018.

[16] A. Pervez, D. Lee, "Learning task-parameterized dynamic movement primitives using mixture of GMMs", *Intelligent Service Robotics*, vol. 11, no. 1, pp. 61-78, 2018.

[17] M. Ewerton., G. Neumann, R. Lioutikov, H. B. Amor, J. Peters, G. Maeda, "Learning multiple collaborative tasks with a mixture of interaction primitives", *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 1535-1542, 2015.

[18] R. Rahmatizadeh, P. Abolghasemi, L. Bölöni, S. Levine, "Vision-based multi-task manipulation for inexpensive robots using end-to-end learning from demonstration", *IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3758-3765, 2018.

[19] A. Paraschos, C. Daniel, J. Peters, G. Neumann, "Probabilistic movement primitives", *Advances in neural information processing systems*, pp. 2616-2624, 2013.

[20] Kinova Robotics, "KINOVA™ Ultra lightweight robotic arm User Guide", https://www.kinovarobotics.com/sites/default/files/ULWS-RA-JAC-UG-INT-EN%20201804-1.0%20%28KINOVA™%20Ultra%20lightweight%20robotic%20arm%20user%20guide%29_0.pdf, (as of Nov 2019).

[21] A. Paraschos, C. Daniel, J. Peters, G. Neumann, "Using probabilistic movement primitives in robotics", *Autonomous Robots*, vol. 42, no. 3, pp. 529-551, 2018.

[22] M. Ewerton, D. Rother, J. Weimar, G. Kollegger, J. Wiemeyer, J. Peters, G. Maeda, "Assisting Movement Training and Execution with Visual and Haptic Feedback", *Frontiers in neurorobotics*, vol. 12, no. 24, 2018.

[23] O. Dermy, A. Paraschos, M. Ewerton, J. Peters, F. Charpillet, S. Ivaldi, "Prediction of intention during interaction with ICUB with probabilistic movement primitives", *Frontiers in Robotics and AI*, vol. 4, no. 45, 2017.