LAMPS: A Novel Robot Generalization Framework for Learning Adaptive Multi-Periodic Skills

Zezhi Liu[1], Hanqian Luo[2], and Yongchun Fang[1]

***Abstract*— Learning from Demonstrations (LfD) methods are applied to transfer human skills to robots from expert demonstrations, enabling them to perform complex tasks. However, existing methods often struggle to handle such long-horizon human skills as cleaning or wiping stains on the surface, which involve multiple periodic and transitional movement primitives. To address this limitation, this paper proposes a novel framework for segmenting, learning, and generalizing multi-periodic human skills, enabling robots to effectively learn different movement primitives and execute these skills in new environments. Specifically, The framework introduces an unsupervised learning method to segment long-horizon human demonstrations into periodic and discrete movement primitives. Further, a novel type of discrete dynamical movement primitives, namely transitional movement primitives, is employed to enhance the fluidity of combining different periodic movement primitives in skills. To validate the effectiveness of the proposed approach, we conduct extensive experimental evaluations, including step-by-step validation of each procedure's methods in simulation and the implementation of the entire presented framework in the real world. The results confirm that the proposed framework accurately learns and generalizes multi-periodic human skills, providing a feasible solution for transferring complex multi-periodic demonstrations to robots in practical applications. The project website can be found at: https://nkrobotlab.github.io/LAMPS/**

I. INTRODUCTION

In daily life, when people clean the whiteboard or wipe the table, several periodic movements and transitional movements are contained in these skills. These kinds of long-horizon skills with multiple distinct types of movements are challenging to represent, learn, and generalize. Hence, the research focus of this paper is on how to learn and generalize such skills effectively.

In the field of Learning from Demonstrations (LfD) [1], human skills are transferred to robots primarily by modeling the separated skills as movement primitives (MPs) and then learning the model parameters from given expert demonstrations [2], [3]. Dynamic Movement Primitives (DMPs) is a prevalent method in LfD [4]–[6], which aims to acquire the forcing term of a system of second-order linear ordinary differential equations by leveraging demonstrations offered by human experts. These acquired skills are subsequently transferred to robots, primarily in either Cartesian space or joint space [7]–[9]. For long-horizon human demonstrations within several distinct types of MPs, robots are expected to autonomously segment and learn all of the included MPs [10]. The realization of learning complex long-horizon demonstrations not only reduces the workload of experts in teaching but also serves as a prerequisite for robots to achieve continuous learning in unstructured environments in the future [11]. Human demonstration data can be represented in feature spaces [12]–[14], and both supervised and unsupervised machine learning methods can be adopted to further MPs segmentation tasks [15] so as to enable robots to learn the well-segmented MPs with the LfD models.

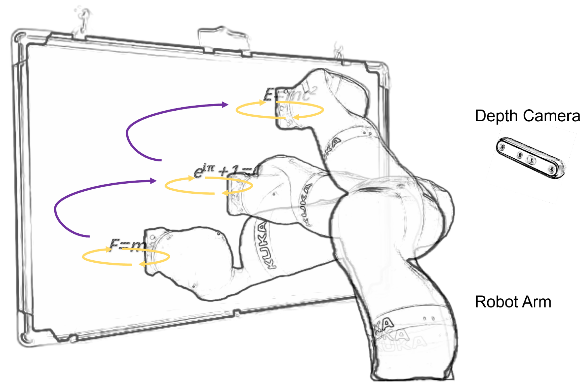

Fig. 1: The executing of the multi-periodic movements skills of the robot (cleaning the whiteboard). The purple curves represent the transitional MPs between the periodic MPs represented by the yellow curves.

Then, these segmented and learned MPs need to be combined and further generalized based on the perceptual information when robots are commanded to execute complex tasks in new environments. In the DMPs methods, three mainstream MPs-merging schemes have been proposed: the velocity threshold method [16], the target crossing method [17] and the basis functions overlay method [18]. These methods efficiently merge different MPs while maintaining their dynamical characters in dynamical spaces [19].

In light of the above analysis, the human skills containing multi-periodic movements is focused, a robot learning framework consisting of skills segmenting, merging and generalizing is proposed for the first time, with the knowledge in unsupervised learning and LfD are used. The executing of the multi-periodic movements is generally shown in Fig.1. The main contributions of this paper are summarized as follows:

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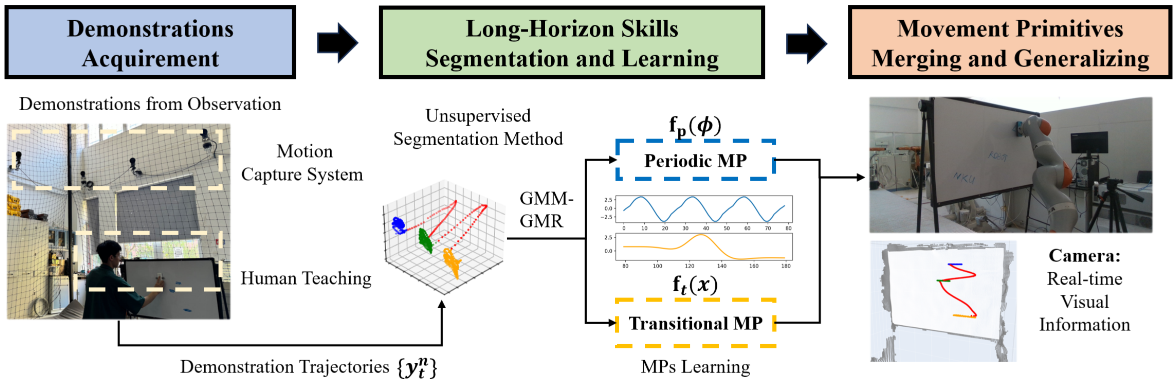

Fig. 2: The brief overview of the proposed robot framework for **L**earning **A**daptive **M**ulti-**P**eriodic **S**kills: LAMPS.

1) This paper models multi-periodic human skills for the first time by seamlessly merging periodic MPs and discrete MPs, successfully providing detailed descriptions of such kind of widely-used tasks in a nuanced manner, addressing a gap in the existing literature.
2) Aimed at learning and generalizing long-horizon multi-periodic skills, a feasible framework is constructed in which i) an unsupervised learning method is proposed and used to segment the long demonstrations, and ii) transitional MPs are introduced to combine with periodic MPs. This framework enables fluent generalization of MPs while preserving the dynamic features of demonstrations, enhancing both validity and efficiency.
3) The efficacy of the proposed framework is rigorously evaluated through both simulations and experiments, which validate the framework's efficacy in learning and generalizing multi-periodic skills, demonstrating robust performance and adaptability across new scenarios.

II. Segmenting, Learning and Generalizing Movement Primitives

This section presents the detailed algorithmic steps of the proposed robot skill framework for multi-periodic movements. First is the segmentation of different MPs from human demonstrations. Next, the transitional MPs are proposed to connect with different periodic MPs. Finally, the framework of segmenting, learning and generalizing MPs is illustrated in a general way. The brief overview is shown in Fig.2.

A. Segmentation and Learning of Movement Primitives

When robots learn skills from human demonstrations, it is crucial to segment long-horizon movement trajectories. These trajectories typically comprise two distinct types of movement primitives (MPs): periodic MPs and discrete MPs [20]. Periodic MPs are repetitive and cyclical, exemplified by actions such as wiping stains on a desktop. The robots must perform periodic wiping motions at each stain, demonstrating high regularity. In long-horizon skills with multiple distinct MPs focused in this paper, discrete MPs facilitate the transition between periodic actions. In this paper, we further refer to this type of discrete MPs as transitional MPs, which play a transitional role between the periodic MPs. Although more discussions of this kind of MPs are presented in Section III.B, we will collectively refer to these discrete MPs as transitional MPs in the following parts for uniformity.

In order to effectively learn and generalize such long-horizon movement trajectories, it is essential first to perform MPs segmentation, which involves distinguishing between periodic MPs and transitional MPs. Data-driven supervised learning approaches can achieve this objective, particularly those leveraging deep learning methods [21]. However, such methods typically require substantial annotated data to train the models effectively. Annotating long trajectory data collected through human demonstrations is often impractical due to the extensive manual labeling required.

To overcome this challenge, unsupervised learning methods, especially clustering algorithms, provide a viable alternative by eliminating the need for labeled data [22], which makes them well-suited for processing complex long-horizon movement trajectories from human demonstrations. Considering the trajectory characteristics of the long-horizon movement trajectories in robotic tasks, we use the OPTICS (Ordering Points To Identify the Clustering Structure) algorithm [23], which is adept at identifying clusters of varying densities by generating an augmented ordering of data points, making it ideal for segmenting periodic MPs and transitional MPs in complex movement trajectories.

The demonstration trajectory segmentation process based on the unsupervised OPTICS method is described in detail in Procedure (1). Beginning by collecting a long demonstration trajectory $\{\mathbf{y}_t^n | t = 1, 2, ..., T\}$, the base metric Euclidean distance $Dist(\mathbf{y}_i^n, \mathbf{y}_j^n)$ is provided by the spatial information of each data points. Starting with the initialization phase, where each data point is marked unprocessed and its neighborhood defined, followed by crucial steps of computing reachability distances and data ordering list. These further metrics obtained by OPTICS process are instrumental in constructing the ordering-reachability plot, a decision graph that serves as a visual tool for identifying clusters. By examining valleys within this plot, we can delineate dense regions of points corresponding to various periodic MPs $\{\mathbf{y}_t^{n_p}\}$. The points not falling within these dense regions are classified as transitional MPs $\{\mathbf{y}_t^{n_t}\}$, thus providing a clear segmentation of the long demonstration trajectory $\{\mathbf{y}_t^n\}$.

Procedure 1 Demonstration Trajectory Segmentation Based on Unsupervised OPTICS Method

Input Data: The long demonstration trajectory performed by human teachers and recorded: $\{\mathbf{y}_t^n | t = 1, 2, ..., T\}$
Output Result: Periodic and Transitional MPs $\left\{\mathbf{y}_t^{n_p}, \mathbf{y}_t^{n_t}\right\}$

% OPTICS Main Phase
initialize the empty data ordering list $orders$
initialize all data points in $\{\mathbf{y}_t^n\}$ as unprocessed
for each unprocessed data point p in $\{\mathbf{y}_t^n\}$ **do**
  record its neighborhood as follows: $N(p) = \{\mathbf{y}_j^n \mid Dist(p, \mathbf{y}_j^n) \leq \infty\}$
  mark p as processed and append p into $orders$
  if $N(p) \geq MinPts$ **then**
    initialize the empty priority queue $seeds$
    Update Priority Queue
    for each next data point q in $seeds$ **do**
      record its neighborhood as follows: $N(q) = \{\mathbf{y}_j^n \mid Dist(q, \mathbf{y}_j^n) \leq \infty\}$
      mark q as processed and append q into $orders$
      if $N(q) \geq MinPts$ **then**
        Update Priority Queue

% Update Priority Queue
caculate the core distance as follows: $CoDist(p) = \min\{Dist(p, \mathbf{y}_j^n) \mid |N(p)| \geq MinPts\}$
for each data point o in neighborhood $N(p)$ **do**
  if o is not processed **then**
    caculate the reachability distance as follows: $ReDist(p, o) = \max(CoDist(p), Dist(p, o))$
    if the o's minimum reachability distance $ReDist[o]$ is not defined **then**
      $ReDist[o] = ReDist(p, o)$
      $seeds[o] = ReDist(p, o)$
    else if $ReDist(p, o) < ReDist[o]$ **then**
      $ReDist[o] = ReDist(p, o)$
      $seeds[o] = ReDist(p, o)$

% Movement Primitives Extraction
while analyze Ordering-Reachability plot from $orders$ and $MinReDist$ **do**
  identify clusters (Periodic MPs $\left\{\mathbf{y}_t^{n_p}\right\}$) from valleys
  identify outliers (Transitional MPs $\{\mathbf{y}_t^{n_t}\}$) from peaks

With the accurate acquirement of several periodic MPs, which are represented as $\left\{(\mathbf{y}_t^{n_p}, \dot{\mathbf{y}}_t^{n_p}, \ddot{\mathbf{y}}_t^{n_p}) | t = 1, 2, ..., T; n_p = 1, 2, ..., N_p\right\}$ in each dimension, periodic DMP model is used to represent the human skill as follows:

$$\dot{\mathbf{y}}_2 = \Omega(\alpha(\beta(\mathbf{y_m} - \mathbf{y}_1) - \mathbf{y}_2) + \mathbf{f}(\phi)), \tag{1}$$

$$\dot{\mathbf{y}}_1 = \Omega \mathbf{y}_2, \tag{2}$$

$$\tau \dot{\phi} = 1, \tag{3}$$

where α, β and τ are constants. $\mathbf{y_m}$ and Ω represent the attraction point of the system and the frequency of the periodic MPs. The forcing term $\mathbf{f}(\phi)$ is written as:

$$\mathbf{f}(\phi) = \frac{\sum_{i=1}^N w_i \psi_i(\phi)}{\sum_{i=1}^N \psi_i(\phi)} r, \tag{4}$$

$$\psi_i(\phi) = \exp(h_i(\cos(\phi - c_i) - 1)), \tag{5}$$

where r is the relative amplitude of periodic MPs. The weight parameters are learned from demonstrations as follows:

$$\mathbf{f}_d(t) = \frac{\ddot{\mathbf{y}}(t)}{\Omega^2} - \alpha \left(\beta(\mathbf{y_m} - \mathbf{y}(t)) - \frac{\dot{\mathbf{y}}(t)}{\Omega}\right). \tag{6}$$

In this way, the segmented demonstrations are learned by robotic agents, which will be used in subsequent pipelines.

B. Combining of Movement Primitives

Using dynamical systems to model human skills can better maintain the features of convergence or periodicity. The specific form of the dynamical system determines the specialty of the learning method. Most proposed dynamical system models are differential equations of one or two orders, which learn demonstrations with the velocity or acceleration-level features. Moreover, modifications of dynamical systems are proposed to merge the learned MPs in a fluent way. However, the two-order ODE system causes discontinuity acceleration in the connection, which may damage motors. Furthermore, the performance of merging between the MPs should be improved, especially when merging the transitional MPs with the dramatically changing periodic MPs. So the following three-order dynamical MPs are used to represent the transitional MPs learned from the human demonstrations:

$$\tau \dot{\mathbf{y}}_3 = \alpha \left(\beta \left(\gamma \left(\mathbf{g} - \mathbf{y}_1\right) - \mathbf{y}_2\right) - \mathbf{y}_3\right) + \mathbf{f}(x), \tag{7}$$

$$\tau \dot{\mathbf{y}}_2 = \mathbf{y}_3, \tag{8}$$

$$\tau \dot{\mathbf{y}}_1 = \mathbf{y}_2, \tag{9}$$

where $\mathbf{y}_1$, $\mathbf{y}_2$ and $\mathbf{y}_3$ are the position, velocity and acceleration of robots in one dimension. α, β and γ are constants of the dynamical system. $\mathbf{g}$ is the goal position of the MP, while τ is the time constant. Furthermore, $\mathbf{f}(x)$ is the forcing term in the dimension of jerk, which consists of basis functions to learn the complex features from human demonstrations:

$$\mathbf{f}(x) = \frac{\sum_{i=1}^N w_i \psi_i(x)}{\sum_{i=1}^N \psi_i(x)} x, \tag{10}$$

$$\psi_i(x) = \exp(-h_i(x - c_i)^2), \tag{11}$$

where N, h_i and c_i are the number, the height constants and the center positions of the base Gaussian function, set by experts beforehand. And ω_i are weight parameters. Moreover, x is the phase signal representing the elapse of time, and the differential equation of x is written as follows:

$$\tau \dot{x} = -\lambda x. \tag{12}$$

To make the dynamical system convergent to the target position, velocity and acceleration in phase space, The three-order dynamical MPs of equation (7) is modified as follows:

$$\tau\dot{\mathbf{y}}_3 = (1-x)\alpha\left(\beta\left(\gamma\left(\widehat{\mathbf{g}}_1-\mathbf{y}_1\right)+\left(\widehat{\mathbf{g}}_2-\mathbf{y}_2\right)\right)+\left(\mathbf{g}_3-\mathbf{y}_3\right)\right)+\mathbf{f}(x). \tag{13}$$

Similar to the target crossing methods [19] [24], to ensure the continuity, the acceleration and velocity features of transitional movement primitive are implicated by the crossing target of velocity $\widehat{\mathbf{g}}_2$ and position $\widehat{\mathbf{g}}_1$:

$$\widehat{\mathbf{g}}_2 = \widehat{\mathbf{g}}_2(0) - \frac{\tau}{\alpha}\ln(x)\mathbf{g}_3, \tag{14}$$

$$\widehat{\mathbf{g}}_2(0) = \mathbf{g}_2 - \frac{T\mathbf{g}_3}{\tau}, \tag{15}$$

$$\widehat{\mathbf{g}}_1 = -\widehat{\mathbf{g}}_2(0)\frac{\tau}{\alpha}\ln(x) + \frac{1}{2}\mathbf{g}_3\left(\frac{\tau}{\alpha}\ln(x)\right)^2 + \widehat{\mathbf{g}}_1(0), \tag{16}$$

$$\widehat{\mathbf{g}}_1(0) = -\widehat{\mathbf{g}}_2(0)\frac{T}{\tau} + \frac{1}{2}\mathbf{g}_3\left(\frac{T}{\tau}\right)^2 + \mathbf{g}_1, \tag{17}$$

where $\mathbf{g}_1$, $\mathbf{g}_2$ and $\mathbf{g}_3$ are the target of position, velocity and acceleration, which are set as the beginning state of the transitional movement primitive: $\mathbf{g}_1 = \mathbf{y}_{next}(0)$, $\mathbf{g}_2 = \mathbf{v}_{next}(0)$ and $\mathbf{g}_3 = \mathbf{a}_{next}(0)$,

Additionally, to remain the convergence feature of critically damped behavior of the dynamical system, the characteristic polynomial of the three-order system is written as:

$$P(s) = s^3 + \frac{\alpha}{\tau}s^2 + \frac{\alpha\beta}{\tau^2}s + \frac{\alpha\beta\gamma}{\tau^3}. \tag{18}$$

To ensure all the poles are located in the left half-plane of the real axis, the following relationship should be satisfied, in which p is an arbitrary constant:

$$\alpha = 3p, \quad \beta = p, \quad \gamma = \frac{1}{3}p. \tag{19}$$

With the three-order dynamical system (13), the robot can learn and generalize transitional MPs to connect periodic MPs in a fluent way, shown in Fig.3. The continuity of position, velocity and acceleration are ensured through the target crossing method in (14)–(17). The continuity in acceleration level can avoid damage due to excessive change of motor acceleration, which is one of the reasons why we propose the three-order differential equation when merging MPs. For another, to connect with changing periodic MPs, both the connected velocity and acceleration should be connected more delicately. Hence, the three-order transitional MPs can perform better to be used to connect periodic MPs than the original two-order dynamical system mat any real-time start or end state in real-world implementation.

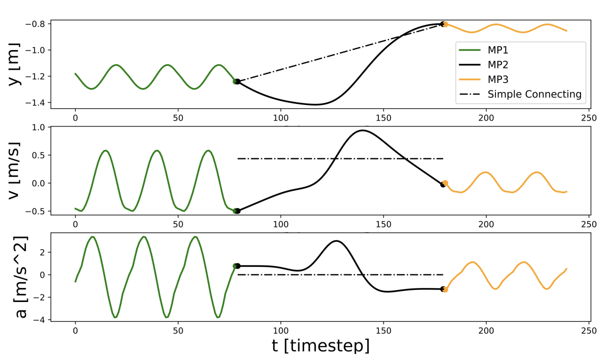

Fig. 3: The effect of the transitional MP. The green and yellow solid lines are the previous and the next periodic MP $\{y_{last}, y_{next}\}$, respectively.

C. The Framework of Segmenting, Learning and Generalizing Movement Primitives

In this part, a novel framework of segmenting, learning and generalizing multi-periodic robot skills LAMPS is introduced. Specifically, the framework focuses on long-horizon human skills, which contain several periodic MPs and the needed transitional MPs. For example, cleaning the whiteboard with a board eraser is such kind of human skill: when wiping draft on one area, the single movement can be described as a periodic movement primitive; when moving the eraser from one area of the draft to another, the movement is a needed transitional MPs. In daily life, there are many more human skills that can be classified under this category, such as wiping tables or screwing several screws.

Firstly, demonstrations are performed by human teachers and recorded. As these demonstrations need to be subdivided further, the unsupervised learning method mentioned before is used to divide each long demonstration $\{\mathbf{y}_t^n\}$ into several periodic MPs $\{\mathbf{y}_t^{n_p}\}$ and transitional MPs$\{\mathbf{y}_t^{n_t}\}$. Then, the well-segmented periodic MPs demonstrations are modeled by GMM-GMR and then learned by the DMPs $\{\phi, \mathbf{f}_{n_p}(\phi)\}$. Meanwhile, the segmented transitional MPs demonstrations are learned, with the calculation of $\{x, \mathbf{f}_{n_t}(x)\}$.

When the robot generalizes these learned skills in new environments, the perception tools provide the environment information $\xi_{prec}(t)$, making the robot adaptively reproduce the learned skills. Robots use perceptual information to judge the estimated number of periodic MPs N_c that should be adopted in a general way. For each MP, the robot could adjust the basic parameters (like the amplitude r, the attract position $\mathbf{y}_m$ and so on) referring to the perceptual information. Moreover, the devices such as visual or mechanical sensing provide the robots a signal $\kappa = 0$ or $\kappa = 1$ representing the completeness of the current periodic MPs (for example, whether the drafts in this area have been cleaned). As soon as the robot finishes the last MP, the expected start state $(\mathbf{y}_{next}(0), \dot{\mathbf{y}}_{next}(0), \ddot{\mathbf{y}}_{next}(0))$ of transitional MPs are computed, and the merging transitional MP written as equation (7)–(17) is generalized by the start $(\mathbf{y}_{last}(t_e), \dot{\mathbf{y}}_{last}(t_e), \ddot{\mathbf{y}}_{last}(t_e))$ and the end $(\mathbf{y}_{next}(0), \dot{\mathbf{y}}_{next}(0), \ddot{\mathbf{y}}_{next}(0))$ state fluently. The above process is repeated until all MPs are completed.

The proposed framework provides a typical processing scheme for the tasks that contain periodic and transitional MPs. With the generalizing process, the learned skills are generalized adaptively by modifying the parameters of MPs.

III. Simulation and Experiments

This section first evaluates the proposed segmentation methods and MPs combining methods. Then, the whole robot skill framework is used in real-world experiments to execute the tasks of wiping the whiteboard with the experiment information, and the results are recorded and analyzed.

A. Movement Primitives Segmentation Results

In this part, we present the key results of applying the trajectory segmentation process to the long demonstration, which features periodic wiping MPs and transitional MPs moving in different wiping areas and is processed using the Procedure (1) as outlined in the previous section.

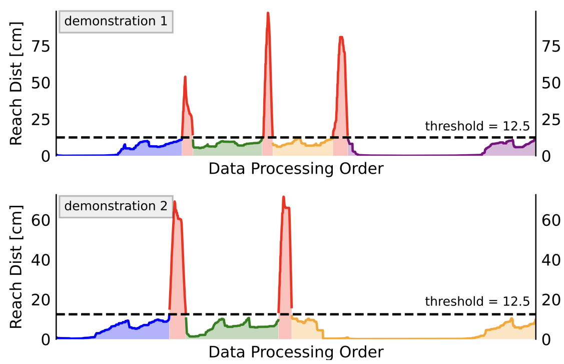

Fig. 4: Ordering-Reachability plots of two demonstration trajectories processed by the Procedure (1).

By calculating reachability distances and data ordering lists in the trajectory, the ordering-reachability plot is generated, which serves as a fundamental tool in understanding the spatial distribution and density of the trajectory points. As shown in Fig.4, we can effectively segment the trajectory into distinct clusters by setting a suitable threshold on the reachability distances. Notably, the valleys in this plot indicate regions of high density, which correspond to periodic MPs $\left\{\mathbf{y}_t^{n_p}\right\}$ in the whiteboard wiping task. Peaks or significant increases (above the threshold) in reachability distance suggest transitional MPs $\{\mathbf{y}_t^{n_t}\}$between these periodic MPs.

To validate the effectiveness of our segmentation approach, we visualized the segmentation results of demonstration 2 in Fig.4 compared with those obtained using two other clustering methods, the K-Means [25] and the Affinity Propagation [26]. As shown in Fig.5, both compared methods are unable to effectively segment different types (periodic and transitional) of MPs, which highlights the superior performance of our method in segmenting complex demonstration trajectories. Unlike the compared methods, our segmentation approach based on unsupervised OPTICS efficiently identifies dense clusters as periods and isolates outliers as transitions without requiring rich prior knowledge such as the number of clusters, which is particularly advantageous in scenarios where the long demonstration trajectory consists of periodic MPs $\left\{\mathbf{y}_t^{n_p}\right\}$ and transitional MPs $\{\mathbf{y}_t^{n_t}\}$.

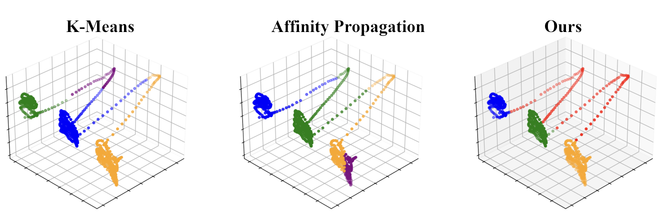

Fig. 5: Comparison of clustering methods for MPs. The two compared algorithms K-means and Affinity Propagation both fail to segment transitional MPs effectively.

B. Movement Primitives Combining Results

The proposed three-order transitional dynamical MPs in equation (13), which learned the dynamical features from the demonstrations, acted as the connected transitional MPs of two periodic MPs. Compared with a target crossing DMP, the transitional MP ensures the continuity of the acceleration and the smooth transitions in velocity level, shown in Fig.6.

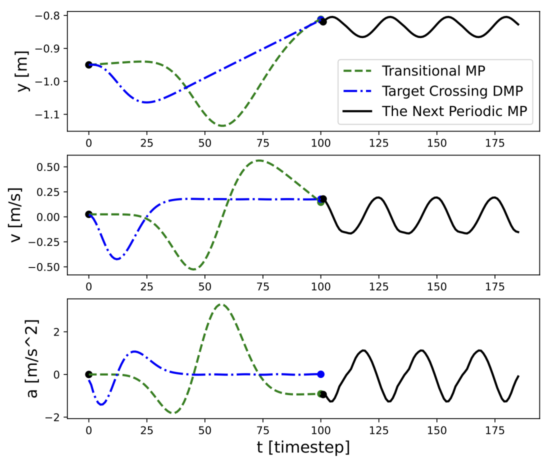

Fig. 6: Comparison of transitional MPs and target crossing DMP.

Represented in the blue dot-dashed line in Fig.6, the mainstream target crossing method causes the discontinuity in the acceleration level, while the transitional MP preserves the continuity. The smoothness in velocity-level (continuity of acceleration) provides safety protection for the operation of the motors and makes the movement more in line with the actual movement process of the human body.

Then, the proposed transitional MP method is tested to combine with periodic MPs in different phases, with different positions, velocities, and accelerations. As shown in Fig.7, the transitional MPs are used to connect to periodic MPs in different phases. Though the connected position, velocity and acceleration are different, the proposed method has good performance when connected with the following MPs.

C. Real-world Experiments

To evaluate the proposed framework, one of the typical multi-periodic movement skills, wiping the whiteboard, is executed and estimated in this part. The whole experimental procedure is shown in Fig.8. Firstly, the human demonstrations are captured and recorded by Qualisys motion capture system with eight cameras. The human teacher performs the

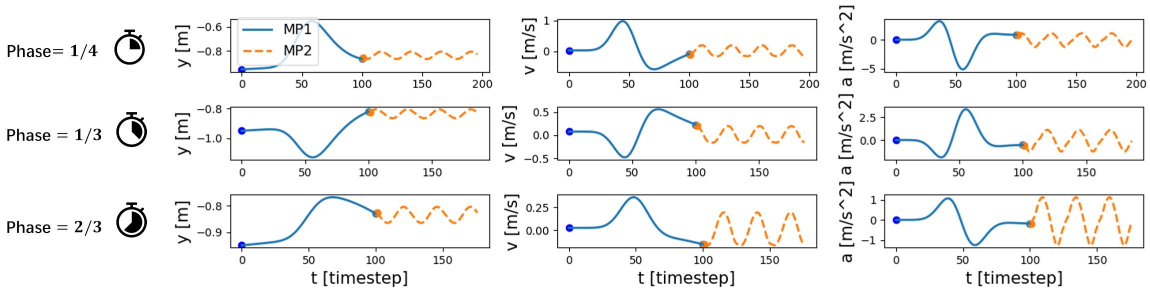

Fig. 7: The merging of movement primitives when the following periodic MP is in different phases, the blue solid line and the orange dashed line represent the transitional MP and the next periodic MP, respectively.

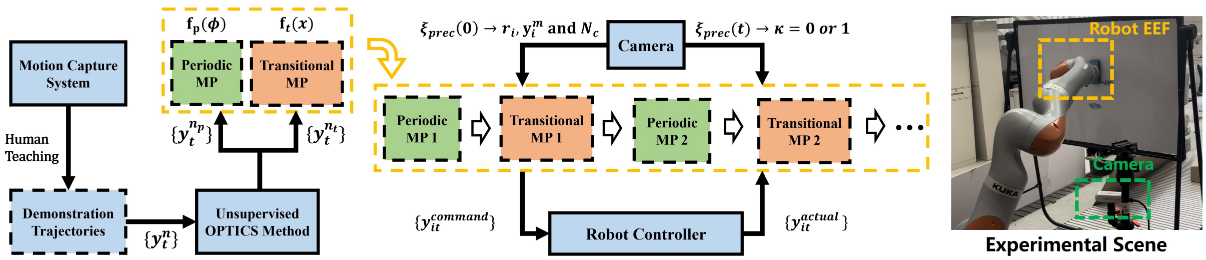

Fig. 8: Experimental procedure diagram. Both periodic MPs and transitional MPs are employed to learn from the human demonstrations and then generalize in new scenarios.

wiping skills by holding a whiteboard eraser on which four markers are stuck. The positions of these markers are calculated to acquire the eraser's positions and rotations. These acquired demonstrations are then segmented by the proposed unsupervised learning method. After that, the periodic MPs and transitional MPs are learned in order to reproduce and generalize the learned skills in new scenarios.

As shown in Fig.8, A whiteboard eraser is attached to the end of the KUKA LBR IIWA 14 robot manipulator, and an Intel RealSense D435i camera is fixed on the ground to acquire visual information during the real-world experiments. The total number of the periodic MPs $\mathbf{N}_c$ are tested by cluster methods from pixel data; the amplitude r_i and the attract position $\mathbf{y}_i^m$ of the periodic MPs are calculated by the pixels in each cluster. With the visual perception $\xi_{prec}(t)$ during the cleaning of the whiteboard, the acquired information $\kappa = 0$ or 1 is used to estimate the completion of the current periodic MP: the periodic MP stops and the next transitional MP starts when the target deep color pixels disappear. The impedance control model is set in the experiments, making gentle contact between the robot and the whiteboard. The communication of the PC and KUKA IIWA robot is based on the iiwa-stack project [27].

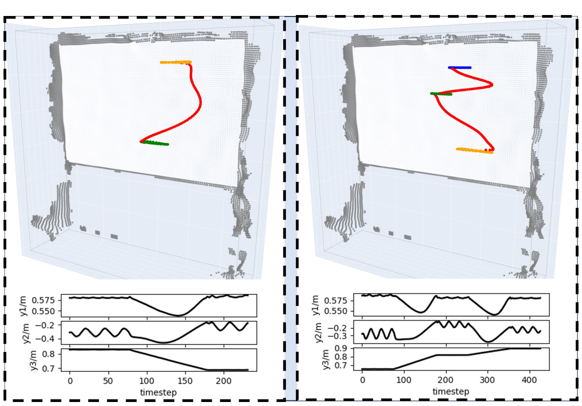

Fig. 9: Experimental result diagram. The results of LAMPS framework when generalizing the learned multi-periodic skills in different new scenarios are shown in the subfigures.

The experiment results are shown in Fig.9. These trajectories are recorded and transmitted by the ROS nodes, which receive the information from robot motors and calculate the forward kinematics of the end-effector. The results show the fluent performance when generalizing the skills into new situations. In general, the experiments show the effectiveness of the proposed framework. On the one hand, The adaptability of the proposed methods provides a feasible way to connect with different periodic MPs, which provides the effectiveness of the generalized skills. On the other hand, the framework can also learn and implement the dynamic features when merging the periodic MPs from the demonstrations, which remains the human-like nature of the actions.

IV. CONCLUSIONS

In this paper, we present a novel robot skill segmenting, learning, and generalizing framework for multi-periodic human skills. As multi-periodic skills play an important role in human daily life, we describe these skills in detail and find a general solution to make robots learn and generalize such kind of skills. The unsupervised segmentation method and transitional movement primitives are proposed to make the generalized skills operate smoothly and effectively. The performance of our proposed methods is evaluated in both simulation and real-world experiments.

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