Progressive Automation of Periodic Movements

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Abstract. This paper presents the extension of the progressive automation framework for periodic movements, where an operator kinesthetically demonstrates a movement and the robotic manipulator progressively takes the lead until it is able to execute the task autonomously. The basic frequency of the periodic movement in the operational space is determined using adaptive frequency oscillators with Fourier approximation. The multi-dimensionality issue of the demonstrated movement is handled by using a common canonical system and the attractor landscape is learned online with periodic Dynamic Movement Primitives. Based on the robot's tracking error and the operator's applied force, we continuously adjust the adaptation rate of the frequency and the waveform learning during the demonstration, as well as the target stiffness of the robot, while progressive automation is achieved. In this way, we enable the operator to intervene and demonstrate either small modifications or entirely new tasks and seamless transition between guided and autonomous operation of the robot, without distinguishing among a learning and a reproduction phase. The proposed method is verified experimentally with an operator demonstrating periodic tasks in the free-space and in contact with the environment for wiping a surface.

1 Introduction

Progressive automation is a framework introduced by the authors in [3], that allows an operator to kinesthetically demonstrate repetitive tasks to a robot for seamless transition of the latter from manual robot guidance to autonomous operation. In [3] the operator demonstrates a task a few times and a variable impedance controller gradually increases the stiffness according to the correspondence between consecutive demonstrations so that the robot accurately tracks the trajectory produced by the motion generation system. Although the tasks are repetitive, they are encoded by joining discrete movement segments. The segmentation of the task into discrete movements is practical in several applications (e.g. pick and place), where the end-points of the segments are associated with the operator's input, such as signaling to the robot to open/close a gripper [10,2]. Although such repetitive movements can be considered periodic, there are other tasks that involve rhythmic movements and need not be segmented, such as the wiping of a surface [5] or the gait of humanoid robots [16].

To encode and determine online the basic frequency and the waveform of a periodic movement, a two layer system was proposed by Gams et al. [7]. The basic frequency is assumed to be the lowest frequency of an input signal, that is appropriate to include one task period. The first layer (Canonical System) of this method uses a number of nonlinear oscillators that adapt to the different frequency components of the input signal and the second layer (Output System) is based on periodic Dynamic Movement Primitives (DMP), which have the ability to encode periodic patterns [9]. By separating the frequency and the waveform learning, there is an advantage of independent temporal and spatial adjustment respectively. A modified approach to the first layer for determining the basic frequency of the input signal, uses a single oscillator with Fourier series approximation [20]. With Fourier approximation, there is no need to extract the basic frequency among the oscillators as in [7], which is a considerable benefit. When the objective of a task is to individually encode multiple degrees of freedom (DOF) that have coupled frequencies, the learned frequencies in each DOF might lead to drift during the reproduction phase because they might not be equal or exact multiples of each other. Another approach for multiple DOF is to use a common Canonical System for both learning and reproduction, with a common frequency. This case usually requires treatments such as logical operations, rounding of frequencies or addition of the input signals from the different DOF, which can lead to side-effects like cancelling or doubling of frequencies [7].

For learning a periodic movement that also consists of a transient part [5], such as the wiping of a surface, the authors in [4] initially segmented the wiping demonstration into the two parts and in the second phase they adapted the learned periodic DMP to apply a predefined force to the surface. Adaptation to the learned periodic movement primitives for modifying the trajectory of the robot was proposed in [8] with respect to the input from the operator (e.g. force or gestures). With this method the robot's movement could gradually adapt to the operator's coaching after multiple iterations, but under the assumption that the environment cannot change rapidly. Similarly, the authors in [14] used a passivity based iterative learning approach to gradually modify the goal of a periodic DMP with a pre-specified pattern, with respect to external forces due to changes of the environment. With the same objective, the authors in [13] proposed an adaptation mechanism to modify the spatial parameters of dynamical systems in periodic and repetitive tasks, but by having predefined motion patterns. These methods aim either to gradually adapt the learned pattern after multiple iteration or to modify the parameters of a certain pattern. As a result, they cannot handle cases in which the operator desires to significantly change the motion pattern or the frequency. Another characteristic of the aforementioned literature is the distinction between the learning and the reproduction phase. In the spirit of progressive automation, a transition between these phases should occur seamlessly, bidirectionally and without interruption [3]. Although a seamless adaptation was proposed for reshaping the task by user interaction in [13], their method assumes an encoded task prior to adaptation as opposed to ours. A seamless transition was also proposed in [19], which considered DMP learning and adaptive frequency oscillators in a single degree of freedom and gradually increased the stiffness of the impedance controller based on the input from EMG sensors attached to the operator. In that way the robot could take over the task when the predefined level of fatigue was reached. In a related approach [18], the robot switched unidirectionally from learning to autonomous execution once a predefined tracking error was reached.

In this paper we propose a method for progressive automation of periodic movements by kinesthetic guidance, extending our previous work [3] that was focused on discrete motion segments. The method utilizes adaptive frequency oscillators and periodic movement primitives for learning the frequency and waveform during the demonstration. A bidirectional seamless transition between learning and autonomous operation of the robot is achieved with the use of a role allocation strategy than can adjust the robot's stiffness and, therefore, the level of automation. This level is adjusted based on the operator's applied force and the agreement between the motion learned by the robot and the user demonstration. The contribution of this work lies in a novel modification method of the learning rules of the frequency oscillators of [20] and of the movement primitives [9], which is based on the automation level. The main advantage of this approach is that it enables autonomous execution of periodic movements through teaching by demonstration, without distinguishing between a learning and a reproduction phase. With the proposed method the learned parameters can be adjusted either for small or for significant task modifications from the operator, even by intervening during the autonomous execution and without requiring external sensors such as EMG. The effectiveness of the proposed method for fast and seamless progressive automation is verified experimentally for periodic tasks without and with contact with the environment, such as wiping of a surface.

2 Progressive automation of periodic movements

This section presents the proposed methodology and is structured as follows. An overview of the system structure is initially presented Sec. 2.1 describing the key variables and the method's sub-components; these are the role allocation strategy that adjust the automation level of the robot described in Sec. 2.2, the adaptive frequency oscillators to determine the task frequency given in Sec. 2.3, the periodic DMP that encode the waveform of the demonstration presented in Sec. 2.4, and a variable stiffness controller presented in Sec. 2.5.

2.1 System structure

Let $\mathbf{p} \in \mathbb{R}^m$ be the task coordinates of a robotic manipulator under impedance control, as shown in the block diagram of Fig. 1. At the beginning of the demonstration, the target stiffness of the robot is zero in order to allow kinesthetic guidance. To continuously adjust the role of the robot between kinesthetic guidance and autonomous operation, the target stiffness is adapted according to a role allocation law, based on the operator's force $\mathbf{F}_h$ and the tracking error of the robot. Without the system having any prior knowledge of the task, the desired trajectory $\mathbf{p}_d \in \mathbb{R}^m$ of the robot is learned incrementally during the demonstration and -simultaneously- is being provided as the reference to the impedance controller. With this approach we do not distinguish between a learning and reproduction phase. Instead, we propose a gradual increase of the target stiffness while the reference trajectory $\mathbf{p}_d$ approximates the demonstrated trajectory $\mathbf{p}$ and the operator does not apply significant forces to the robot. A decrease of the stiffness can also occur to re-enable kinesthetic guidance and allow modifications of the learned task though the application of corrective forces to the robot.

The user kinesthetically demonstrates a periodic movement to the robot and the movement is encoded by periodic DMP with incremental regression learning in each coordinate. An adaptive frequency oscillator in each coordinate i determines the basic frequency ω_i of the input signal p_i. Under the assumption that a periodic signal is available in all demonstrated degrees of freedom, then the basic frequency $\Omega \in \mathbb{R}$ of the task can be extracted as the minimum among the components:

$$\Omega = \min\{\omega_1, ..., \omega_m\}. \tag{1}$$

Synchronization of the produced trajectory $\mathbf{p}_d$ generated by the m periodic DMP, is achieved by having a common basic frequency Ω.

The concept of the proposed system involves the operator demonstrating a periodic task to the robot multiple times until the system has learned the basic frequency Ω, the phase of the periodic movement $\Phi \in \mathbb{R}$ and the desired trajectory $\mathbf{p}_d$. These estimates are updated continuously aiming to reduce the tracking error $\widetilde{\mathbf{p}} = \mathbf{p} - \mathbf{p}_d$. Within this paper we only consider movement in the translational coordinates of the end-effector ($m \leq 3$), with the orientation being fixed. While the system learns the demonstrated task, the target stiffness increases and the robot gradually obtains the leading role, which is determined by the variable $\kappa \in \big[0, 1\big]$, denoting the automation level. When $\kappa = 0$, the robot can be passively guided kinesthetically with zero stiffness. While $0 < \kappa < 1$, the role is shared between the human and the robot. When $\kappa = 1$, the stiffness of the robot is maximum and it can autonomously execute the task, so it does no longer require further adaptation. For that purpose, we use the term $(1 - \kappa)$ as a weight in the adaptation rules to suspend the adaptation when the robot has learned the task. The user can intervene at any time while the robot moves autonomously -causing κ to decrease- and either modify the task (spatially or temporally) or demonstrate an entirely new task. In the following subsections we present each module of the proposed system in detail.

2.2 Role allocation strategy

The automation level κ transitions the role of the robot from passively following the user's demonstrations to accurately following the reference trajectory produced by the DMP. The variable Cartesian stiffness $\mathbf{K}_v$ of the robot is:

$$\mathbf{K}_v = \kappa(t) k_{max} \mathbf{I}_{m \times m} \tag{2}$$

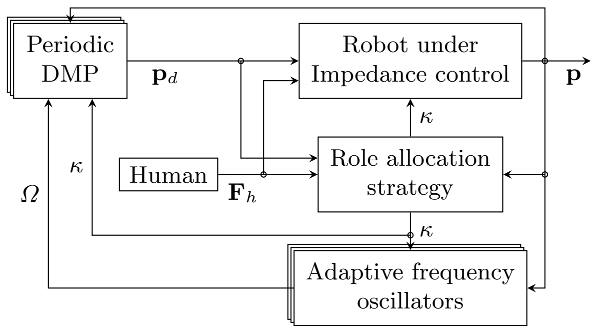

Fig. 1. Block diagram of the proposed system.

where $k_{max} \in \mathbb{R}^{>0}$ is the maximum desired stiffness for autonomous operation. The rate of change κ_r of the automation level κ depends on the external interaction force $\mathbf{F}_h$, on the tracking error $\widetilde{\mathbf{p}}$ and on the current value of $\kappa(t)$. It was originally introduced in our previous work [3] and is given here for completeness:

$$\dot{\kappa} = \begin{cases} \max\{\kappa_r, 0\}, & \kappa = 0 \\ \kappa_r, & 0 < \kappa < 1 \\ \min\{\kappa_r, 0\}, & \kappa = 1 \end{cases}, \qquad \text{with } \kappa(0) = 0, \tag{3}$$

$$\kappa_r = (\frac{\kappa}{f_r} + f_{min}) \left(1 - \left(\frac{||\mathbf{F}_h||}{\lambda_2}\right)^3 - \frac{||\widetilde{\mathbf{p}}||}{\lambda_1}\right). \tag{4}$$

The design parameters $\lambda_1,\ \lambda_2$ affect the impact of the tracking error and of the interaction force respectively on the rate of change. We utilize a power of 3 of the force magnitude to highlight the importance of the interaction force on role revoking beyond a threshold, reflected on the choice of λ_2. For example, when the robot moves autonomously with almost zero tracking error, the application of an interaction force such that $||\mathbf{F}_h|| > \lambda_2$ will revoke the leading role back to the operator. The parameter f_{min} is a positive constant to induce a gain increase when $\kappa = 0$, and f_r is a scaling term.

While the level κ increases, the robot is gradually allocated with the leading role. The transition rate κ_r depends on the current value of κ. This rate is initially slow, requiring the user to demonstrate a few periods of the movement until the frequency and waveform is learned. The rate increases with the increase of κ. When the robot moves autonomously ($\kappa = 1$), a high interaction force reverts the leading role back to the human for allowing modifications. The loss of passivity that occurs because of the variable stiffness matrix is handled with energy tanks as it is discussed in Sec. 2.5.

2.3 Adaptive frequency oscillators

To learn the basic frequency of the demonstrated movement, we utilize the adaptive frequency oscillators with Fourier approximation, proposed in [20]. An objective of progressive automation involves the ability of the robot to continue executing the demonstrated task autonomously after it has been encoded sufficiently. Another objective involves the ability of the operator to intervene during the autonomous execution and demonstrate any spatial or temporal modification. Regarding the temporal modification, the frequency adaptations need to stop and restart accordingly. To avoid using exteroceptive sensors such as EMG [19] and to allow continuous and bidirectional transition, in contrast to unidirectional switching as in [18], we propose the modification of the adaptation rules according to the automation level κ.

The proposed adaptation is weighted by $(1-\kappa)$ to smoothly stop the learning when the robot is in the autonomous mode $\kappa = 1$ and to smoothly re-enable it when the operator intervenes to make modifications. The oscillators are then structured as:

$$\dot{\boldsymbol{\phi}} = (1-\kappa)(\boldsymbol{\omega} - a\ \mathbf{E}\ \sin(\boldsymbol{\phi})), \tag{5}$$

$$\dot{\boldsymbol{\omega}} = -(1-\kappa)\ a\ \mathbf{E}\ \sin(\boldsymbol{\phi}), \tag{6}$$

$$\mathbf{E} = \mathrm{diag}\left(\mathbf{p} - \hat{\mathbf{p}}\right), \tag{7}$$

where $\boldsymbol{\omega} \in \mathbb{R}^m$ is the vector of frequencies, $\boldsymbol{\phi} \in \mathbb{R}^m$ is the vector of the corresponding phases, $a \in \mathbb{R}$ is a coupling constant and $\mathbf{E} \in \mathbb{R}^{m \times m}$ is a diagonal matrix with the error between the input signal $\mathbf{p}$ and the estimate $\hat{\mathbf{p}} \in \mathbb{R}^m$. The vector of estimates $\hat{\mathbf{p}} = [\hat{p}_1, ..., \hat{p}_m]^T$ is given by:

$$\hat{p}_i = \sum_{c=0}^{M} (\alpha_{i,c} \cos(\mathrm{c}\phi_\mathrm{i}) + \beta_{i,c} \sin(\mathrm{c}\phi_\mathrm{i})), \quad i = 1, 2, ..., m, \tag{8}$$

where the parameter M is the number of Fourier components. The amplitudes $\alpha_{i,c}, \beta_{i,c}$ are updated according to the following rule:

$$\dot{\alpha}_{i,c} = (1-\kappa)\ \eta\ \cos(c\phi_i)\ e_i, \tag{9}$$

$$\dot{\beta}_{i,c} = (1-\kappa)\ \eta\ \sin(c\phi_i)\ e_i, \tag{10}$$

where η is the learning constant and the error e_i is the i^{th} diagonal element of $\mathbf{E}$. Notice that the adaptation rate of the parameters in (5), (6), (9), (10) is reduced while the automation level increases ($\kappa \to 1$) and completely stops when the robot is fully autonomous ($\kappa = 1$). An intervention by the operator thought the application of an external force/torque causes the automation level to drop and the adaptation of the oscillators to be re-enabled.

Parameters a, η determine the speed of convergence and the parameter M determines the accuracy of the approximation. A sinusoidal input signal can be accurately approximated with M=1. A more complex periodic signal requires more components. If we encode the complex input signal from a demonstration using less components than required, the system will learn only the strongest frequency component which is sufficient in our case, since the proposed system requires only the basic frequency. On the other hand, when more components than required are utilized, some will either converge to the same frequency or to zero frequency [20].

In the simple case when the demonstrated movement is a circle on a plane ($m = 2$), the vector $\boldsymbol{\omega}$ will converge to approximately equal frequencies. However, a slightly more complex demonstration such as the shape "8" on a plane, as the one shown in Fig. 2, consists of two frequencies where one of them is twice the value of the other. By selecting the minimum frequency for both of them according to (1), the value of Ω can be used as a common clock for the motion generation system in each coordinate. However, this can affect the accuracy of the approximated trajectory, but as we demonstrate in the experiments, this is not a problem when the frequency difference is not high. Moreover, this problem can be resolved by utilizing more basis functions in the periodic DMP that we present in the following subsection.

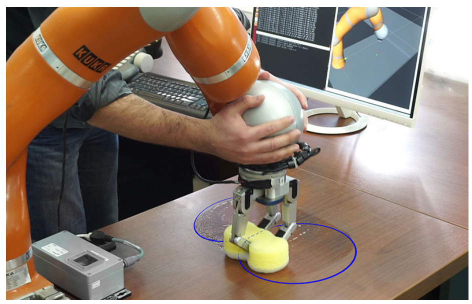

Fig. 2. Demonstrating kinesthetically a periodic wiping movement of shape "8" on a surface.

2.4 Periodic DMP

In parallel with the learning of the frequency, the waveform of the demonstrated trajectory is also learned with periodic DMP which produce the reference trajectory $\mathbf{p}_d$ to the impedance controller. This trajectory is specified by an attractor landscape towards an anchor point $\mathbf{g} \in \mathbb{R}^m$ and is governed by the phase $\Phi \in \mathbb{R}$ that is the common canonical system among the coordinates, given by:

$$\dot{\Phi} = \Omega, \quad \text{with } \Phi(0) = 0. \tag{11}$$

The reference trajectory is produced by the periodic DMP according to:

$$\dot{\mathbf{z}} = \Omega \left(a_y(\beta_y(\mathbf{g} - \mathbf{p}_d) - \mathbf{z}) + r \frac{\sum_{j=1}^{N} \mathbf{w}_j \Psi_j(\Phi)}{\sum_{j=1}^{N} \Psi_j(\Phi)} \right) \tag{12}$$

$$\dot{\mathbf{p}}_d = \Omega \mathbf{z}, \tag{13}$$

where a_y, β_y are constants and r is the amplitude control parameter which in this system is set to 1. Parameter N is the number of basis functions Ψ that are defined by:

$$\Psi_j(\Phi) = \exp(h(cos(\Phi - c_j) - 1)), \quad \forall\ j = 1, 2, ...,\ N \tag{14}$$

where $h,\ c_j$ are the width and centres of the basis functions over a period.

The weights in matrix $\mathbf{w} \in \mathbb{R}^{m \times N}$ are updated online with recursive least squares. Each weight vector $\mathbf{w}_j \in \mathbb{R}^m$ of the basis function Ψ_j is updated with the Recursive Least Squares algorithm (RLS) [15]:

$$\mathbf{w}_j(t+1) = \mathbf{w}_j(t) + \Psi_j\ \mathrm{diag}(\mathbf{P}_j(t+1))\ \mathbf{e}_{r_j}(t), \tag{15}$$

where $\mathbf{P}_j \in \mathbb{R}^m$ is the vector of inverse covariance associated to the weights $\mathbf{w}_j$ with a forgetting factor λ and with elements of $\mathbf{P}_j$ $(i = 1, 2, ..., m)$:

$$P_{i,j}(t+1) = \frac{1}{\lambda}\left(P_{i,j}(t) - \frac{P_{i,j}(t)^2}{\frac{\lambda}{\Psi_j} + P_{i,j}(t)}\right). \tag{16}$$

The aim of the RLS is to minimize the error $\mathbf{e}_r$, which in this work is weighted by $(1-\kappa)$ to smoothly stop the learning when the robot is in the autonomous mode and to smoothly re-enable it when the operator intervenes to make modifications:

$$\mathbf{e}_{r_j}(t) = (1-\kappa)(\mathbf{f}_d(t) - \mathbf{w}_j(t)), \tag{17}$$

where $\mathbf{f}_d$ is the target trajectory shape:

$$\mathbf{f}_d = \frac{\ddot{\mathbf{p}}}{\Omega^2} - a_y(\beta_y(\mathbf{g} - \mathbf{p}) - \frac{\dot{\mathbf{p}}}{\Omega}). \tag{18}$$

Notice in (17) that when the automation level is $\kappa = 1$, the error $\mathbf{e}_r$ is zero and the adaptation of the DMP weights stops.

2.5 The proposed controller for progressive automation

To achieve progressive automation with variable robot stiffness, the following Cartesian impedance is achieved, considering a n-dof manipulator with gravity compensation, that imposes a desired Cartesian stiffness $\mathbf{K}_d \in \mathbb{R}^{6\times6}$ and damping $\mathbf{D}_d \in \mathbb{R}^{6\times6}$ without reshaping the inertia:

$$\mathbf{\Lambda}_x(\mathbf{q})\dot{\widetilde{\mathbf{v}}} + (\mathbf{C}_x(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{D}_d)\,\widetilde{\mathbf{v}} + \mathbf{K}_d\widetilde{\mathbf{x}} = \mathbf{F}_h, \tag{19}$$

where $\mathbf{F}_h \in \mathbb{R}^6$ is the external force from the operator, $\mathbf{q}, \dot{\mathbf{q}} \in \mathbb{R}^n$ are the robot joint position and velocity, $\widetilde{\mathbf{x}} \in \mathbb{R}^6$ is the generalized tracking error described as $\widetilde{\mathbf{x}} = [\widetilde{\mathbf{p}}^T\ \boldsymbol{\epsilon}_e{}^T]^T$ with $\boldsymbol{\epsilon}_e = \mathrm{vec}(\widetilde{\mathbf{Q}})$, where $\widetilde{\mathbf{Q}} = \mathbf{Q} * \mathbf{Q}_d^{-1}$ is the quaternion error between the desired orientation $\mathbf{Q}_d$ and the current orientation $\mathbf{Q}$ of the robot end-effector. The velocity error is described as $\widetilde{\mathbf{v}} = [\dot{\widetilde{\mathbf{p}}}^T\,\widetilde{\boldsymbol{\omega}}^T]^T$ where $\widetilde{\boldsymbol{\omega}} = \boldsymbol{\omega} - \boldsymbol{\omega}_d$. Within this paper, we consider a fixed orientation of the end-effector with a constant $\mathbf{Q}_d$ and $\boldsymbol{\omega}_d = \mathbf{0}_{3\times1}$. By setting the desired Cartesian inertia equal to the robot's inertia $\mathbf{\Lambda}_x$, we avoid the direct feedback of $\mathbf{F}_h$.

For a constant desired stiffness $\mathbf{K}_d$ and $\mathbf{D}_d = \left[d_p\mathbf{I}_{3\times3}\ \mathbf{0}; \mathbf{0}\ d_r\mathbf{I}_{3\times3}\right]$, it can be easily proved that the system is passive with respect to the pair $\widetilde{\mathbf{v}}$, $\mathbf{F}_h$ [10]. In this work we consider a constant orientation of the end-effector, hence we choose a high constant torsional stiffness (with $k_{rot}\mathbf{I}_{3\times3}$) but a variable stiffness in the translation (2). Since $\mathbf{K}_d$ is now a variable matrix, then the system can lose its passivity property [6]. This problem can be overcome by introducing the varying stiffness $\mathbf{K}_v$ (with $m = 3$), of the translational components via a tank energy system, as proposed in [1,6,21]. The concept is that a virtual bounded energy is transferred from and to the dynamic system of the robot so that the whole system is passive. Thus, the variable stiffness applied by the progressive automation controller is defined as follows:

$$\mathbf{K}_d = \begin{bmatrix} \beta_r(p_t, v)\mathbf{K}_v & \mathbf{0}_{3\times3} \\ \mathbf{0}_{3\times3} & k_{rot}\mathbf{I}_{3\times3} \end{bmatrix}, \tag{20}$$

where $v = -\widetilde{\mathbf{p}}\mathbf{K}_v\dot{\widetilde{\mathbf{p}}}$ and p_t is the virtual tank energy described by:

$$\dot{p}_t = d_p\frac{\mu(p_t)}{2}\dot{\widetilde{\mathbf{p}}}^T\dot{\widetilde{\mathbf{p}}} + \beta(p_t, v)\widetilde{\mathbf{p}}^T\mathbf{K}_v\dot{\widetilde{\mathbf{p}}}. \tag{21}$$

The functions $\mu(p_t)$, $\beta(p_t)$, $\beta_r(p_t)$ are defined in [10,11] and control the flow of the energy between the energy tank and the robot so as p_t belongs to $\mathcal{C}$ for all $t \geq 0$ with $\mathcal{C} = \{p_t \in \mathbb{R}^{\geq 0} : p_t \leq \overline{p}_t\}$ where $\overline{p}_t > 0$ is the upper limit of the virtual energy.

The whole system can be written in the following state space form:

$$\dot{\mathbf{s}} = \mathbf{H}(\mathbf{s}, \mathbf{F}_h),\ \mathbf{s}_0 = \mathbf{s}(0) \in \mathcal{Z} \tag{22}$$

where $\mathbf{s} = [\widetilde{\mathbf{v}}^T\ \boldsymbol{\xi}^T\ p_t]^T \in \mathcal{Z}$, $\mathcal{Z} = \{\mathbf{s} : \mathbf{s} \in \mathbb{R}^6 \times (\mathbb{R}^3 \times \mathbb{S}^3) \times \mathcal{C}\}$ with $\boldsymbol{\xi} = [\widetilde{\mathbf{p}}^T\ \widetilde{\mathbf{Q}}^T]^T$and

$$\mathbf{H}(\mathbf{s}, \mathbf{F}_h) = \begin{bmatrix} \boldsymbol{\Lambda}_x^{-1}\left(-\left(\mathbf{C}_x + \mathbf{D}_d\right)\widetilde{\mathbf{v}} - \mathbf{K}_d\widetilde{\mathbf{x}} + \mathbf{F}_h\right) \\ \mathbf{J}_x\widetilde{\mathbf{v}} \\ d_p\frac{\mu(p_t)}{2}\dot{\widetilde{\mathbf{p}}}^T\dot{\widetilde{\mathbf{p}}} + \beta(p_t, v)\widetilde{\mathbf{p}}^T\mathbf{K}_v\dot{\widetilde{\mathbf{p}}} \end{bmatrix} \tag{23}$$

where $\mathbf{J}_x = \mathrm{diag}\left(\mathbf{I}_{3\times3}\ ,\ \frac{1}{2}\mathbf{J}_{\widetilde{Q}}\right) \in \mathbb{R}^{7\times6}$, with $\mathbf{J}_{\widetilde{Q}}$ is the matrix which maps the angular velocity error to $\dot{\widetilde{\mathbf{Q}}}$. i.e., $\dot{\mathbf{Q}} = \mathbf{J}_{\widetilde{Q}}\widetilde{\boldsymbol{\omega}}$ which is valid for $\boldsymbol{\omega}_d = \mathbf{0}$, which is true in our case as we consider a constant orientation.

Using the storage smooth function:

$$V = \frac{\widetilde{\mathbf{v}}^T\boldsymbol{\Lambda}_x\widetilde{\mathbf{v}}}{2} + (\mathbf{Q} - \mathbf{Q}_d)^T k_{rot}(\mathbf{Q} - \mathbf{Q}_d) + p_t, \tag{24}$$

its time derivative yields:

$$\dot{V} \leq -\widetilde{\mathbf{v}}^T\mathbf{D}_x\widetilde{\mathbf{v}} + \mathbf{F}_h^T\widetilde{\mathbf{v}} \tag{25}$$

while $\mathbf{D}_x = \text{diag}\left(\frac{d_p}{2}\mathbf{I}_{3\times 3}\ ,\ \ d_r\mathbf{I}_{3\times 3}\right) \in \mathbb{R}^{6\times 6}$. Hence, (23) is strictly output passive under the exertion of the user force $\mathbf{F}_h$ with respect to the output $\widetilde{\mathbf{v}}$ (see Definition 6.3 in [12]).

Notice that if the manipulator is redundant, (22) describes the Cartesian behavior but not the nullspace behavior. However, introducing an extra control signal like the one proposed in [17] the passivity in the redundant manipulator can be guaranteed.

3 Experimental evaluation

To verify the effectiveness of the proposed method, an operator was asked to demonstrate periodic movements to a 7-DOF KUKA LWR4+ robot, as it is shown in Fig. 2. The operator demonstrated a movement until the robot was able to execute it autonomously and then modified the learned task spatially or temporally. In these experiments we only considered movement in the translation components of the end-effector by keeping a constant orientation (k_{rot}=100Nm/rad) and using the parameters of Table 1. The operator's force $\mathbf{F}_h$ was estimated from the robot's internal torque sensors. Two series of experiments were conducted, one with demonstration of free-space movements to evaluate the ability of the system in encoding a planar periodic movement, and another with a more practical application of progressively automating the wiping of a surface while keeping a constant normal force[1].

3.1 Free-space movements

In the first set of experiments, the user demonstrated periodic planar movements without considering contact with the environment. For m=2, we chose a high stiffness for the Z direction with $K_v^Z = k_{max}$. The user initially demonstrated four different planar movements throughout this experiment. The results of the demonstrated tasks on the XY plane are depicted in Fig. 3. In particular, the robot's position $\mathbf{p}$, the DMP trajectory $\mathbf{p}_d$, the adapted basic frequency Ω, the automation level κ and the user's force $\mathbf{F}_h$ are shown in Fig. 3a-e. At the beginning of the experiment, the user started demonstrating a small circular motion of Ω=2.4rad/s. After t=15s, when the DMP has successfully encoded the trajectory and the frequency oscillators have extracted the basic frequency, the automation level increases towards κ=1 and the adaptation stops. The user then stops interacting with the robot, which continues to execute the circular motion autonomously. At t1=24s the trajectory has been encoded by the system as it is shown in Fig. 3f. At approximately t=34s the operator starts interacting again with the robot and applies a force in order to demonstrate a circular motion of bigger radius at another location. The application of the high force (Fig. 3e) reduces the automation level at κ=0 and re-activates the adaptation

[1] Video of the experiment: `https://youtu.be/uWM8VlM5y-A`

until the system has learned the parameters for the new circular motion that is shown in Fig. 3g with Ω=1.8rad/s. Similarly, at t=66s the user intervenes again in order to increase the frequency of the circular motion to Ω=2.6rad/s (Fig. 3h). Finally, at t=96s the user intervenes to demonstrate a shape “8” movement. While at the circular motions the frequency components are almost the same, in this motion pattern the frequency ω_2 in the Y coordinate is twice the ω_1 (Fig. 3c). Nevertheless, the shape has been successfully encoded (Fig. 3i) with the basic frequency of 1.1rad/s after just 3 demonstrated periods. During this experiment, the state p_t of the energy tank remains below the upper level $\overline{p}_t$=10 with $\beta_r(p_t, v) = 1$, so it is not illustrated. In the case the level of the tank overflows, the term $\beta_r(p_t, v) < 1$ will cause reduction of the target stiffness to maintain passivity.

Table 1. Parameters Values

Param	Value	Param	Value	Param	Value
k_{max}	2500	α	50	N	30
f_r	1	η	1	λ	0.999
f_{min}	0.01	M	1	a_y	20
λ_1	0.02m	λ_2	10N	β_y	5

3.2 Force controlled wiping task

In this experiment, the user’s objective was to progressively automate a surface wiping task, while the robot applied a normal force to the surface with a sponge attached to its wrist, as shown in Fig. 2. To this aim, a hybrid impedance/force controller was implemented [19] by setting K_v^Z=0N/m in the Z direction and by adding the term $\mathbf{F}_f \in \mathbb{R}^6$ in the left part of (19), which is a PI force controller with a feed-forward:

$$\mathbf{F}_f = [0, 0, F_f^Z, 0, 0, 0]^T, \tag{26}$$

$$F_f^Z = f_{sp} + k_P(F_h^Z - f_{sp}) + k_I \int (F_h^Z - f_{sp})\mathrm{d}t, \tag{27}$$

where k_P=1, k_I=1 are the gains of the PI controller, f_{sp}=10N is the set-point for the desired normal force and F_h^Z is the reaction force along the Z direction estimated by the robot.

The results of the wiping task are presented in Fig. 4. After the contact of the robot with the environment is established at t=2.5s (Fig. 4f), the user starts demonstrating at t=5s a periodic wiping pattern on the surface. The proposed method achieves progressive automation within approximately 15s, having learned the frequency and the waveform of the pattern successfully (Fig. 4c,g). The robot is at maximum stiffness after t=18s (with κ=1) and the user stops interacting with the robot at 20s (Fig. 4e). Then, the robot continues executing the task autonomously maintaining the desired force f_{sp}.

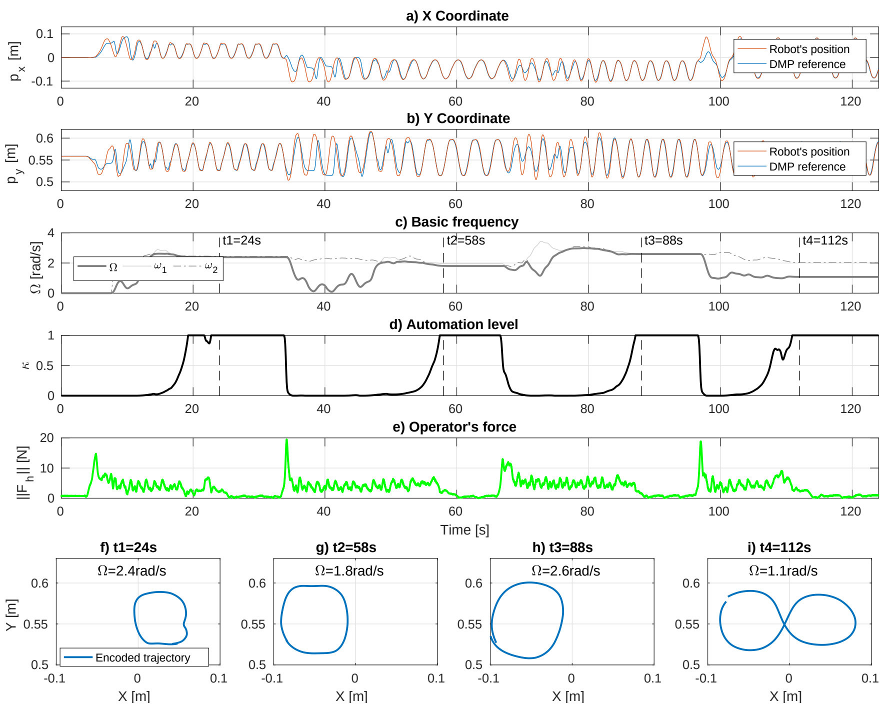

Fig. 3. Experimental results of the proposed method where a user demonstrates periodic movements in 2D and then makes modification.

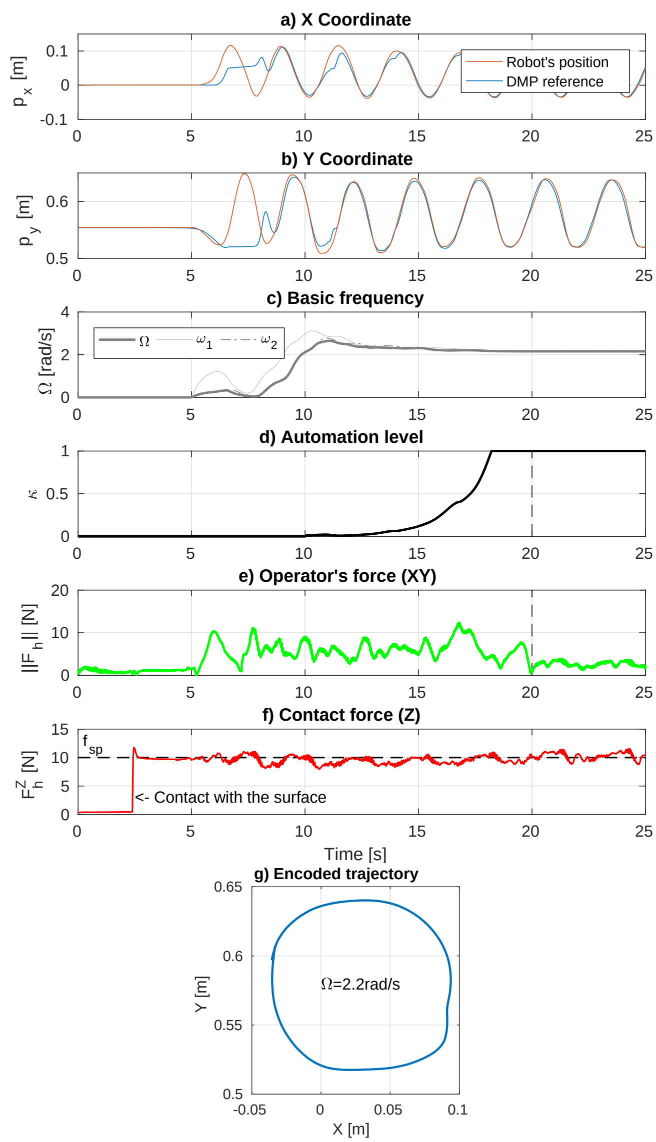

Fig. 4. Progressive automation of wiping on a surface while keeping a desired contact force.

Notice that in this experiment, only the XY components of the external force $\mathbf{F}_h$ (Fig. 4e) and of the tracking error $\widetilde{\mathbf{p}}$ are considered for the role allocation strategy of Eq. (4). While the robot moves autonomously and the user has stopped interacting with it, non-zero forces appear in the XY components of $\mathbf{F}_h$ because of the friction between the sponge and the surface (shown in Fig. 4e for t>20s). To prevent these disturbances and the tracking errors they produce from reducing the automation level κ, the parameters λ_2, λ_1 need to be set higher than the values of the disturbances respectively. Also, notice that the proposed method assumes knowledge of the surface orientation to correctly define the position and force subspaces.

4 Conclusions

In this work we have proposed the progressive automation of periodic movements, extending our previous work. Adaptive frequency oscillators and periodic DMP are combined with a role allocation strategy to adjust the adaptation rate and to seamlessly transition between kinesthetic robot guidance and autonomous operation. The proposed method is verified experimentally with an operator demonstrating periodic tasks in the free-space and in contact with the environment. In all of the experiments the robot was able to learn and autonomously execute a task very quickly, within 15s to 20s of demonstration. The user was able to intuitively determine when the robot had reached maximum stiffness and could very easily intervene to make modifications. Future work includes the achievement of progressive automation under uncertain surface orientation with a thorough passivity analysis of the hybrid controller and the ability to learn tasks that involve transitions between periodic and discrete movements.

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