Learning optimal variable admittance control for rotational motion in human-robot co-manipulation

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Abstract: *In this paper the problem of variable admittance control in human-robot cooperation tasks is investigated, considering rotational motion of the robot's end-effector. A Fuzzy Model Reference Learning algorithm is used to determine online the appropriate virtual damping of the admittance controller with partial state representation of the system. The learning algorithm is trained according to the minimum jerk trajectory model for rotational motion by exploiting the measured angular velocity and the torque applied by the operator. Experiments conducted for a rotational movement of an LWR robot in cooperation with multiple subjects, indicate that the method is able to react to the movement characteristics, by improving low effort cooperation and accurate positioning.*

Keywords: rotational motion, variable admittance control, human-robot cooperation, fuzzy model reference learning.

1. INTRODUCTION

Physical interaction of a human with a robot is a rapidly emerging field that aims to combine the complementary skills of the two. Tasks that can benefit from such a synergy include effortless cooperation for carrying long or heavy objects, programming by demonstration, precise co-manipulation of objects for assembly, and robotic surgery. A widely used control scheme that allows the compliant behaviour to external forces is admittance control (Hogan, 1984). This technique imposes a relationship of a mass-spring-damper system between the applied forces/torques and the motion of the manipulator.

Ikeura et al. (1994) showed that the virtual damping is the most dominant parameter of the admittance controller in the effectiveness of the cooperation. Low damping facilitates the capability of the robot to follow the operator's movements without applying high resistive forces/torques, but it limits the accuracy in fine positioning tasks because the manipulator becomes over-responsive. This problem has been addressed with variable admittance control, a technique to regulate online the admittance parameters during the cooperation. Using variable admittance, the damping can remain low during fast movements and it can be increased automatically only when the operator intends to position the robot with high accuracy. In the literature, a plethora of techniques appear that implicitly estimate the operator's intention and regulate the admittance gains either with intuitive methods based on trial and error, as in Erden and Marić (2011); Duchaine and Gosselin (2007); Lecours et al. (2012); Bascetta et al. (2013) or by using optimisation criteria as in Tsumugiwa et al. (2002); Ficuciello et al. (2014); Dimeas and Aspragathos (2014).

A typical co-manipulation task involves the human being the leader of the motion and the robot being the follower. Since the interaction point lies at the robot's end-effector, the admittance controller is expressed as a decoupled controller along the Cartesian frame attached to the end-effector. Although the controller enables the compliant behaviour in both the translational and rotational directions, the rotational motion of the end-effector remains a challenging task since it is not as straightforward as a translation. Specifically, the representation of the robot's orientation with Euler angles and the effect of tool weight in the torque measurements, significantly limit the seamless implementation of rotational motions during cooperation. To the authors' knowledge the problem of variable admittance control for efficient human-robot co-manipulation in rotational movements has not been addressed, since in the vast majority of the literature only the translational motion is investigated.

In previous work by Dimeas and Aspragathos (2014), a Fuzzy Model Reference Learning Controller (FMRLC) was proposed that combines human domain knowledge and a supervised learning algorithm in order to regulate online the virtual damping during a point-to-point cooperative translational motion, towards the minimum jerk trajectory model (Flash and Hogan, 1985). The minimum jerk model describes the trajectory followed by the human arm both for translational and rotational motions. By learning a variable damping policy that minimises the deviation of the human-robot cooperative trajectory from that model a smooth motion is facilitated and the cooperation becomes more efficient with respect to the operator's effort. The

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optimisation of the variable admittance controller occurs through the supervised learning procedure of the FMRLC.

In this paper, we introduce a variable admittance controller that regulates the virtual damping for rotational motion in human-robot cooperation, by extending the FMRLC method. Using partial state representation of the system, the controller is trained to regulate the virtual damping appropriately by minimising the trajectory deviation of the cooperative rotational motion from the minimum jerk model. The trained system is able to regulate the virtual rotational damping by reducing the required effort for the cooperation and by facilitating accurate positioning. The problem of tool weight compensation in rotational motion is encountered using an online tool compensation technique. The proposed system is validated experimentally in an experimental setup with a number of subjects using a KUKA LWR robot.

2. LEARNING VARIABLE ADMITTANCE FOR ROTATIONS

2.1 Description of the Admittance Controller

A human-robot cooperation task involves the operator interacting with the robot by applying forces and torques to the end-effector and by moving it to a desired position and orientation respectively (as illustrated in the photo of Fig. 1). The admittance control scheme imposes a desired dynamic behaviour to the manipulator along and around the Cartesian directions of the frame attached to the end-effector that is described from:

$$\mathbf{M_d}\dot{\mathbf{V}}_{\mathbf{ref}} + \mathbf{C_d}\mathbf{V}_{\mathbf{ref}} = \mathbf{F_h} \tag{1}$$

where $\mathbf{V}_{\mathbf{ref}} \in \mathbb{R}^6$ is the desired robot Cartesian velocity and $\mathbf{F_h} \in \mathbb{R}^6$ the input force/torque vectors, composed from a linear and angular part:

$$\mathbf{V}_{\mathbf{ref}} = \begin{bmatrix} \dot{\mathbf{p}}_r \\ \boldsymbol{\omega}_r \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \text{ translational velocities} \\ \in \mathbb{R}^3, \text{ angular velocities} \end{matrix}$$

$$\mathbf{F_h} = \begin{bmatrix} \mathbf{f}_h \\ \boldsymbol{\tau}_h \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \text{ forces} \\ \in \mathbb{R}^3, \text{ torques} \end{matrix}$$

The admittance controller gains $\mathbf{M_d}, \ \mathbf{C_d} \in \mathbb{R}^{6\times 6}$ are positive definite diagonal matrices that describe a decoupled controller in the Cartesian frame and represent the desired inertia and damping of the second order-relationship that is imposed to the manipulator. The virtual stiffness $\mathbf{K_d}$ term is omitted because in the case of cooperation in free space, no restoring forces/torques are desired to the equilibrium point of the virtual spring.

The desired Cartesian velocities $\mathbf{V}_{\mathbf{ref}}$ from Eq. (1) can be transformed into robot joint velocities $\dot{\mathbf{q}}_{\mathbf{ref}} \in \mathbb{R}^6$ for an 6-DOF manipulator using the inverse Jacobian matrix:

$$\dot{\mathbf{q}}_{\mathbf{ref}} = \mathbf{J}^{-1}(\mathbf{q})\mathbf{V}_{\mathbf{ref}} \tag{2}$$

and be provided to the manipulator's position control system via incremental joint position commands. $\mathbf{J}(\mathbf{q})$ is the Jacobian matrix expressed in the end-effector frame {C}, as it is illustrated in Fig. 2. In the case of n-DOF redundant manipulators (n >6), where $\mathbf{J}$ is a non-square matrix, the transformation of Eq. (2) still can be acquired using the pseudo-inverse of $\mathbf{J}$. The actual velocity $\mathbf{V}$ of the end-effector is realised by the inner joint control of the robot that operates at higher sampling frequency than the

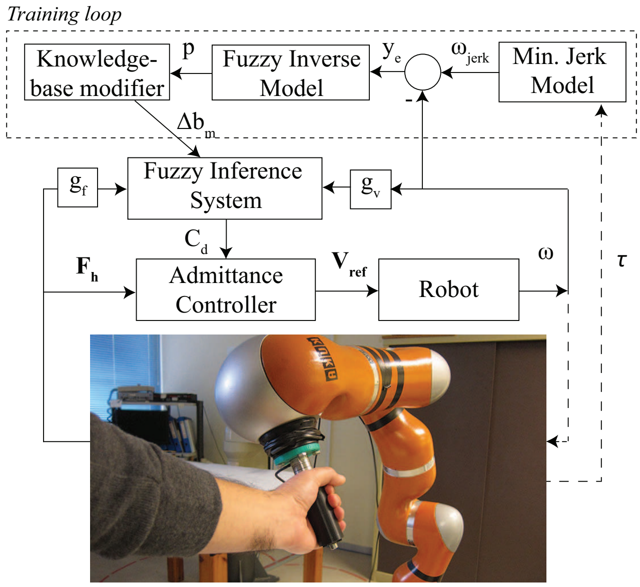


Fig. 1. Fuzzy Model Reference learning of variable admittance control for human-robot cooperation in rotational motion.

admittance control loop of Eq. (1). This control scheme is also known as position based admittance control and can be implemented in the majority of motion controlled robots.

Among the admittance control gains $\mathbf{M_d}$ and $\mathbf{C_d}$, we focus on the damping parameter because it has a greater impact on the effectiveness of the cooperation than the inertia (Ikeura et al., 1994). The gains can be interpreted physically, since by applying a force/torque $\mathrm{F_h^i}$ along/around the i^{th} direction of the frame attached to the end-effector, the operator perceives that the robot has an inertia $\mathrm{M_d^{ii}}$ in that direction and moves within a viscous environment of $\mathrm{C_d^{ii}}$. The lower the damping of the admittance, the more responsive the manipulator is to external forces/torques. A movement of the human arm in a reaching task can be divided into two major phases (Burdet and Milner, 1998): a high velocity motion with low accuracy to approach the target, that benefits from low damping, and a lower velocity motion for accurate positioning to the target that is facilitated with an increased damping.

The vector $\mathbf{F_h}$ can be measured either with a 6-DOF force/torque sensor mounted between the end-effector and the robot, or with estimation techniques from the joint torque sensors. In the majority of the literature for variable admittance, the applied torques are neglected by considering $\mathbf{F_h} = \mathbf{f}_h \in \mathbb{R}^3$. Without the ability to change the orientation of the end-effector, the usefulness of the robot is significantly reduced. In this paper, a method is proposed that allows the training of a supervised learning algorithm to regulate the damping coefficient of the admittance controller in rotational motion of the end-effector.

2.2 Fuzzy Model Reference Learning for Rotations

To regulate online the virtual damping of the admittance during cooperation, the current phase of the motion has to be obtained. It has been investigated in (Dimeas and Aspragathos, 2014) that the Cartesian velocities $\mathbf{V}$ and the applied forces $\mathbf{F_h}$ can be utilised to acquire the motion features in each direction independently. Fuzzy logic is a very efficient tool in order to determine the appropriate damping depending on the state of the system. A Fuzzy Inference System (FIS) implements a non-linear mapping between its inputs and outputs and is able to represent expert knowledge in the form of rules such as:

$$R_i := IF\ Force\ is\ PLarge\ AND\ Velocity\ is\ PLarge\ THEN\ Damping\ is\ VSmall$$

The terms "Force", "Velocity", "Damping" are the linguistic values of the inputs and output of the FIS. The terms "PLarge", "VSmall" represent the linguistic values that are used to describe the variables as "positive large" and "very small" respectively. Each linguistic value corresponds to a membership function. The rules of the knowledge base, the number, location and type of the membership functions incorporate the function approximation of the FIS. Although domain-knowledge can be embedded to the fuzzy system in the form of rules, the selection of the FIS parameters and consequently the damping produced by the FIS, is heavily based on the designers intuition.

In order to improve the performance of the cooperation, we incorporate a Fuzzy Model Reference Learning Controller (FMRLC) (Passino and Yurkovich, 1997) that has the ability to learn which is the most appropriate action though interaction with the environment. The training of the FMRLC is conducted during the cooperation of the human with the robot in a movement with predetermined start and target positions/orientations. In the case of pure translational motion, these positions can be everywhere within the reachable workspace of the manipulator, assuming that the robot does not go through a singular configuration. The trajectory can then be projected to the principal directions and be treated independently for each direction. For rotational motion around an arbitrary axis, a projection is not applicable because the rotation matrix describing the end-effector's orientation is derived using Euler angles, which represent sequential rotations around the principal axes. Changing the sequence of the rotations results into an altered orientation. Therefore the training either has to be conducted around a Cartesian direction of the end-effector frame {C}, or this frame has to be transformed in order to coincide with the desired rotational direction.

The training procedure investigated here involves a rotational movement between two orientations of the end-effector around an axis that coincides with the transformed frame {C}. Let $\mathbf{R}_0,\ \mathbf{R}_f \in SO(3)$ represent the initial and target orientation matrices of the end-effector relative the reference frame of the base of the robot {B} (see Fig. 2). The rotation to the target orientation $\mathbf{R}_f$ as observed from the initial orientation $\mathbf{R}_0$ is given by:

$$\mathbf{R}_{0f} = \mathbf{R}_0^T \mathbf{R}_f \tag{3}$$

According to Euler's transformation theorem, a rotation in 3D space can be considered as a single rotation by an angle θ around an axis represented by the unit vector $\hat{\mathbf{e}}$. Given the desired rotation $\mathbf{R}_{0f}$, the axis $\hat{\mathbf{e}}$ can be calculated from the eigenvector of $\mathbf{R}_{0f}$ that corresponds to the eigenvalue of 1. The angle θ_f is derived as:

$$\theta_f = cos^{-1}\frac{tr(\mathbf{R}_{0f}) - 1}{2},\ 0 < \theta_f \leq \pi \tag{4}$$

The learning mechanism of the FMRLC involves the minimisation of the error y_e, which is the difference of the actual angular velocity ω of the robot from the angular velocity ω_{jerk} of the minimum angular jerk model:

$$y_e = \omega_{jerk} - \omega \tag{5}$$

It was found in (Dimeas and Aspragathos, 2014) that by minimising the error y_e, the FMRLC is able to find a suitable policy to regulate the virtual damping so that the cooperative rotational motion approaches the minimum jerk trajectory. Such a policy produces smooth motion, assists low-effort cooperation and reduces the time required to accomplish a given task. The minimum jerk trajectory θ_{jerk} is the rotational trajectory followed by the human hand in a orientation-to-orientation motion (Flash and Hogan, 1985). This trajectory suggests that the change in angular acceleration throughout the movement is minimal and is given by the following equation:

$$\theta_{jerk}(\hat{t}) = \theta_0 + (\theta_f - \theta_0)(6\hat{t}^5 - 15\hat{t}^4 + 10\hat{t}^3) \tag{6}$$

where t_f is the duration of the motion, $\hat{t} = t/t_f$ $(0 \leq \hat{t} \leq 1)$ is the normalised time of the motion, $\theta_0 = 0$ is the initial angle and θ_f is the final angle of the rotation. In order to calculate the deviation y_e, we acquire the reference angular velocity ω_{jerk} from the first derivative of Eq. (6):

$$\omega_{jerk}(\hat{t}) = \theta_f(30\hat{t}^4 - 60\hat{t}^3 + 30\hat{t}^2) \tag{7}$$

The deviation y_e is then provided to an inverse model of the controlled system, which is a rough characterisation of the plant. The inverse model is a fuzzy system that consists of one input (y_e), one output (p) and has three membership functions, uniformly distributed around zero. The rule-base of the inverse fuzzy includes the following rules:

- IF y_e is zero THEN p is zero.
- IF y_e is positive THEN p is negative.
- IF y_e is negative THEN p is positive.

The term p is an instructive signal used by the knowledge-base modifier for the adaptation of the output membership functions of the forward FIS:

$$\Delta b_m(kT) = p\mu_m(\tau_h(kT - T), \omega(kT - T)) \tag{8}$$

At each time step (kT), the output membership functions centres b_m of the activated rules are adapted by the amount p and in proportion to the premise strength of the corresponding rule R_i from the previous time step ($kT - T$). A detailed description of the FMRLC can be found in (Passino and Yurkovich, 1997; Dimeas and Aspragathos, 2014)

2.3 Adaptive input scaling gains

The universe of discourse U_i for the fuzzy input variables τ_h, ω is typically the set of real numbers. The physical limits of the application such as the sensor limits and the maximum achievable velocity of the robot, confine the universe of discourse in a subset of the real numbers. Each linguistic value of the FIS uses a descriptive term (e.g. "VLarge") to characterise a fuzzy input variable. The linguistic values are quantified at the initialisation of the FIS according to the *effective* universe of discourse of each variable defined by the expected minimum and maximum values of that variable.

The cooperation task investigated here is an episodic task, in the sense that each movement begins and terminates at the target with zero velocity. Among consecutive episodes, the minimum and maximum values of the FIS input variables may differ because of the adaptation mechanism. In order to map the effective universe of discourse to that of the FIS, the scaling gains g_v, g_f are used for the angular velocity and torque respectively. These gains are constant during each movement and are calculated from the maximum absolute values of each variable from the previous episode:

$$g_i = \frac{U_i}{max(|u_i|)} \tag{9}$$

where $i = \{v, f\}$ is the index of the input variable, U_i the effective universe of discourse for that variable and u_i is the effective universe of discourse of the last episode. It is shown experimentally that a convergence of the FMRLC also yields convergence of the scaling gains.

2.4 Tool weight compensation

The forces/torques $\mathbf{F_h}$ applied by the operator are measured by a 6 DOF force/torque sensor mounted between the robot flange and the tool, as shown in Fig. 2. $\mathbf{F_h}$ is expressed relative to frame {C} attached to the sensor. Apart from the operator's forces/torques, the actual measurement also includes the tool weight $\mathbf{W} \in \mathbb{R}^6$ that has to be compensated in order to avoid any involuntary motion of the manipulator. When the sensor is initialised, all values of $\mathbf{F_h}$ are biased to zero. This removes the tool weight effect and uncalibrated measurements from the sensor such as the temperature effect on the strain gauges. However, a change in the orientation of the frame {C} reintroduces the tool weight in $\mathbf{F_h}$. This problem can be mitigated given the tool mass m_t and the position of the centre of mass $\mathbf{p}_C \in \mathbb{R}^3$ relative to {C}.

The tool weight force vector $\mathbf{W} \in \mathbb{R}^6$ consist of a force and a torque component and can be represented by a wrench (Murray et al., 1994):

$$\mathbf{W} = \begin{bmatrix} \mathbf{f}_W \\ \boldsymbol{\tau}_W \end{bmatrix} \begin{matrix} \in \mathbb{R}^3, \; \textit{forces} \\ \in \mathbb{R}^3, \; \textit{torques} \end{matrix} \tag{10}$$

The tool weight $\mathbf{W}$ is expressed relative to {T} as:

$$\mathbf{f}_W = [0 \;\; 0 \;\; -m_t g]^T \quad \boldsymbol{\tau}_W = [0 \;\; 0 \;\; 0]^T \tag{11}$$

The frame {T} is attached to the centre of mass and is expressed relative to the base frame {B} by the identity rotation matrix $\mathbf{R}_{BT} = \mathbf{I}$. The tool weight is given by expressing $\mathbf{W}$ with respect to {C} using the adjoint transformation (Murray et al., 1994):

$$\begin{bmatrix} \mathbf{f}_W^C \\ \boldsymbol{\tau}_W^C \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{CT} & 0 \\ -\mathbf{R}_{CT}\hat{\mathbf{p}}_T & \mathbf{R}_{CT} \end{bmatrix} \begin{bmatrix} \mathbf{f}_W^T \\ \boldsymbol{\tau}_W^T \end{bmatrix} \tag{12}$$

where $\mathbf{R}_{CT} = \mathbf{R}_{BC}^T \mathbf{R}_{BT}$ is known and $\hat{\mathbf{p}}_T$ is the skew-symmetric matrix of the vector $\mathbf{p}_T$, which represents the position of the origin O_C relative to the frame {T}. The vector $\mathbf{p}_T$ is obtained using a transformation from the invariant vector $\mathbf{p}_C$, which is the position of the origin O_T relative to {C}:

$$\mathbf{p}_T = -\mathbf{R}_{TC}\mathbf{p}_C \tag{13}$$

During initialisation of the sensor, when no external forces are applied, the sensor values include the uncalibrated measurements $\mathbf{F}_{uncal}$ and the tool weight at the initial configuration:

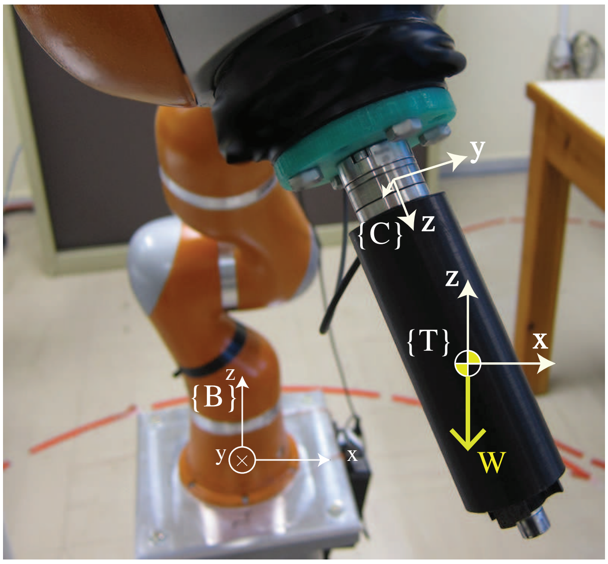


Fig. 2. Tool weight compensation from the 6DOF force/torque sensor at the robot's end-effector.

$$\mathbf{F}_{tot}^{init} = \mathbf{F}_{uncal} + \begin{bmatrix} \mathbf{f}_{W,init}^C \\ \boldsymbol{\tau}_{W,init}^C \end{bmatrix} \tag{14}$$

After the initialisation, the externally applied forces are calculated by subtracting the initialisation bias from the sensor measurement:

$$\mathbf{F}_{ext} = \mathbf{F}_{tot} - \mathbf{F}_{tot}^{init} \tag{15}$$

The total measurement $\mathbf{F}_{tot}$ consists of:

$$\mathbf{F}_{tot} = \mathbf{F_h} + \mathbf{F}_{uncal} + \begin{bmatrix} \mathbf{f}_W^C \\ \boldsymbol{\tau}_W^C \end{bmatrix} \tag{16}$$

By substituting (14), (16) in (15) the external force to the sensor is compensated by the tool weight and the operator's force is derived:

$$\mathbf{F_h} = \mathbf{F}_{ext} - \begin{bmatrix} \mathbf{f}_W^C \\ \boldsymbol{\tau}_W^C \end{bmatrix} + \begin{bmatrix} \mathbf{f}_{W,init}^C \\ \boldsymbol{\tau}_{W,init}^C \end{bmatrix} \tag{17}$$

3. EXPERIMENTAL EVALUATION

In order to evaluate the performance of the proposed variable admittance controls scheme, an experimental investigation is conducted using a 7DOF LWR manipulator in a cooperation task involving rotational motion around the X axis of the Cartesian frame {C}. In the experiment participated 7 subjects, aged from 23 to 32 years old, 5 of them are male, 2 female and all right handed. Each subject stands in front of the robot, where two targets are visually marked in a white surface, as it is illustrated in Fig. 3. A laser pointer attached to the end-effector projects a red dot onto the surface indicating the current orientation of the robot. The subject is then asked to cooperate with the robot by rotating the end-effector and move the red pointer from one target to the other, back and forth. A transition between the two orientations indicates an episode. Two sets of 30 episodes are recorded for each subject. The subject is informed that in each episode the robot will adapt it's behaviour in the sense that it might feel "lighter" or "heavier". After the experiment,

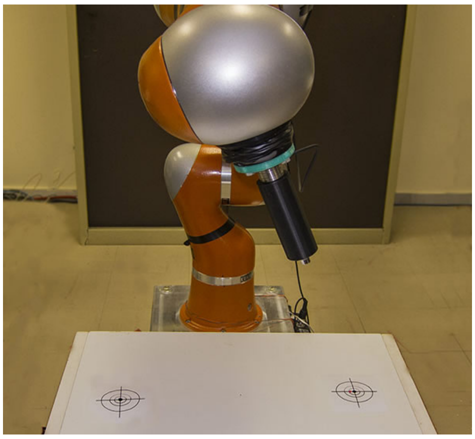


Fig. 3. Experimental setup for human-robot cooperation in a rotational motion between to targets.

each subject is asked to characterise the overall assistance provided by the manipulator as "helpful", "unhelpful" or "indifferent".

To accomplish the required task, the robot is constrained along and around all directions apart from the rotation around the X axis of frame {C}. The angle θ_f between the two orientations is $\pi/4$ rad and the desired duration of the movement is selected equal to $t_f = 1s$. The FIS is initialised using 5 triangular membership functions for each input and output, that are uniformly spread to the effective universe of discourse. The rule base is complete and consistent and is formed by 25 rules so that for each possible input pair there is a valid conclusion. In order to avoid subjectivity to the experimental results, the initial rule base for each subject at the beginning of each set is randomly selected using a uniform distribution between $c_d^{min} = 0Nms/rad$ and $c_d^{max} = 10Nms/rad$.

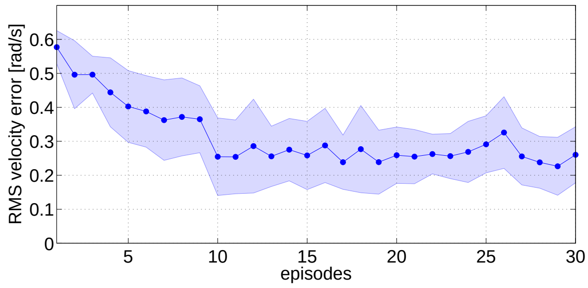
Instability of the human-robot system can occur for very low values of damping and virtual inertia. To prevent it, the virtual inertia during the experiment is constant and equal to half the effective inertia of the manipulator in the direction of the rotational motion, maintaining the passivity of the system. The effective mass around X axis (M_t) is calculated from:

$$\mathbf{M_t^{-1}}(\mathbf{q}) = \mathbf{J}(\mathbf{q})\mathbf{M^{-1}}(\mathbf{q})\mathbf{J^T}(\mathbf{q}) \tag{18}$$

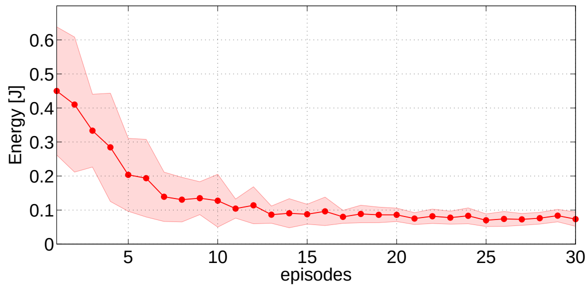
where $\mathbf{M} \in R^{7\times7}$ is the mass matrix of the manipulator's configuration space and $\mathbf{M_t} \in R^{6\times6}$ the effective mass in the frame {C}. A latching mechanism prevents the centres of output membership functions to drop to zero c_d^{crit} where the sensor noise deteriorates the cooperation. The critically low damping value is found experimentally equal to $c_d^{crit} = 0.1Nms/rad$.

3.1 Results

The derived results by the second set of experiments with all subjects are illustrated in Fig. 4a-d with the mean values (bold lines with dots) and standard deviation (coloured areas) for each episode. Since in the cooperation task there is a bilateral flow of information, not only the robot is trained according to the operator's behaviour but also the operator acquires knowledge on how to interact with the robot. In order to eliminate as much as possible



(a)



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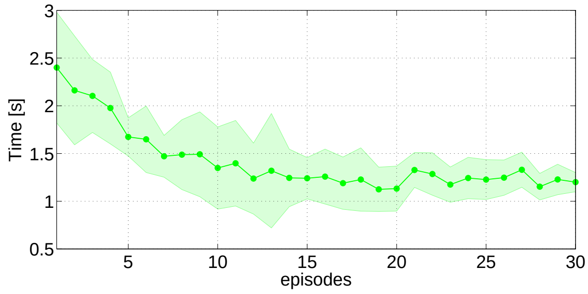

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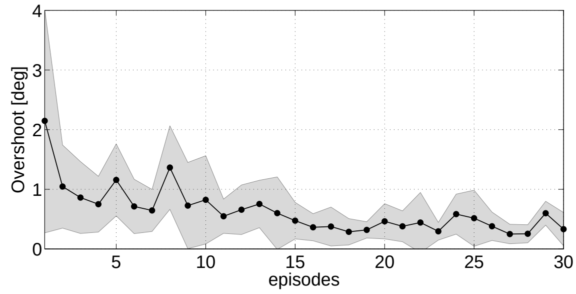
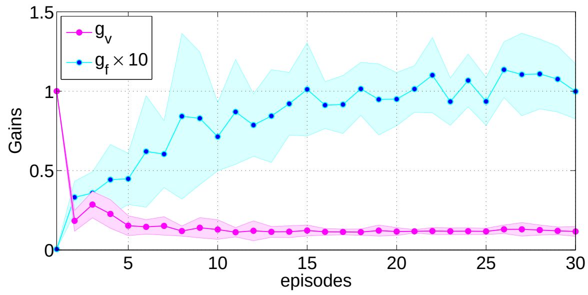


(d)



(e)

Fig. 4. Mean values (lines) and standard deviation (areas) of the RMS velocity error, the energy provided by the operator to the robot, time required to complete the movement, overshoot of the target and scaling gains.

the effect of the human factor in the training procedure, the second set of episodes is analysed here, assuming that the operator has obtained sufficient knowledge of the environment and is familiar with the cooperation task. The evaluation criteria selected, include the RMS value of the deviation y_e between the actual angular velocity and the minimum jerk angular velocity, the energy transferred from the operator to the robot to fulfil the movement calculated as $\int_0^{\theta_f} |\tau| d\theta$, the time required to complete each movement and the overshoot of the target.

The RMS velocity error illustrated in Fig. 4a, indicates the objective function that the proposed FMRLC tries to minimise by regulating the virtual damping. The training procedure is based on the assumption that if the trajectory of the cooperation follows the minimum jerk trajectory, then the cooperation is more effective. This assumption is verified because after 10 episodes the operator's effort is reduced and the accuracy of the positioning is increased. The mean value of the RMS error in episode 10 has been reduced by 56% relative to the initial values. The energy required by the operator (Fig. 4b) to rotate the robot is significantly decreased by 82%, indicating low-effort cooperation. The effectiveness of the cooperation is also evident by the 50% reduction of the total time required to complete the rotation, as it is shown in Fig. 4c. Low energy requirements and completion time can also be achieved with constant low virtual damping of the admittance controller. However, this makes the robot over-responsive to forces/torques. On the contrary, the proposed FMRLC is able to detect the phase of the movement and increase the damping in order to assist accurate positioning. The mean overshoot of the target orientation expressed in degrees, is illustrated in Fig. 4d and indicates that there is an improvement of approximately 80%.

Overall, the proposed method converges within 10 episodes. This can also be illustrated in Fig. 4e, where the scaling gains g_v, g_f of the FIS inputs are presented. All of the subjects characterised the assistance provided of the robot as "helpful". All of them also acknowledged that after the first 5 to 10 episodes the assistance provided by the robot improved significantly. Interestingly, some of the subjects pointed out that the robot *somehow* learned the target position and all they had to do is "give a little push". These results suggest that the proposed FMRLC training algorithm is able to successfully identify the movement characteristics and regulate the damping of the admittance controller accordingly for smooth and efficient cooperation.

4. CONCLUSION

A novel method is presented for regulating the damping parameter of a variable admittance controller in human-robot co-manipulation involving rotational motion. Using a FMLRC, the training of a fuzzy inference system is achieved that can determine the appropriate damping by implicitly identifying the phase of the movement through torque and angular velocity feedback. Using the minimum rotational jerk trajectory as a reference to the FMRLC, the experimental results with 7 subjects show that the proposed method can converge to a variable admittance policy that improves the operator's effort, the time required for the task and the accuracy of the positioning. This approach constitutes a systematic approach to regulate the admittance parameters, unlike trial and error methods proposed in the literature for variable admittance control in pure translational movements. The positive feedback provided by all subjects who participated in the experiment is very encouraging for the potentials of this method in optimising human-robot cooperation in arbitrary motions.

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