Fuzzy Learning Variable Admittance Control for Human-Robot Cooperation

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Abstract— **This paper presents a method for variable admittance control in human-robot cooperation tasks, that combines a human-like decision making process and an adaptation algorithm. A Fuzzy Inference System is designed that relies on the measured velocity and the force applied by the operator to modify on-line the damping of the robot admittance, based on expert knowledge for intuitive cooperation. A Fuzzy Model Reference Learning Controller is used to adapt the Fuzzy Inference System according to the minimum jerk trajectory model. To evaluate the performance of the proposed controller a point-to-point cooperation task is conducted with multiple subjects using a KUKA LWR robot.**

I. Introduction

Advances in robot control have enabled the cooperation between robots and humans through active compliant motion control of manipulators. Assisting robots that interact physically with a human can enhance the physical capabilities of the latter and can facilitate everyday tasks e.g. manipulation of heavy or long bulky objects. Particularly in industry, where assembly of heavy parts requires the high flexibility of the human, a cooperative manipulation would facilitate the task since it will reduce the burden from the human.

Impedance control [1] is widely used in physical human-robot interaction (pHRI), since it has the ability to establish a dynamic relationship between the robot and the environment. Instead of controlling the position or the force independently, the dynamic behaviour of the robot is regulated by modifying the parameters of virtual stiffness, damping and inertia. In human-robot collaboration, where the robot does not usually interact with stiff environments, admittance control is incorporated, which creates a mapping from forces into motion enabling the robot to comply to any forces applied by the human at a predefined manner.

Since it was shown that the most dominant parameter of admittance control in human-robot collaboration is the virtual damping [2], a lot of research has been conducted on tuning this factor for more intuitive interaction. A variable admittance control scheme was introduced in [3] to adapt the damping factor with respect to the speed of the cooperation. Duchaine et al. [4] adjusted the damping by estimating the human intentions from the differentiation of the force applied by the operator to the robot. A combination of the operator's velocity and acceleration was proposed in [5], however numeric differentiations yield noisy signals that require filtering and cause delays. Although the results with variable admittance on the mentioned papers demonstrate superior performance compared with constant admittance parameters in terms of intuitiveness, precision and transparency of motion, the functions that tune the parameters are obtained according to the researcher's intuition and in a heuristic manner.

A more systematic approach for adapting the robot admittance was proposed by Rahman et al. [6] who investigated the human arm characteristics. The authors identified the human arm impedance in a human-human cooperation task and derived a function to tune the robot damping accordingly for a similar human-robot task. A method to on-line estimate the human arm stiffness and adjust the damping coefficient accordingly was proposed by Tsumugiwa et al. [7]. Most of these methods along with others [8], [9] use the minimum jerk trajectory model [10], which suggests that the human arm moves with minimal acceleration during a point-to-point linear motion. However, this model requires a priori knowledge of the movement, that restricts the usage of these methods in unstructured tasks.

Summarizing, there are different approaches to implement variable admittance control in order to achieve effective interaction, which share the basic idea; the modification of the damping coefficient based either on monitored variables or optimisation criteria. On the one hand, by monitoring variables such as the velocity or the applied force by the human no optimal solution is guaranteed since the proposed algorithms are derived in a heuristic way. On the other hand, these optimisation techniques are task dependent and cannot be easily extended to other motion profiles.

In this paper, a method to combine human knowledge with a learning method is introduced for an optimal variable admittance control scheme. To emulate the human decision making process an on-line Fuzzy Inference System (FIS) is proposed that determines the desired damping of the admittance controller using only the joint position sensors of the robot and an external force sensor. In order to tune the FIS for optimal cooperation a Fuzzy Model Reference Learning Controller (FMRLC) is used for adapting the FIS towards the minimum jerk trajectory model. Although explicit knowledge is required for the FMRLC training procedure, the trained FIS presents better performance than the heuristically tuned FIS even in unknown motion profiles. The proposed system is evaluated on an experimental set-up of a linear point-to-point motion using a KUKA LWR robot and the performance is measured with a number of subjects in terms of the required effort and the overall completion time.

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II. Admittance Controller

In pHRI admittance control is mainly used because it can establish a dynamic relationship between the forces/torques applied to the robot and the displacement/velocity. In a human-robot cooperation task that is investigated here, the human acts as the leader and defines the motion, while the robot is the follower and must comply to the applied forces by the human. The admittance controller of the robot is described by a typical second-order relationship:

$$m_d \dot{V}_e + c_d V_e = F_h \tag{1}$$

where $V_e = V_{ref} - V$ is the deviation of the actual velocity from the reference velocity $V_{ref} = 0$, m_d is the virtual inertia and c_d the virtual damping. The virtual stiffness k_d is set equal to zero since no restoring force is desired. The operator by applying a force F_h, which is the input to the admittance, perceives a mass m_d in a viscous environment c_d. The virtual inertia has a negligible effect on the cooperation although it is suggested that it should be adjusted proportionally to the damping for stability issues [5]. Furthermore, the lower limits of the admittance parameters have to be defined to avoid unstable behaviour [11]. Before the parameter update law is developed, the cooperative motion is studied.

A. Cooperative Motion

In order to select the optimum parameters of the variable admittance controller the point-to-point movement of the human alone and then in cooperation with a robot is investigated. In both cases the motion follows the minimum jerk trajectory in a straight line [10] and can be divided into two phases; a rapid movement with low accuracy for approaching the target and a high accuracy movement with lower velocity for accurate positioning [12]. In a leader-follower cooperation between two humans a blindfolded follower that does not have knowledge about the target constantly adapts the impedance characteristics of his/her arm by following the same trajectory.

The minimum jerk trajectory minimizes the change in acceleration of the movement of the human hand and it is expressed by the following objective function:

$$M = \int_0^{t_f} \left\| \dddot{x} \right\|^2 dt \tag{2}$$

where t_f is the duration of motion. Assuming that the velocity at the beginning and end of the movement is zero ($\dot{x}_0 = \dot{x}_{t_f} = 0$) and that the movement takes place along a straight axis, the position as a function of time is:

$$x(t) = x_0 + (x_f - x_0)(6\tau^5 - 15\tau^4 + 10\tau^3) \tag{3}$$

where $\tau = t/t_f$, $0 \leq \tau \leq 1$ and x_0, x_f are the initial and final positions respectively. From Eq. (3) the velocity of the minimum jerk model can be calculated through numeric differentiation.

By monitoring the measured velocity during the cooperation and by adapting the admittance controller to the minimum jerk trajectory a human-like performance can be achieved. With large damping large force is required by the human but it is easier to perform high accuracy movements since the robot motion is smoother. On the other hand, low damping reduces the human effort in the expense of less accurate movements. In a point-to-point motion, the rapid movement phase would benefit from a low damping while a higher damping would assist the human in more accurate positioning. This observation raises the need for on-line adjustment of the damping parameter to enable both effortless motion and high precision.

B. Fuzzy Variable Admittance

For the development of low complexity and low cost robot assistants, the robots should use information from a minimum number of sensors with low computational cost, so computer vision techniques with visual cues are excluded. For the minimum jerk model explicit knowledge of the motion is required which is not efficient for arbitrary tasks. Therefore, we wish to combine expert knowledge with a learning algorithm for efficient human-robot cooperation on arbitrary point-to-point movements. Fuzzy logic is a very effective tool to represent expert knowledge with linguistic rules and create a human-like inference mechanism. Examples of fuzzy logic and impedance control can be seen in rehabilitation robotics [13] where a fuzzy inference system was implemented to adjust the controller parameters according to the patient's arm impedance.

In this paper an on-line fuzzy variable admittance control scheme is proposed that adapts on-line the damping coefficient. A point-to-point movement is selected on a single direction of the Cartesian workspace of the robot, as it is shown in Fig. 1. To minimise the cost and complexity of the proposed method only the joint position encoders of a robot are used along with a force/torque sensor at the end-effector. The proposed FIS is a standard fuzzy system [14] consisting of two inputs, the measured Cartesian velocity V along a single direction and the corresponding force F_h along the same direction. The output of the FIS is the virtual damping c_d of the robot admittance controller. For each input and output five triangular type membership functions are selected that are uniformly spread around zero. The selected rules form a complete and consistent rule base meaning that for every possible inputs there are valid conclusions. The

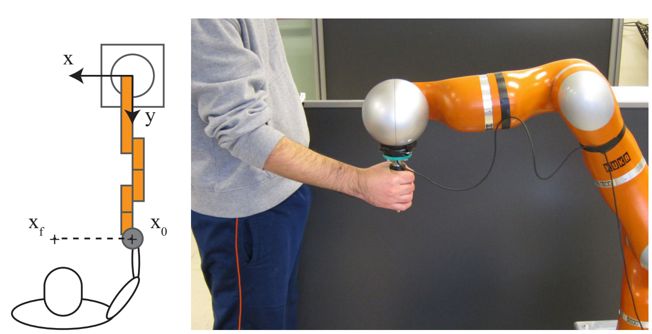

Fig. 1: Experimental set-up.

initial rule base for the FIS, that is shown in Tab. I, can be interpreted by the following sentences:

- IF Force is high (-2 or +2) AND Velocity is high (-2 or +2) THEN Damping is very low (1).
- IF Force is zero (0) AND Velocity is zero (0) THEN Damping is very high (5).
- IF Force is positive small (+1) AND Velocity is negative small (-1) THEN Damping is very high (5).

This initial rule base of the FIS is created in a heuristic manner. The selected rules reduce the damping when the velocity V and force F_h are high, to facilitate the rapid movements and increase the damping at lower velocities for smoother positioning. Alternatively, an arbitrary rule-base is created by assuming that there is no knowledge about the control of the plant. A comparison within these two alternatives is conducted in section IV.

C. Stability Considerations

In pHRI the human uses haptic and visual feedback from the plant to regulate his/her action. Therefore, the human is part of the controller and is very difficult to model and prove the overall stability of the system. Experimental studies on impedance control [15] showed that the robot could present unstable behaviour with very low virtual damping, high virtual inertia or stiff environment. It is suggested that the human arm has a maximum impedance [16], that occurs when the human stiffens his arm. To guarantee the stability of the proposed system, the lowest value of c_d^{crit} is experimentally found equal to $10Ns/m$, given a value for $m_d = 1kg$ and high stiffness of the operator's arm.

III. Fuzzy Model Reference Learning Controller

In this section a learning system is developed in order to improve the performance of the heuristically created FIS in section II. A Fuzzy Model Reference Learning Controller (FMRLC) is proposed that combines feedback information from the plant and a reference model in order to adapt the FIS system [14]. The FMRLC loop consists of the reference model, the fuzzy inverse model and the adaptation mechanism which is the knowledge-base modifier of the FIS, as it is illustrated in the block diagram of Fig. 2. The minimum jerk model of Eq. (3) is used as reference for adapting the FIS knowledge-base so as to perform similarly to a blindfolded human assistant that relies only on haptic information. During the cooperation, the error y_e between the actual measured velocity V and the minimum jerk model velocity V_{jerk} is calculated as:

$$y_e = V_{jerk} - V \quad (4)$$

and is passed to the Fuzzy Inverse Model (FIM). The FIM characterises the inverse function of the cooperation, has only one input and determines a value p that is used by the knowledge-base modifier to reduce the error y_e. Each input/output of the FIM consists of five triangular shaped membership functions evenly distributed around zero. Since the value y_e is the error between the velocities, the rules of the inverse model of the cooperation have the following form:

- 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 knowledge-base modifier adapts the FIS by adjusting the centres b_m of the output membership functions that are associated with the rules responsible for the previous controller action $V_{ref}(kT - T)$. T is the sampling period in the discrete time domain. The centres of the FIS output membership functions are then updated according to the following equation:

$$b_m(kT) = b_m(kT-T) + p\mu_m(F_h(kT-T), V(kT-T)) \quad (5)$$

This update formula shifts the centres $b_m(kT - T)$ by the amount p and in proportion to the certainty of the premise $\mu_m(F_h(kT-T), V(kT-T))$, $0 \leq \mu_m \leq 1$. In that way, the output membership functions with higher premise certainty are tuned at a larger amount because they have greater impact in the output c_d of the FIS. For example, if the actual velocity V during the cooperation at time kT is lower than the optimal minimum jerk velocity V_{jerk}, then $y_e > 0$ and $p < 0$. The knowledge-base modifier reduces the centres b_m according to Eq. (5) and the FIS produces a lower damping for the admittance controller, enabling the operator to move at a higher velocity with less effort. Such an adaptation algorithm creates an input-output mapping to the FIS between the velocity V, force F_h and damping c_d that facilitates the cooperation according to the minimum jerk trajectory model.

TABLE I: Manually tuned initial FIS rule-base.

Cd		F_h				
		−2	−1	0	1	2
V	−2	1	2	3	5	5
	−1	2	3	4	5	5
	0	3	4	5	4	3
	1	5	5	4	3	2
	2	5	5	3	2	1

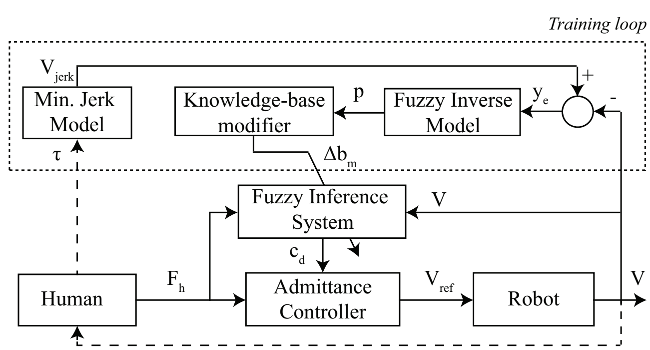

Fig. 2: Block diagram of the proposed fuzzy model reference learning variable admittance controller. The dashed line represents the proprioceptive visual and haptic feedback of the human operator.

To avoid unstable behaviour, the centres of the FIS must not drop below the critical damping value c_d^{crit}. To ensure stability and the safety of the operator the following latching criterion is added that restrains the minimum damping above $c_d^{crit} = 10Ns/m$:

$$If\ b_m(kT)\ <\ c_d^{crit}\ Then\ b_m(kT) =\ c_d^{crit} \tag{6}$$

The training (FMRLC) loop operates at the same frequency as the admittance control loop and the overall point-to-point motion is iterated a number of times until the method converges. After the training is completed, the FMRLC loop is no longer required, since the trained FIS has adapted to infer the optimal damping coefficient for cooperation. Although the selection of both the FIS and the FIM is conducted in a heuristic way, the trained FIS contains the association between the velocity, the force and the virtual damping adapted to the minimum jerk model rather than an association between the position and the damping. As a result, the FIS is not related explicitly to the minimum jerk model and it can be scaled to different movements as it is shown in section IV-B.

IV. Experimental Evaluation

The evaluation of the proposed variable admittance control scheme is conducted in two stages. The first stage includes the training process, where the FIS is adapted to the minimum jerk trajectory using the FMRLC and in the second stage the trained FIS is tested into different movements. The experimental set-up consists of a KUKA LWR IV robot with a force/torque sensor mounted at the end effector, as it is shown in Fig. 1. The human cooperates with the robot in a single direction of the Cartesian workspace using the handle. The force sensor measures the force F_h applied by the human, which is the input to the variable admittance controller. The output velocity of the admittance controller V_{ref} is translated into reference joint velocities $\mathbf{\dot{q}_{ref}}$ using the inverse Jacobian matrix:

$$\mathbf{\dot{q}_{ref}} = \mathbf{J^{-1}}(\mathbf{q})\mathbf{V_{ref}} \tag{7}$$

Since the redundant joint of the robot is not used, $\mathbf{J}(\mathbf{q})$ is the 6x6 Jacobian matrix, $\mathbf{\dot{q}_{ref}}$ a 6 element vector and $\mathbf{V_{ref}} = [V_{ref}\ 0\ 0\ 0\ 0\ 0]^T$ for motion into axis x of robot base Cartesian coordinates. Each joint incorporates an internal position controller and the reference velocity $\mathbf{\dot{q}_{ref}}$ is derived through incremental position commands:

$$\mathbf{q}(kT) = \mathbf{\dot{q}_{ref}}(kT)T + \mathbf{q}(kT - T) \tag{8}$$

where $T = 0.001s$ is the sampling period of the admittance control loop.

A. FMRLC Training

To train the FIS into the minimum jerk model of Eq. (3), the initial x_0 and final x_f position as long as the required time of the motion t_f have to be specified. In order to measure the time t_f, five subjects are recorded individually (without cooperating with another human or robot) during a linear constrained point-to-point motion with visible initial x_0 and final x_f positions. During the movement each subject holds a mass equal to $m_d = 1kg$ which is equal to the virtual mass used in the admittance controller later. After multiple iterations it is found that for a distance of 0.3 metres the mean time t_f for an individual human to complete the minimum jerk trajectory is 1.3 seconds with a standard deviation of 0.19 seconds.

The same movement is then conducted by a human in cooperation with the robot for the adaptation process. The human is asked to move the robot from the initial position $x_0 = 0m$ to the target $x_f = 0.3m$. A laser pointer attached to the handle projects the position of the robot to the ground where the initial and the target points are visually marked in order to assist the human with visual feedback. During the movement the FIS constantly calculates a corresponding damping according to the current velocity and force. The FMRLC measures the deviation y_e from the minimum jerk trajectory, which is known for the specific movement and adapts the FIS according to the knowledge-base modifier. The movement is repeated 10 times by a human and it is observed that the error y_e converges towards zero.

To evaluate the performance of the proposed adaptation method three different scenarios are investigated involving human-robot cooperation in a point-to-point motion. For each scenario the actual velocity V of the human-robot system over time τ is compared with the theoretical minimum jerk model velocity V_{jerk} as it is illustrated in Fig. 3. Specifically, in Fig. 3a the manually tuned FIS without the adaptation mechanism is investigated and the corresponding surface of the fuzzy system is illustrated. It is clear that the heuristic tuning of the FIS is insufficient for optimal results, since the mean velocity profile differs significantly from the minimum jerk model and the root mean square error (RMSE) is quite high (Tab. II). On the contrary, the FMRLC adaptation with the initial rule-base of Tab. I (shown in Fig. 3b) demonstrates very close approximation of the velocities to the optimal model and has the smallest RMSE. Finally, in Fig. 3c an arbitrary initial rule-base for the FIS is selected with the initial centres of all output membership functions being $b_m = 55,\ m = 1, 2, ..., 25$. Although, the initial FIS does not contain any knowledge about the plant, the mean velocity approaches the minimum jerk model at a large percentage with a small RMSE.

By comparing the surfaces of the resulted FIS it can

TABLE II: The root mean square error (RMSE) between the actual velocity and theoretical minimum jerk velocity, the mean values and standard deviation for the energy and completion time for the three different scenarios.

Method	RMSE	Energy (J)		Time (s)	
		mean	std	mean	std
Untrained FIS	0.0428	1.73	0.12	1.73	0.19
FMRLC with manual FIS	0.0264	1.57	0.09	1.55	0.11
FMRLC with arbitrary FIS	0.0271	2.80	0.12	1.73	0.14

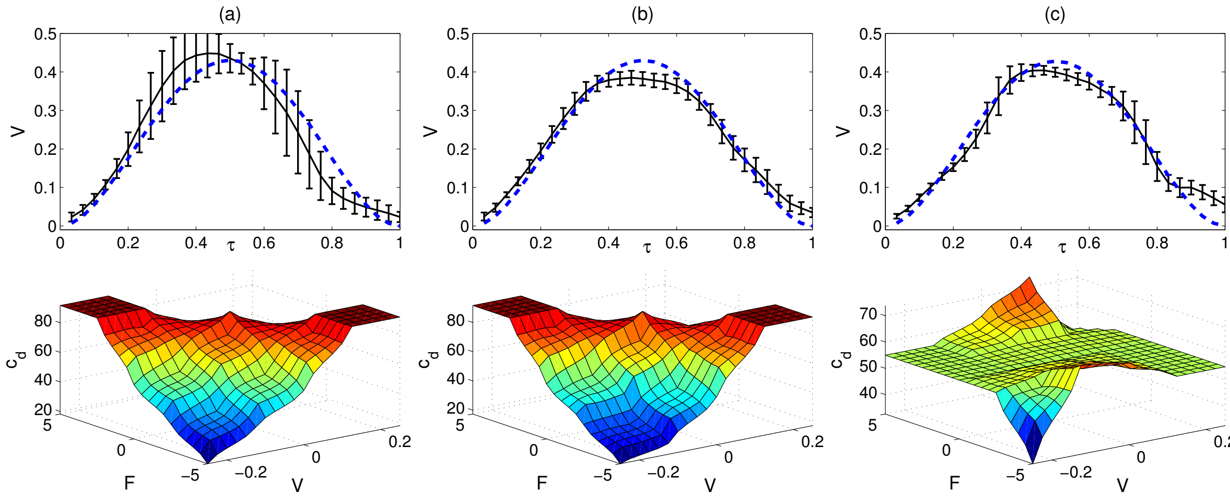

Fig. 3: Experimental results using (a) the untrained, (b) the trained FIS (FMRLC) with initial expert knowledge of Tab. I and (c) the trained FIS of the arbitrary initial knowledge-base. In the top row the mean measured velocities and the standard deviations (continuous lines with vertical bars) are overlaid on the optimum minimum jerk trajectories (dashed lines). In the bottom row are illustrated the input-output surfaces of the used FIS.

be concluded that the rules with the most impact on the performance of the overall system, include the cases where both the velocity V and the force F have the same direction (symmetric on positive and negative direction) and large values. For example, the surface of the arbitrary initial rule-base (Fig. 3c) has similar appearance to the manually tuned rule-base in the ranges around $F = -5N$ and $V = -0.2m/s$ (Fig. 3a). In such large values the desired damping should be as low as possible in order to assist the human. As it is depicted in the surfaces of Fig. 3a and Fig. 3c the FMRLC successfully adapts the variable admittance controller in the optimal values. Between surfaces (a) and (b), although differences are not very obvious, there is an improvement of the FMRLC over the manually tuned FIS as it is shown in Tab. II. The mean energy transferred by the human to the robot and the mean time required for completing the movement appear to be lower for the FMRLC with the initial rule base of Tab. I. The FMRLC with the arbitrary initial rule base requires the most effort for the human although the time required is similar to the untrained FIS. Summarizing the results, the combination of the human knowledge and the FMRLC adaptation algorithm presents the best performance in terms of human effort and completion time.

B. Testing

To validate the results of the trained FMRLC adaptation algorithm, the trained FIS with the initial rule base of Tab. I is tested against the untrained, manually tuned FIS into different movements that are unknown to the robot. The movements are performed by 12 subjects aged from 24 to 42 years old, ten of them male, two female and all right handed. One of the subjects participated in the training procedure and ten of them have never interacted with the robot before. Each subject is asked to grab the robot handle from the starting position, guide it to a target position, rest in that position for a second and guide it back to the starting position for a total of 10 point-to-point movements. A laser pointer in the handle projects a red dot in a white surface with marked targets in front of the subjects assisting them with visual feedback. For each subject, three different movements are conducted with distances $x_f = 0.2m,\ 0.3m,\ 0.4m$ and each movement is repeated for the trained FIS of Fig. 3b and the untrained FIS of Fig. 3a. To reduce the effects of the human learning through the process, half of the subjects are initially tested to the trained FIS, while the other half are tested to the untrained FIS first. The subjects are asked to complete every movement with the velocity and precision they prefer.

For a total number of 720 movements, the applied forces and the corresponding velocities in the direction of motion are recorded. In the first iterations of each movements it is observed that subjects without previous interaction with the robot move with a very small velocity until they become familiar with the robot operation. As a results, the first two iterations of each movement are not taken into consideration.

The mean energy and elapsed time of all subjects are illustrated in Fig. 4 for the three distances and the two different FIS. As expected, the energy provided by the human increases proportionally with the distance of the point-to-

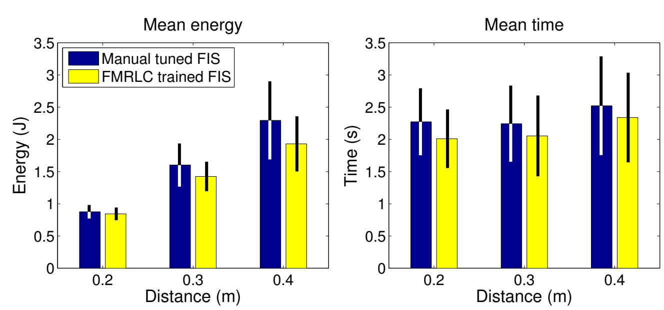

Fig. 4: Mean values and standard deviation of energy and time from all subjects in three different movements.

point movement. The mean energy required with the FMRLC trained FIS appears to be lower than the untrained FIS particularly in large movements. For $x_f = 0.2m$ there is a negligible improvement 1% in the effort with the FMRLC trained FIS, which increases at 7% for $x_f = 0.3m$ and finally at 13% for $x_f = 0.4m$. These results suggest that for large displacements subjects tend to apply larger forces and velocities which benefit from the FIS adapted to the minimum jerk model. Moreover, the standard deviation of the effort in the trained FIS is 38% lower than the untrained. Although the effort appears to increase proportionally to the distance of the movement, the required time does not, mainly because in the first movements the subjects are overcautious on applying large forces. However, by comparing the two FIS it appears that in the trained FIS the mean time is lower than the untrained for a total average of 12%, since the FMRLC trained FIS facilitates the accurate positioning to the target through the optimal variable damping. It is observed that with the untrained FIS most subjects tend to overshoot the target and apply correcting movements that increase the overall time.

With a questionnaire given to the subjects right after the experiment, they were asked to rate the two controllers in each of the three movements in terms of intuitiveness. The subjects were not aware of the type of each controller. The results listed in Tab. III show that in lowest displacement of $x_f = 0.2m$ most subjects (58%) cannot distinguish the difference between the controllers mainly because of the low velocities and forces. For $x_f = 0.3m$, 42% prefer the FMRLC trained FIS while the rest 50% still are not able to distinguish any difference. Finally, for the largest displacement of $x_f = 0.4m$ all of the subjects could distinguish between the two methods with 84% preferring the FMRLC trained FIS. In the overall experiment the FMRLC trained FIS is preferred over the untrained and the higher the displacement the more evident the performance gain is to the subjects.

TABLE III: Questionnaire results on the most intuitive controller.

User selection	$x_f = 0.2m$	$x_f = 0.3m$	$x_f = 0.4m$
Untrained FIS	8%	8%	16%
FMRLC trained	34%	42%	84%
No difference	58%	50%	0%

V. Conclusions

In this work a variable admittance control scheme is proposed for human-robot cooperation that combines a human-like inference mechanism with an adaptation algorithm for optimal tuning of the damping coefficient. Based on the velocity of the cooperation and the force applied by the operator, a heuristically created FIS infers an appropriate damping for the admittance controller, that assists both the rapid movements of the human and the accurate positioning. A model-reference training procedure based on FMRLC adapts the manually tuned initial knowledge-base of the FIS to the minimum jerk model.

It is observed that the initial knowledge-base of the FIS has a significant performance improvement in the cooperation in terms of the required effort of the human and the duration of the motion. Experimental results with multiple subjects suggest that the trained FIS enables a more intuitive interaction than the untrained, by reducing the effort and by assisting accurate positioning, even in different movements that those used to adapt the controller. Future work on the proposed control scheme involves the generalisation of the methods in arbitrary motion profiles by decoupling the goal position from the controller.

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