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Adaptive Hybrid System Framework for Unified Impedance and Admittance Control

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Abstract Impedance and Admittance Control are two well-known controllers to accomplish the same goal: the regulation of the mechanical impedance of manipulators interacting dynamically with the environment. However, they both are affected by a strong limitation deriving from their fixed causality, which causes their inability to provide good performance over a large spectrum of environment stiffnesses. In this paper an adaptive hybrid system framework is proposed to unify Impedance and Admittance formulations and consequently overcome this limit. Indeed, the hybrid framework interpolates the opposite performance and stability characteristics of the above-mentioned impedance-based control strategies leading to a family of controllers with intermediate properties, and thus suitable for several conditions. Moreover, the adaptivity allows the hybrid system to operate properly in an environment characterized by unknown and even time-varying stiffness. Especially, the work focuses on the development of this latter aspect and an adaptive solution based on a feedforward Neural Network is presented. The effectiveness of the novel control strategy is demonstrated by means of numerical simulations.

Keywords Impedance control · Admittance control · Hybrid system · Adaptive system · Neural network · Manipulator Control

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1 Introduction

In the last 40 years, the impact of robots in human life has increased significantly. Advances in mechatronics and robotics have enabled the development of many machines capable of supporting human beings in a growing number of activities.

Many efforts have been focusing on manipulation tasks involving dynamic interaction between robot and environment, since they would open to new and fascinating perspectives. The dynamic coupling between a manipulator and the environment generates reaction forces that must be handled properly to avoid undesired effects. In this situation, classical position control fails: contact forces cause deviations from the desired trajectory that the control system tries to compensate leading to a build-up of that forces, until breakage of robot hardware or manipulated object [22].

Historically, two fundamental control methodologies have been proposed to deal with the manipulation issue. The first strategy is known as ”Hybrid Position and Force Control”, proposed by Raibert and Craig [17] and then developed by Mason [14]. It is based on formal models of the manipulator and the task geometry: since it is not possible to control both position and force along the same degree of freedom (dof), the task space is split into two domains, the position and the force subspaces. The reaction force is controlled in the force subspace and the position of the end effector is controlled in the position subspace. However, this approach does not consider the dynamic coupling between the robot and the environment and this can be considered the main limit of this strategy.

On the other hand, Hogan [6, 7, 8] suggested a method to face this dynamic issue based on the control of the relation between position and force: impedance control. He started from the observation that two interacting physical systems must be complementary and since the environment can be typically described as an admittance, i.e. it receives forces as input and it gives displacements as output, the controller must be an impedance, which accepts motion inputs and yields force outputs. Therefore, the idea behind the impedance control is the regulation of the mechanical impedance of the manipulator.

Typically, impedance-based control can be implemented in two different ways, known as ”Impedance Control” and ”Admittance Control” which differ from each other in the causality. In the Impedance Control, the controller is an impedance and consequently the controlled plant is treated as an admittance. Conversely, in the Admittance Control the plant is position-controlled and it behaves as an impedance, and thus the controller must be an admittance.

Later, some hybrid systems were introduced in order to combine the qualities of the Hogan and Raibert and Craig methodologies. Anderson and Spong [1] pointed out the force control inability of handling unmodelled dynamics due to coupling and impedance control inadequacy in following a commanded force trajectory. Their solution is based on an inner feedback linearization loop with force cancelation and an outer loop which joins Impedance and Hybrid Force$\backslash$Position Control in one strategy.

Afterwards, Liu and Goldenberg [11] pushed forward the idea of Anderson and Spong proposing to add desired inertia and damping terms in force-controlled subspace in order to improve the dynamic behavior. In addition, they introduced a PI controller to tackle the uncertainties of the manipulator dynamic model.

Recently, Ott, Mukherjee and Nakamura [15, 16] developed a new way to implement impedance-based control. They proposed a hybrid system which combines the advantages of the Impedance and Admittance Control by rapidly switching between them. Indeed, the two strategies have complementary performances, as shown by Lawrence [10], who investigated their stability properties in the presence of non ideal effects, such as time delay. Starting from Eppinger and Seering observations [4] about the effects of high feedback gains on stability, Lawrence pointed out opposite stability requirements for Impedance and Admittance control. For the Admittance Control, low values of stiffness and damping produce high feedback gains, therefore it suffers the inability to provide soft impedance, giving as a result instability during interaction with stiff environment. On the contrary, in the Impedance Control high feedback gains are consequences of high values of stiffness and damping, and thus it is difficult to provide large stiffness, causing poor accuracy in soft environment and free motion.

Different attempts of overcoming the two control laws limitations have been investigated through the application of adaptive strategies to either Impedance or Admittance Control. Slotine and Li [24] and Lu and Meng [13] proposed the adaptation of unknown parameters in robot and payload models in order to mitigate the effects of uncertainties on the Impedance Control. Singh and Popa [23] exploited a Model Reference Adaptive Control (MRAC) applied to Impedance Control and combined impedance and force control.

Conversely, Seraji [21] applied adaptive PID and PD controllers to Admittance Control in an unknown environment.

Contrary to the previous studies, the aim of the strategy proposed by Ott, Mukherjee and Nakamura is not to improve the performance of either Impedance or Admittance Controls, but to combine them. Indeed, their proposal is an unified framework for Impedance and Admittance Controls, which may even take advantage of advanced implementations of each of the two controllers.

The hybrid system interpolates the response between Impedance and Admittance Control depending on the duty cycle of the switching system. Currently, the limit of the strategy lies in the fact that the environment must be known in order to set the duty cycle properly. Needless to say, a system capable of adapting itself to unknown and time-varying environment would lead to considerable improvements in the performance and versatility of the hybrid solution.

To deal with uncertain environment, some authors proposed algorithms to estimate online the environment stiffness [3, 12, 18, 19, 20, 25]. However, this strategy may be unfeasible in some applications due to the inevitable delay in the estimation and the fact that some algorithms require particular excitations to work properly. In addition, if a time-varying environment is considered, these algorithms may have some difficulties in following the continuous variations, leading to bad performances of the control system.

In this paper a different strategy to face unknown and time-varying environment is proposed. The duty cycle is adapted by a feedforward Neural Network with a single hidden layer made up of four neurons. The network obtains information about the dynamic system and the environment through the acquisition of the states and the interaction force. The training of the network is carried out exploiting a genetic algorithm as optimization method. Moreover, a step forward with respect to the work done in [16] is performed extending the concept of the hybrid system to a 2-dof system.

The current paper is organized in the following way: in section 2 an overview of the hybrid system is presented with application to the 2-dof case. In section 3 the problem of making the hybrid system adaptive is introduced and the structure and training of the adopted feedforward Neural Network are explained. Afterwards, some simulation results considering fixed-stiffness and time-varying environment cases are shown in section 4. Finally, in section 5 the conclusions of the work are summarized.

2 Overview of the hybrid system

Impedance and Admittance Control have opposite stability and performance characteristics due to their different implementations and causalities, as highlighted in [10, 15, 16]. The main limitation in Impedance Control concerns the impossibility of providing stiff behavior and compensating friction adequately, resulting in poor accuracy in soft environments and free motion. Conversely, it is robust to uncertainties in model parameters and can guarantee very good performance and stability in very stiff environments thanks to its soft behavior, that can limit the interaction forces.

On the other hand, Admittance Control can assure better performances in the interaction with soft environments, thanks to its stiff feature, while it results in instabilities when the environment stiffness increases.

Both formulations are limited by their fixed causality, which causes their incapability of providing good performances in a large spectrum of environment stiffness, as illustrated in Fig. 1. An ideal controller should provide consistently good performance, independent of the environment stiffness.

The adaptive hybrid control aims to accomplish this task by rapidly switching between Impedance and Admittance Control, overcoming the fixed causality and unifying the benefits from both the controllers in a single framework.

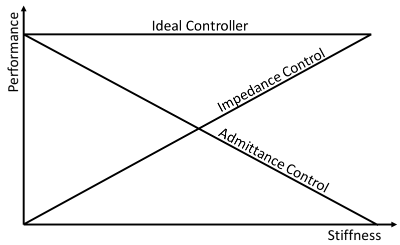

Fig. 1: Qualitative illustration of the performance of Impedance Control and Admittance Control for different environment stiffness.

Before presenting the adaptive system, a brief introduction of the hybrid formulation, along with the underlying Impedance and Admittance Control, is given. The discussion is carried out extending the results in [16] for the 1-dof case to a 2-dof system.

2.1 Problem statement

A manipulator made up of 2 rigid joints connected by as much rigid links is considered (see Fig. 2). It interacts with an environment modeled as an inclined frictionless wall. Considering a point contact, the system is governed by the equation of motion:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \tau + \mathbf{J}^{\mathbf{T}}\mathbf{F}_{\mathbf{ext}} \tag{1}$$

where $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ are respectively the joints position, velocity and acceleration vectors, $\mathbf{J}$ is the geometric Jacobian, τ is the control action, applied to the joints, and $\mathbf{F}_{\mathbf{ext}}$ the external

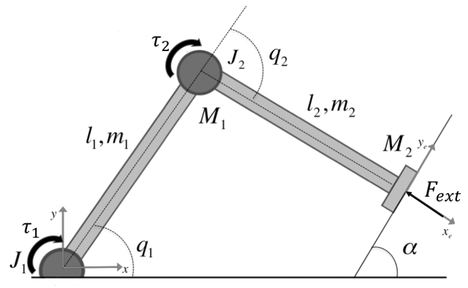

Fig. 2: 2-dof system graphic representation.

force vector. $\mathbf{M}(\mathbf{q})$, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$ and $\mathbf{g}(\mathbf{q})$ represent the system inertia matrix, the centrifugal and Coriolis matrix and the gravitational terms, respectively.

Manipulator control based on the impedance/admittance scheme aims to provide a control action realizing a prescribed relation between external force and the error response of the system:

$$\mathbf{M_{d,e}}\ddot{\mathbf{e}} + \mathbf{D_{d,e}}\dot{\mathbf{e}} + \mathbf{K_{d,e}}\mathbf{e} = \mathbf{F_{ext,e}} \tag{2}$$

with:

$$\mathbf{e} = \mathbf{x_e} - \mathbf{x_{0,e}} \tag{3}$$

where $\mathbf{M_{d,e}}$, $\mathbf{D_{d,e}}$ and $\mathbf{K_{d,e}}$ are the desired inertia, damping and stiffness matrices, respectively, $\mathbf{F_{ext,e}}$ is the external force vector, $\mathbf{x_e}$ is the end-effector position and $\mathbf{x_{0,e}}$ is the commanded virtual position. All the quantities are expressed in the environment reference frame, illustrated in Fig. 2. The desired impedance relation is considered in the external force direction, which is orthogonal to the wall.

2.2 Impedance Control

In the Impedance Control, the plant is an admittance, i.e., it receives force as input and gives position as output, while the controller behaves as an impedance, as schematically represented in Fig. 3.

Considering the 2-dof manipulator, the expression of the desired control force can be derived from Eqs. (1) - (2). Once the quantities are rotated in the base reference frame $x-y$ (see Fig. 2), the desired end-effector acceleration can be computed as follows:

$$\ddot{\mathbf{x}} = \mathbf{M_d^{-1}}(-\mathbf{D_d}\dot{\mathbf{x}} - \mathbf{K_d}(\mathbf{x} - \mathbf{x_0}) + \mathbf{F_{ext}}) \tag{4}$$

where commanded velocity and acceleration are considered equal to zero.

Since a control action expressed in the joint space is required, the joint acceleration can be derived from the velocities relationship encoded by the Jacobian.

$$\dot{\mathbf{x}} = \mathbf{J}\dot{\mathbf{q}} \tag{5}$$

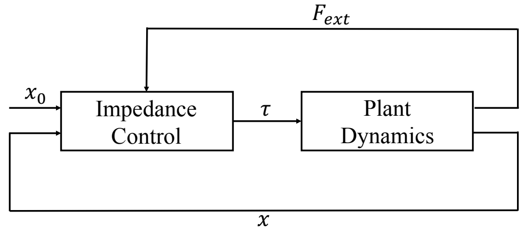

Fig. 3: Impedance Control system structure.

then

$$\ddot{\mathbf{q}} = \mathbf{J^{-1}}(\ddot{\mathbf{x}} - \dot{\mathbf{J}}\dot{\mathbf{q}}) \tag{6}$$

At this point the end-effector acceleration is substituted by the desired one reported in Eq. (4).

$$\ddot{\mathbf{q}} = \mathbf{J^{-1}M_d^{-1}}(-\mathbf{D_d}\dot{\mathbf{x}} - \mathbf{K_d}(\mathbf{x} - \mathbf{x_0}) + \mathbf{F_{ext}}) - \mathbf{J^{-1}}\dot{\mathbf{J}}\dot{\mathbf{q}} \tag{7}$$

From the dynamics (see Eq. (1)) the control torque can be derived as:

$$\tau_{\mathbf{Imp}} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) - \mathbf{J^T F_{ext}} \tag{8}$$

Combining Eq. (7) with Eq. (8) the Impedance Control torque can be obtained:

$$\begin{aligned} \tau_{\mathbf{Imp}} =& \mathbf{M}(\mathbf{q})\mathbf{J^{-1}M_d^{-1}}(-\mathbf{D_d}\dot{\mathbf{x}} - \mathbf{K_d}(\mathbf{x} - \mathbf{x_0}) + \mathbf{F_{ext}}) + \\ & -\mathbf{M}(\mathbf{q})\mathbf{J^{-1}}\dot{\mathbf{J}}\dot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) - \mathbf{J^T F_{ext}} \end{aligned} \tag{9}$$

The $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}}$ and $\mathbf{g}(\mathbf{q})$ terms compensate the centrifugal, Coriolis and gravitational effects.

In an ideal case, without friction, uncertainties and measurement delays, the controlled system satisfies exactly the desired impedance relation in Eq. (2).

2.3 Admittance Control

In the Admittance Control, the motion control problem and the impedance control problem are separated. One controller generates a motion trajectory from the interaction force measurement, guaranteeing the desired dynamic behavior (Eq. (2)). A second controller receives the reference trajectory and provides the related control action to the plant. Fig. 4 shows a schematic representation of the Admittance Control.

Different kind of control law can be implemented to realize the position controller. In this case a simple PD regulator is used:

$$\tau_{\mathbf{Adm}} = \mathbf{k_p}(\mathbf{q_d} - \mathbf{q}) - \mathbf{k_v}\dot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) \tag{10}$$

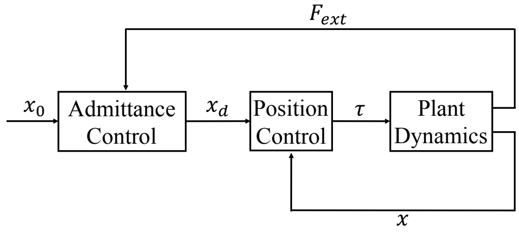

Fig. 4: Admittance Control system structure.

where $\mathbf{k_p}$ and $\mathbf{k_d}$ are the proportional and derivative coefficients of the PD controller, $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}}$ and $\mathbf{g}(\mathbf{q})$ are the centrifugal, Coriolis and gravitational compensating terms, respectively, and $\mathbf{q_d}$ represents the desired joint trajectory, which can be found from Eq. (4) by inverse kinematics.

2.4 Hybrid system structure

The hybrid system switches between Impedance and Admittance Control providing the following control action $\tau_{\mathbf{Hyb}}$:

$$\tau_{\mathbf{Hyb}} = \begin{cases} \tau_{\mathbf{Imp}} & : t_0 + k\delta \leq t \leq t_0 + (k+1-n)\delta \\ \tau_{\mathbf{Adm}} & : t_0 + (k+1-n)\delta \leq t \leq t_0 + (k+1)\delta \end{cases} \tag{11}$$

where $\tau_{\mathbf{Imp}}$ and $\tau_{\mathbf{Adm}}$ are the control torques provided by Impedance and Admittance Control, respectively, t_0 is the initial time, δ is the switching period, $n \in [0,1]$ is the duty cycle and k is an integer that takes on values 0,1,..., N, where N is the considered number of switching periods.

Note that for $n = 0$ the hybrid system behaves exactly as the Impedance Control, whereas for $n = 1$ it uses the Admittance Control with periodic resetting.

The continuity in the control force can be maintained by defining a proper state variable mapping when the system switches from Admittance to Impedance Control and viceversa, as explained in [16].

Figure 5 shows the scheme of the hybrid controller.

2.5 Simulation example

In order to illustrate the performances of the the hybrid system, some simulations are presented in this section.

The 2-dof system described in section 2.1 is considered and friction, model uncertainties, time delays and noise are introduced. The equations of motion become:

$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \tau + \mathbf{J^T F_{ext}} + \tau_{\mathbf{f}} \tag{12}$$

with the unmodelled friction term:

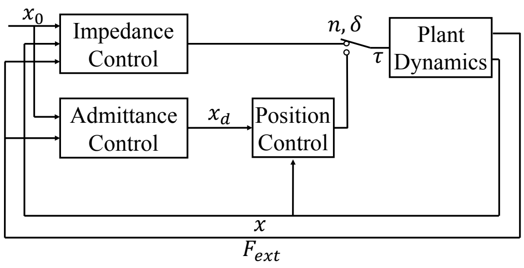

Fig. 5: Concept of Hybrid Control.

$$\tau_{fi} = -sign(\dot{q}_i)(c_v|\dot{q}_i| + \tau_c) \qquad i \in [1,2] \tag{13}$$

where c_v and τ_c represent the viscous coefficient and the Coulomb friction for the i^{th} joint, respectively.

The parameter values used in the simulation are reported in table 1.

Table 1: Simulation parameters.

Real Parameters		
M_1	1.0	kg
M_2	1.0	kg
m_1	0.8	kg
m_2	0.8	kg
J_1	0.001	kgm^2
J_2	0.001	kgm^2
l_1	0.7	m
l_2	0.5	m
c_v	4	Nms/rad
τ_c	1	Nm
α	45	deg

Model Parameters	
$\hat{M}_1$	$0.8 * M_1$
$\hat{M}_2$	$0.8 * M_2$
$\hat{m}_1$	$0.9 * m_1$
$\hat{m}_2$	$0.9 * m_2$
$\hat{J}_1$	$0.8 * J_1$
$\hat{J}_2$	$0.8 * J_2$

$\hat{M}_1$, $\hat{M}_2$, $\hat{m}_1$, $\hat{m}_2$, $\hat{J}_1$ and $\hat{J}_2$ are the masses and inertias implemented in both impedance and admittance strategies, introducing a certain level of uncertainties. In addition, a time delays of 2 ms is added in the state measurements and a Gaussian noise with zero mean and unity variance is considered on the external force measurement.

The control parameters set in the simulation are as follows:

$$\mathbf{M_{d,e}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \mathbf{K_{d,e}} = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$$

$$\mathbf{D_{d,e}} = 2 * 0.7 * \sqrt{\mathbf{K_{d,e}} * \mathbf{M_{d,e}}}$$

$$\mathbf{k_p} = \begin{bmatrix} 10^6 & 0 \\ 0 & 10^6 \end{bmatrix}, \quad \mathbf{k_v} = \begin{bmatrix} 500 & 0 \\ 0 & 500 \end{bmatrix}$$

$$\delta = 0.02s$$

At the initial time the mass is considered to be already in contact with the wall and the environment stiffness is expressed as:

$$\mathbf{K_e} = \begin{bmatrix} k_e & 0 \\ 0 & 0 \end{bmatrix}$$

in the environment reference frame, and thus:

$$\mathbf{F_{ext,e}} = -\mathbf{K_e x_e} \tag{14}$$

Without loss of generality the rest position of the environment is considered equal to zero.

Figs. 6-7-8 show the error response, with respect to the ideal behavior of the closed loop system (see Eq. 2), of the hybrid system to a step position command, considering different value of n. Results are shown for stiffness equal to 10 N/m, 1400 N/m and 3200 N/m, respectively.

As expected, in a soft environment the performance improves as n tends to 1, i.e. when the hybrid system behaves as the Admittance Control. On the contrary, when k_e increases, n must decrease, and the hybrid system tends to behave as the Impedance Control. These results prove the capability of the hybrid system of interpolating the response between Impedance Control and Admittance Control by properly choosing the value of n. The hybrid system combines the robustness property of the Impedance Control in stiff contact with the accuracy of the Admittance Control in soft contact.

Note that the results for the 2-dof system are similar to the ones found in [16] for the 1-dof case. This fact represents a first evidence of the scalability of the presented control strategy to more complex robotic systems.

Finally, it should be mentioned that the idea behind the design of the hybrid system is the development of a general framework capable of unifying Impedance and Admittance Control. This means that, in order to reach the desired impedance relation, potentially, every already existent Impedance or Admittance Control formulation can be added to the hybrid system, depending on the application.

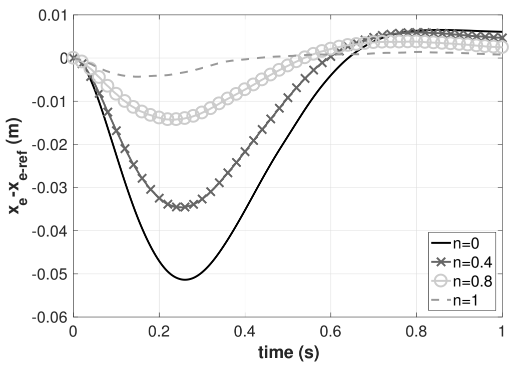

Fig. 6: 2-dof system error response with hybrid control for the soft environment $k_e = 10\,\text{N/m}$.

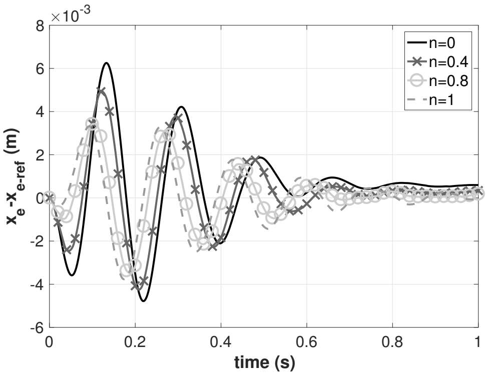

Fig. 7: 2-dof system error response with hybrid control for the intermediate environment stiffness $k_e = 1400$ N/m.

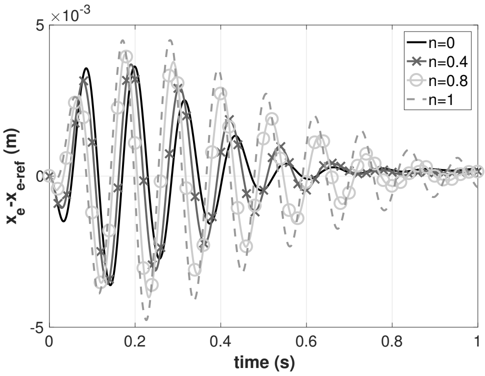

Fig. 8: 2-dof system error response with hybrid control for the stiff environment $k_e = 3200$ N/m.

3 Adaptive strategy

Once the impedance and admittance controllers are chosen, the stability and performance characteristics of the hybrid system are determined by the values of the switching period δ and the duty cycle n [16]. In particular, this latter parameter decides the contribution of each control laws, embedded in the framework, to the overall response of the system, and thus it represents the design parameter to be adapted.

If the environment stiffness is known, a proper value of n, minimizing the error with respect to the ideal behavior (see Eq. 2), can be easily found. However, in many applications this information can not be obtained *a priori* and a system capable of adapting itself depending on the external conditions is required.

Even though the effects of varying the duty cycle n in different environment is clear, an explicit expression relating this parameter to the interaction force or the continuous states of the system is particularly hard to be found, due to the high nonlinearity of the system. Moreover, the main differences between Impedance and Admittance Control are related to the presence of uncertainties, unmodelled friction and delays.

These considerations, along with the already-stated difficulties in estimating the environment properties online, led to the development of an adaptive system based on a Neural Network.

3.1 Neural Network

A Neural Network is a powerful tool to deal with high nonlinear problems providing approximate relations among the involved quantities[2, 9]. The strengths of the Neural Network are, first, the computation power thanks to the massively parallel distributed structure and, second, the generalization property derived from its ability to learn[5]. This last feature means that a Neural Network can produce reasonable outputs for inputs different from the ones received during the training.

These characteristics are exploited to create a relation between the external force and the states of the system and the design parameter, the duty cycle n. The network receives the information from the dynamic system and the environment and, elaborating them, provides a suitable n minimizing the error with respect to the desired behavior.

This solution can guarantee a prompt reaction to variations of the external conditions making the hybrid system capable of working in unknown and even time-varying environment.

3.2 Neural Network structure

The structure adopted for the adaptive system is a *fully connected* multilayer feedforward network with a single hidden layer. The number of layer and neurons per layer is the result of a trade-off among simplicity, performance and training time. Since the input layer receives the states of the end-effector and the interaction force as input, it is made up of a number of nodes that depends on the dimension of the considered problem (e.g., six nodes for the 2-dof system) . The hidden layer and the output layer are constituted of 4 neurons and 1 neuron, respectively (see Fig. 9). It was observed that adding hidden neurons does not improve significantly the performance.

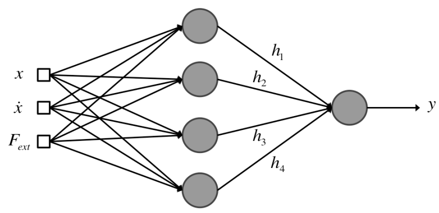

Fig. 9: Neural Network adaptive system diagram

Each neuron features a weight which multiplies its inputs, a bias, summed to the product, and an activation function, in this case a sigmoid function. In the proposed solution a single bias common to all the neurons of the hidden layer is used in order to simplify the optimization problem during the training.

Therefore, the output of the $k-th$ hidden neuron is expressed as follows:

$$h_k = \sigma(\mathbf{w}_{1k}^T\mathbf{x} + \mathbf{w}_{2k}^T\dot{\mathbf{x}} + \mathbf{w}_{3k}^T\mathbf{F_{ext}} + b_h) \qquad k \in [1,2,3,4] \tag{15}$$

where σ is the sigmoid function, $\mathbf{w}_{ik}$ is the vector of the weights of the $k-th$ neuron and b_h the layer bias.

The outputs of the hidden layer enter in the output neuron providing:

$$y = \sigma\left(\mathbf{w_o}^T\mathbf{h} + b_o\right) \tag{16}$$

where $\mathbf{w_o}$ is the vector of the output weights, $\mathbf{h}$ is the vector containing the outputs of the hidden layer and b_o is the output bias.

It should be noted that y would tend asymptotically to 1 or 0 when the argument of the sigmoid function approaches +∞ or -∞, excluding possible solutions, i.e., $n = 0$ and $n = 1$. Hence, an additional weight w_f is added to the output of the Neural Network and the constraint on the duty cycle n, which varies in a range between 0 and 1, is recovered applying the square of the sine function to the weighted output:

$$n = \sin^2(w_f y) \tag{17}$$

It is worth observing that the Neural Network is not limited to select a constant fixed duty cycle for each scenario. The only restriction is that n should be bounded between 0 and 1 and constant within the switching period δ, for a proper functioning of the switching system. This results in improved performance in certain environment, especially for the 2-dof robot, as it will be shown in the simulations later.

3.3 Neural Network training

The training of the network, i.e., the definition of all the weights and biases, is carried out exploiting a genetic algorithm as optimization method to minimize a fitness function based on the error with respect to the ideal behavior (see Eq. (2)). The choice of exploiting a genetic algorithm is dictated by the need to deal with a non-smooth optimization problem with many local minima.

First of all, the training conditions and a proper fitness function must be defined. The Neural Network must be trained with the command position and in the stiffness range required by the application. In this case, two separated command positions are considered, i.e. a step $x_0 = 0.5\ m$ and a step $x_0 = -0.5\ m$ in the direction of the controlled impedance; in this way the network can learn how to deal with both forward and backward commands, and with circumstances where the interaction force is positive or negative. The selected stiffness range varies between 10 N/m and 3200 N/m and it is discretized with a step of 200 N/m as a trade-off between the necessities of training the network on a sufficiently wide number of stiffnesses, requiring different n value, and avoiding overtraining. The choice of the range is motivated by the will of comparing the results with the ones reported in [16]. The Neural Network should provide the duty cycle n in such a way to realize the desired impedance relation, and thus the training set is made up of the system ideal responses derived from the integration of Eq. (2) for each condition of stiffness and command position.

The genetic algorithm generates randomly a population composed of individuals representing different sets of Neural Network weights. The training is carried out performing two simulations of the robot operation (two step command positions) for each individual and for each stiffness of the discretized range. Then, the fitness function, which has to be minimized by the genetic algorithm, is computed. The fitness function is based on the cost function

$$J = \frac{1}{2}\int_0^{T_{sim}} (\mathbf{x}-\mathbf{x}_{ref})^T(\mathbf{x}-\mathbf{x}_{ref})d\tau \tag{18}$$

where $\mathbf{x}$ is the actual position and $\mathbf{x}_{ref}$ is the ideal one, taken from the training set. T_{sim} is set to 1 s: in this time all the main characteristics of the response can be recognized. For each simulation this cost function is computed leading to the definition of two reward functions:

$$R_{forward} = \sum_{i=1}^{N} J_{fi} \tag{19}$$

$$R_{backward} = \sum_{i=1}^{N} J_{bi} \tag{20}$$

where N is the number of stiffnesses, J_{fi} and J_{bi} are the cost functions evaluated for the response to a step forward and backward, respectively, in the environment characterized by the $i-th$ stiffness.

Finally, the fitness function is defined as follows:

$$F = \max(R_{forward}, R_{backward}) \tag{21}$$

The optimization algorithm looks for a solution minimizing the worst reward function keeping the other one bounded.

Therefore, to be clear, the training process can be summarized in the following steps:

1. Discretization of the expected environment stiffness range.
2. Computation of the ideal closed-loop system response from integration of Eq. (2) for each stiffness of the selected range and desired command position (in this case 17 stiffnesses and 2 different command positions are considered, and thus 34 ideal responses are computed).
3. Genetic algorithm starts
   i. Random generation of an initial population of individuals, representing different sets of Neural Network weights.
   ii. Considering a single individual, computation of the closed-loop system response giving a step forward command position for each environment stiffness and computation of the reward function $R_{forward}$.
   iii. Considering a single individual, computation of the closed-loop system response giving a step backward command position for each environment stiffness and computation of the reward function $R_{backward}$.
   iv. Considering a single individual, computation of the fitness function F.
   v. Considering all the individuals, comparison between the best fitness function and the mean fitness function: if their difference is less then a specified tolerance the genetic algorithm stops, otherwise
   vi. Generation of a new population and repetition of steps from ii to v.
4. Genetic algorithm stops and the set of Neural Network weights, providing the best fitness function, is selected.

When a genetic algorithm is used, it is important to set the population size and weights and biases boundaries properly. The followed procedure is reported in the flowchart of Fig. 10. In defining the boundaries, the fact that the inputs of the Neural Network have different order of magnitude and nature is taken into account.

Finally, note that uncertainties, unmodelled friction and delay must be added in the simulation since they reveal the differences in the performance of the Impedance and Admittance Control and are necessary to represent the conditions in which the manipulator operates.

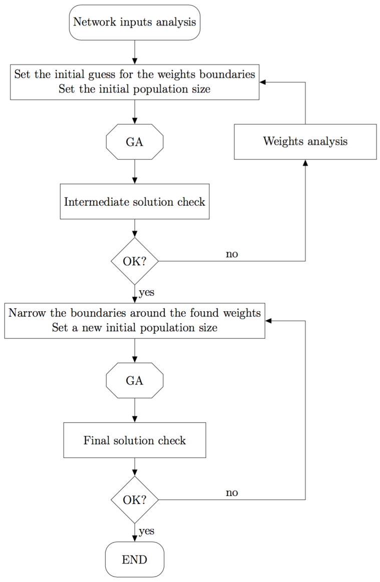

Fig. 10: Flowchart of the procedure for the weights boundaries and population size setting.

4 Results

This section provides the main results of the adaptive hybrid system. It is shown that the proposed solution can achieve the goal of working in an unknown environment, even time-varying. In addition to the 2-dof case, the results of the 1-dof system are shown to compare them with the ones in [16], where its trivial dynamics is described too and thus it is not reported here. The data used in the simulations are reported in table 1.

4.1 Fixed environment stiffness

Figs. 11-13 show the error response of the 1-dof and 2-dof system, with the adaptive hybrid system, the hybrid system with an optimal fixed n, the Impedance and Admittance Control in a soft, intermediate and stiff environment. For the 2-dof system, the error is considered along the direction orthogonal to the wall. The optimal fixed n is found as the n minimizing Eq.

(18) for each environment stiffness. It should be noted that this procedure can be followed only if the stiffness is *a priori* known.

It can be observed that the adaptive solution provides performance comparable to the one with the best fixed n and in any case improves the performance with respect to the Impedance and Admittance Control. As example, Fig. 14 reports the related n trend for the 1-dof case.

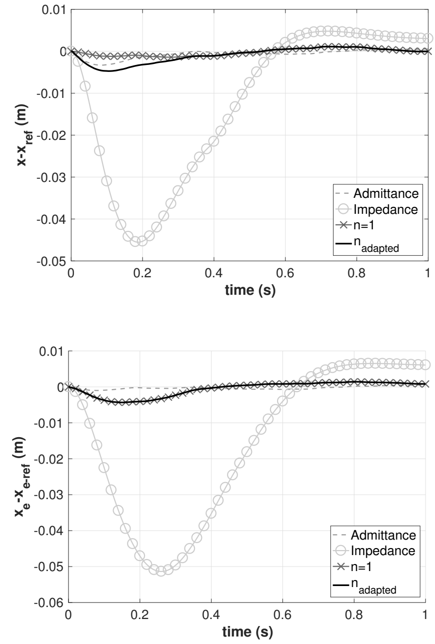

Fig. 11: Error responses of the 1-dof (above) and 2-dof (below) systems to a step command position from 0 m to 0.5 m for $k_e = 10$ N/m.

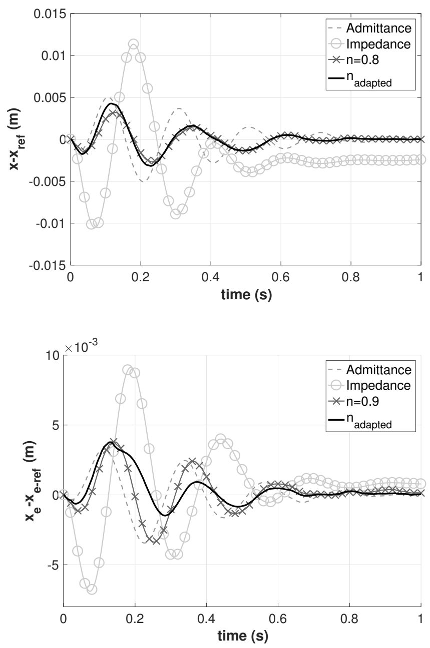

Fig. 12: Error responses of the 1-dof (above) and 2-dof (below) systems to a step command position from 0 m to 0.5 m for $k_e = 700$ N/m.

4.2 Time-varying environment stiffness

Thank to the capability of the Neural Network of selecting a value of n depending on the states and the measured interaction force with the environment, the system can react promptly to changes in the external conditions, even if they vary suddenly. Examples of these situations could be a legged robot or a robot wiping a large thin plate, fixed at its sides. In the former case, the leg moves repeatedly from a free-motion condition to a contact with environment with different stiffness, depending on the terrain. In the latter case, the stiffness of the plate will be lower in the middle with respect to the boundaries.

Figs. 15-16 show two situations of time-varying environment reported in [15, 16] and exploited here to assess the performance of the adaptive hybrid system with respect to Impedance and Admittance Control. The first case is applied to the 1-dof system as in [16] and the error response is reported in Fig. 17. On the other hand, the second situation is applied to the 2-dof system and the error response is shown in Fig. 18.

These results highlight the limitations of the Impedance and Admittance Control and show clearly the improved performance of the adaptive hybrid system. In both Figs. 17-18 it can be noticed that the Impedance Control shows a large steady state error when the environment becomes softer. On the contrary, the Admittance Control loses stability as the stiffness increases, but the steady state error is always negligible. Instead, the adaptive hybrid system follows the variation of the environment guaranteeing the properties of an almost zero steady state error and low overshoot for low contact stiffness, and an high stability in stiffer situation. Especially, this fact can be observed in Fig. 18, where about 1.7 s there is a

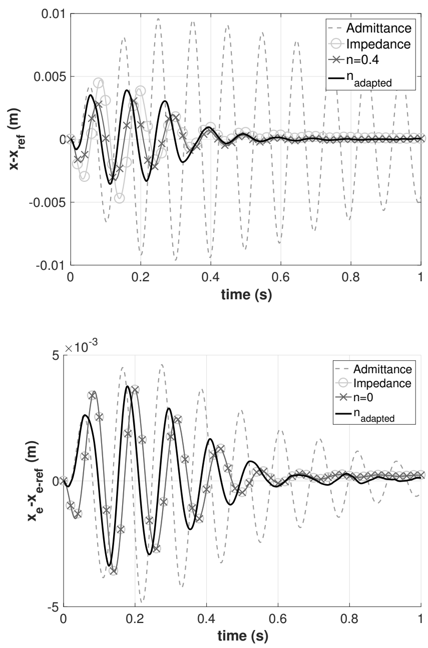

Fig. 13: Error responses of the 1-dof (above) and 2-dof (below) systems to a step command position from 0 m to 0.5 m for $k_e = 3200$ N/m.

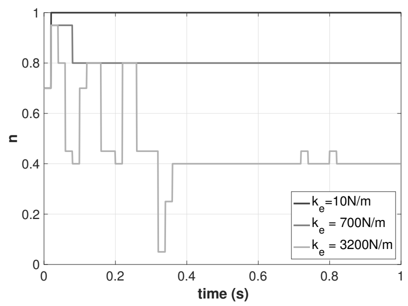

Fig. 14: n trend for the 1-dof system with $k_e = 10$ N/m, $k_e = 700$ N/m and $k_e = 3200$ N/m.

sharp transition between two opposite environments and only the adaptive control manages to face the situation properly.

5 Conclusions

In this paper the hybrid system framework has been introduced as a new solution to the impedance control problem, unifying the impedance and admittance formulation. Especially, this novel concept has been developed extending it to a 2-dof manipulator and proposing an adaptive strategy based on a feedforward Neural Network.

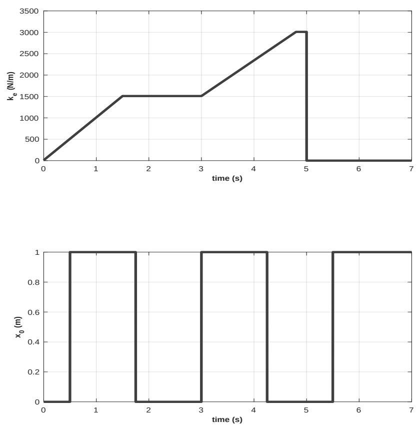

Fig. 15: First case: time-varying contact stiffness k_e and command position x_0 for the 1-dof system.

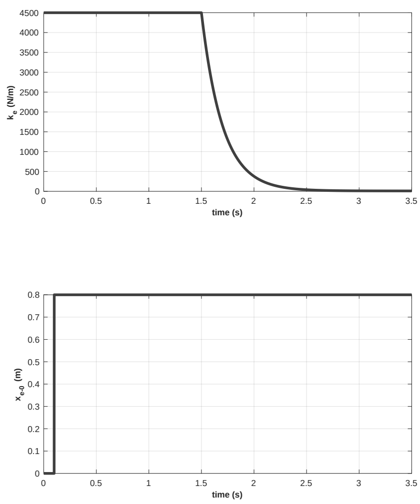

Fig. 16: Second case: time-varying contact stiffness k_e with exponential trend and related command position x_{e0} for the simulation in the 2-dof system cases.

It has been shown that the presented adaptive hybrid system overcomes the fixed-causality limitations of Impedance and Admittance Control leading to a controller which provides consistently good performance, independent of the environment stiffness. Indeed, acting on the duty cycle, the Neural Network modifies the behavior of the controller automatically moving from impedance-based to admittance-based, and viceversa, depending on the interacting environment. Through simulations, the effectiveness of the novel strategy has been proved considering unknown and time-varying conditions.

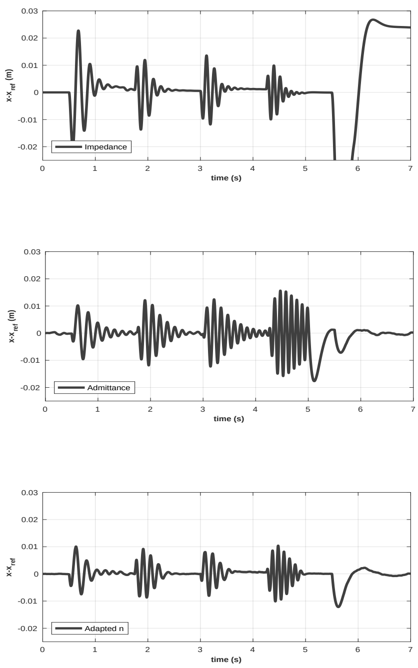

Fig. 17: First case: comparison of errors for the time-varying contact stiffness k_e for the 1-dof system.

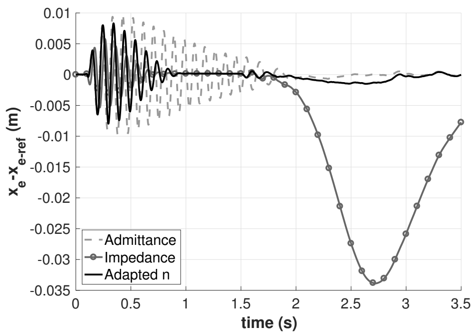

Fig. 18: Second case: comparison of errors for the time-varying contact stiffness k_e, with exponential trend, in the 2-dof system case.

Moreover, the results on the 2-dof manipulator can be considered as a first evidence of the scalability of the presented framework to a more complex system.

A further step in the development of this approach should be an experimental validation of the simulated results. Afterwards, an extension of the strategy, including analysis, simulations and experiments, to more complex situations is an important goal for future research.

Finally, in this work a physical system remaining in contact with the environment has been considered. However, contact transition from free to constraint motion may occur and they are characterized by impulsive forces. Future studies should analyze the behavior of the system including this phenomenon.

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