Optimized Fuzzy Impedance Control for Empowering Human in Execution of Onerous Task with Manipulators

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***Abstract*— The proposed contribution describes a fuzzy impedance control based approach to assist the human operator in industrial applications while executing onerous tasks. The developed method allows to set in real-time the set-point of the impedance control on the basis of the humans intentions. Moreover, an off-line optimization of the fuzzy impedance control parameters has been performed through an optimization algorithm based on a neural network approach. The proposed method has been verified in an experimental procedure with 20 human subjects interacting with the manipulator (KUKA iiwa 14 R820). The proposed algorithm has been also validated in an industrial task, performing the installation of a heavy and bulky hatrack component, case-study related to the H2020 CleanSky 2 EURECA project at the KUKA Innovation Award 2017.**

I. Introduction

Human-robot interaction (HRI) is one of the most relevant topics since the early stage of robotics research [1]. The co-operative execution of onerous tasks (*e.g.*, lifting/installation of heavy components [2]) is one of the main goal of human-robot cooperation research, in order to improve the task ergonomy to avoid/limit musculoskeletal disorders [3]. Many control schemes have been developed to improve the human capabilities while executing cooperative industrial tasks in interaction with standard industrial manipulators [4]. However, only few proposed methods face the problem of lifting unknown inertia properties objects (very common scenario in industrial applications where different components have to be manipulated). Moreover, the applied force of the human operator (to the robot or to the manipulated component) is continuously required even to statically compensate for the component weight.

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The proposed contribution describes a fuzzy impedance control based approach to assist the human operator in industrial applications while executing onerous tasks (*e.g.*, lifting heavy loads). The developed method allows to set in real-time the set-point of the impedance control on the basis of the humans intentions. Two fuzzy membership functions have been defined, respectively, on the basis of force derivative and velocity signals to describe human intention. Such membership functions allow to on- line calculate an assistance level through the task execution, deforming the impedance control set-point to enhance the capabilities of the human operator. Moreover, an off-line optimization of such membership functions, together with the impedance control parameters (*i.e.*, stiffness and damping parameters) has been performed through an optimization algorithm consisting of neural networks to automatically tune all impedance control parameters for a specific component by minimization of standard normalized jerk-related indexes. The proposed method has been verified in an experimental procedure where 20 human subjects interact with the manipulator (KUKA iiwa 14 R820) to collaboratively lift a heavy component while evaluating the task by scoring seven different criteria (including naturalness, smoothness, detection of intention, motion, stability, effort and performance). During the validation procedure, the developed control strategy has been compared with the standard impedance controller. Experimental results show the capabilities of the designed control strategy including both fuzzy impedance control and the optimization algorithm in empowering the human operator executing the target task. The proposed algorithm has been also validated in an industrial task, performing the installation of a heavy and bulky hatrack component, case-study related to the H2020 CleanSky 2 EURECA project [5]. The proposed application has been shown during the KUKA Innovation Award at Hannover Messe - 2017, where ITIA-CNR MACHAMP team participated as a finalist in the competition.

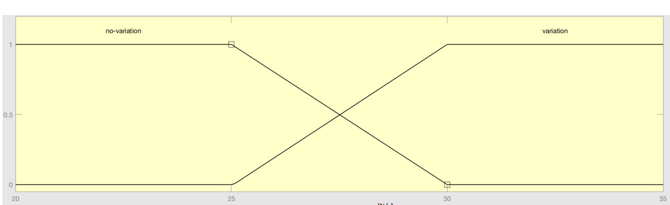

Fig. 1. Force derivative membership function.

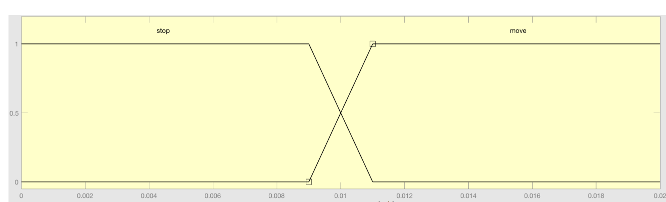

Fig. 2. Velocity membership function.

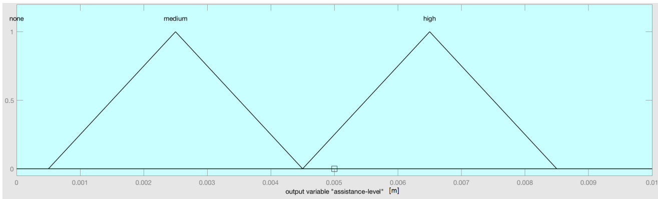

Fig. 3. Assistant level membership function.

II. Fuzzy Impedance Controller

General Notation

$\mathbf{f}_r$:	measured robot forces/torques
$\dot{\mathbf{f}}_r$:	derivative of robot forces/torques
$\dot{\mathbf{x}}_r$:	measured robot forces/torques
$\mathbf{A}_L$:	on-line calculated assistant level diagonal matrix

The control law here presented aims at deforming on-line the impedance control set-point based on the user exerted force and robot velocity. The impedance control set-point deformation is therefore regulated by a fuzzy controller, defining two membership functions on the basis of the above measured signals $\dot{\mathbf{f}}_r$ and $\dot{\mathbf{x}}_r$, as in Figure 1 and Figure 2. Considering Figure 1, two states have been defined: *no variation* and *variation*. While in the first state no human intention to move the robot is defined, in the second state the human aims to move the robot (since the force applied by the human on the robot is changing). Considering Figure 2, two states have been defined: *stop* and *move*. While in the first state the robot is not moving, in the second state the robot is in motion. Let us denote the diagonal assistant level matrix $\mathbf{A}_L$ as the target impedance set-point deformation to enhance the capabilities of the human during the cooperative task. The corresponding membership function is defined as in Figure 3, where three levels of assistance have been defined: *none*, *medium* and *high*.

The following rules have been implemented to calculate the target assistant level:

$$\begin{cases} \#1\ If\ no\ variation\ \&\&\ stop\ then\ none \\ \#2\ If\ no\ variation\ \&\&\ move\ then\ medium \\ \#3\ If\ variation\ \&\&\ stop\ then\ high \\ \#4\ If\ variation\ \&\&\ move\ then\ high \end{cases} \tag{1}$$

Rule #1 aims at impose no-assistance when no force variation, either motion of the robot is observed. This means that the human does not want to move the manipulator. Rule #2 aims at impose a medium level of assistance when no force variation is measured but a motion of the robot is observed. This means that the human would like to continue the robot motion. Rule #3 and #4 aim at impose a high level of assistance. In #3 the robot is not moving and the human would like to start a motion, while in #4 the robot is already moving and the human would like to modify the robot motion. In both cases, the robot + component inertia have to be compensated with a higher assistance level. The impedance control set-point is then on-line computed as follows:

$$\mathbf{x}_r^0 = \mathbf{x}_r + \mathbf{A}_L sign(\dot{\mathbf{x}}_r) \tag{2}$$

III. Neural Networks Design and Training

The optimization algorithm have been design on the basis of the neural networks approach, in particular considering the Levenberg-Marquardt (LM) backprogation algorithm [6]. Control quantities such as impedance control parameters (*i.e.*, stiffness and damping parameters) and the fuzzy control assistance level and the weight of the manipulated component are considered as inputs of the neural network, while the calculated normalized jerk index in [7] represent the output quantities of the neural networks. Such index represent the smoothness of the motion performed by the human in cooperation with the robot, giving an indication of the human stress during the task execution. The following values to train the neural network have been used during the experiments:

- Weight : 0, 5, 9 (Kg)
- Stiffness : 1000, 3000, 5000 (N/m)
- Damping ratio : 0.1, 0.25, 0.5, 0.75, 0.9
- Medium Assistance Level (MAL): low, medium, high
- High Assistance Level (HAL): low, medium, high

405 experiments have been therefore performed to train the neural network in order to optimize the control parameters on the basis of the target component weight and with respect to the calculated standard jerk index. Furthermore, a rating scale was proposed to assess the HRI shown in Figure 4.

IV. Results

A. Experimental Evaluation Scheme

The evaluation scenario was established based on [8] where a comprehensive evaluation scheme was proposed to evaluate the power-assist control algorithms in all relevant HRI by defining performance criteria addressing both physical human-robot interactions (pHRI) and cognitive human-robot interactions (cHRI). The evaluation procedure aims to express the HRI in a few terms to completely address human's expectations and task goals as follows:

- Naturalness: humans overall likability, normalcy, ease of use, convenience, non- complexity in operation and collaboration.
- Smoothness: whether the movement is smooth.
- Effort: amount of effort, hardship or endeavor required to achieve the performance level satisfying the mental, physical and temporal demand.
- Detection of intention: whether the robot follows human intention in accelerating or de-accelerating the motion.

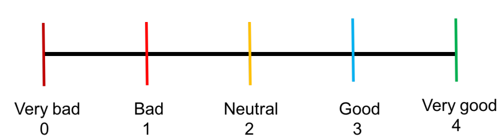

Fig. 4. Rating scale with possible scores for evaluating the HRI.

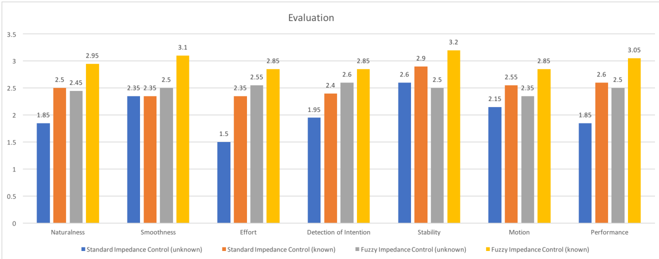

Fig. 5. Evaluation results. Mean scores of seven defined criteria for different control algorithms with and without considering inertia properties of the component.

- Stability: presence/absence of oscillations, sudden inactivity of the system, and their effects on manipulation, object, system structure, and environment.
- Motion: nature of object velocity and acceleration felt by the human (*i.e.*, whether the velocity, acceleration is low or high compared to human expectation).
- Performance: the overall performance, *e.g.*, lifting the object to the desired position within the specified time and attempting to avoid user-unfriendly events.

Twenty (15 male, 5 female, mean age = 29.8 years, standard deviation = 3.1 years) human subjects (researchers of ITIA-CNR group, Milan, Italy) with normal vision and memory, without any physical or mental problems, were recruited voluntarily for executing evaluation experiments. Two different control algorithms were implemented on the robot including the standard impedance control and the proposed control algorithm in two modes of known and unknown inertia properties (which results in four different applications). The human subjects were supposed to lift a component (2.5 kg) cooperatively with the manipulator up to a certain height three times for each application and score seven defined criteria with respect to the running controller. Order of running control algorithms for the subjects were randomized to balance the evaluation results. Table I indicates the value of control parameters imposed to both control algorithms while assistance level values only refer to the proposed fuzzy-impedance controller along the three translational directions (X, Y and Z). Such parameters have been calculated using the trained nerual network and considering the component weight related to the manipulated component in the target experiment. The evaluation procedure indicates the effectiveness of proposed approach (*e.g.*, the fuzzy impedance controller) in the sense of naturalness, smoothness, stability, effort, detection of intention, motion and performance for empowering human operator in industrial tasks as shown in Figure 5. Moreover, from the operator point of view, both control algorithms perform significantly better when knowing the inertia properties of the manipulated component.

TABLE I

CONTROL PARAMETERS VALUES DURING THE EXPERIMENTAL EVALUATION PROCEDURE.

	X	Y	Z
Damping ratio	0.95	0.95	0.95
Stiffness $[N/m]$	1000	2000	1000
Medium assistance level $[m]$	0.0015	0.0045	0.0030
High assistance level $[m]$	0.005	0.016	0.0095

B. *Industrial Application*

Beside the experimental evaluation procedure, the proposed method has been validated in an industrial task performing the installation of a heavy and bulky hatrack component inside an aircraft, case-study related to the H2020 CleanSky 2 EURECA project. Such industrial task is a complete 6 DoFs task. First and foremost, the application focused on relieving production employees of physically strenuous work. The solution results in a manually-guided robotic system programmed by demonstration that does all heavy lifting. During the execution of assembly task, only one worker is needed to manipulate the heavy parts. Virtual features has been imposed for guiding assembly operations. The proposed approach has been shown during the KUKA Innovation Award admitting the fact that the proposed scenario is ready to be implemented on manipulators to assist operators in real industrial tasks.

V. ACKNOWLEDGEMENT

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