Expert Systems With Applications 42 (2015) 8929–8935

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Indirect adaptive fuzzy control for industrial robots: A solution for contact applications

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ARTICLE INFO

Keywords:
Adaptive fuzzy control
Hybrid force/motion control
Robot contact
Robotics

ABSTRACT

Robots have been increasingly used in uncertain environments where direct contact with the surrounding environment exists. A design procedure of an adaptive fuzzy control, which can be carried out systematically, is suggested in this paper. The developed adaptive laws learn on-line the fuzzy rules of the control system and the uncertainties of the plant. Adaptive fuzzy control is integrated in a hybrid force/motion control system of an industrial robot to deal with a scenario of contact between the end-effector of the robot and a given surface. The controller is designed according to the previous knowledge about the process. The effectiveness of the proposed control system is shown through simulation and experimental results. Experimental results demonstrate superior stability and robustness of the proposed controller in relation to controllers of the same nature applied to industrial robotics, namely when there is contact between robot and surround environment.

1. Introduction

Traditionally, industrial robots are designed to allow accurate and repeatable control of the position and velocity of the robot's end-effector. Increasingly, robots are often also required to perform complex tasks requiring robust and stable force control strategies to deal with uncertain environments. In addition, task constraints sometimes require position or velocity control in some Degrees-Of-Freedom (DOF) and force control in others. Thus, to fulfill these extra demands, an important area of robotics research is the implementation of stable and accurate force control. However, this is often difficult to achieve in practice due to the technological limitations of current controllers, coupled with the demanding requirements placed upon them by the advanced control schemes that are needed in cases where robots are operating in unstructured environments. Hybrid control (force and motion) allows forces to be controlled in the constraint directions by a force controller, while simultaneously, positions in the free direction are controlled by a motion controller (Mendes, Neto, Pires, & Loureiro, 2013).

A survey on industrial applications of fuzzy control is presented in Precup and Hellendoorn (2011). Some techniques of adaptive fuzzy control are highlighted and industrial applications are pointed out. An observer-based indirect adaptive fuzzy sliding mode controller is proposed in Kung and Chen (2005). This controller is tested by simulation in an inverted pendulum system. Results of the simulation report that this control strategy presents a good tracking performance and is robust against external noise. A fuzzy adaptive output feedback control based on an observer for a single-input-single-output (SISO) is proposed by Boulkroune, Tadjine, M'Saad, and Farza (2008). An approach to adaptive fuzzy sliding mode control with a self-tuning mechanism adapting control parameters and switching gains is introduced in Cerman and Hušek (2012). Other authors suggest an adaptive fuzzy system to reduce the oscillation in power systems (Hussein, Saad, Elshafei, & Bahgat, 2009). An adaptive fuzzy control scheme for trajectory tracking of mobile robots is proposed by Liang, Xu, Wei, and Hu (2010). A Takagi–Sugeno fuzzy model for indirect adaptive control is proposed to SISO and multiple-input-multiple-output (MIMO) (Qi & Brdys, 2009). Other studies report the contact along the entire length of the robotic arm using force control strategies based on probabilistic estimation (Petrovskaya, Park, & Khatib, 2007). An interesting paper in the field exposes from a practical point of view the importance of sensor integration and force control for the application of robots in new manufacturing scenarios (Blomdell et al., 2005). An intelligent adaptive control system for MIMO uncertain nonlinear systems is proposed to control a mass–spring–damper mechanical system and a Chua's chaotic circuit (Chen, Lin, & Chen, 2008). A design method of an adaptive fuzzy logic controller for DC-DC converter is proposed by Elmas, Deperlioglu, and Sayan (2009).

A study approaching adaptive cruise control of a hybrid electric vehicle using sliding mode control is presented by Ganji, Kouzani, Khoo, and Shams-Zahraei (2014). The design of an in-process

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http://dx.doi.org/10.1016/j.eswa.2015.07.047
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surface roughness adaptive control system for a CNC turning operation, using fuzzy-nets modeling and tool vibrations measurements, is presented by Kirby, Chen, and Zhang (2006). Macías-Escrivá, Haber, del Toro, and Hernandez (2013) presented a survey about recent progress on self-adaptive systems. An industrial system composed by two DC motors was employed to study the performance of three different adaptive fuzzy control architectures: direct adaptive; indirect adaptive; and combined direct/indirect adaptive (Mendes, Araújo, Sousa, Apóstolo, & Alves, 2011). A learning method of a Takagi–Sugeno fuzzy model is performed to approximate unknown nonlinear processes by a hierarchical genetic algorithm (Mendes, Araújo, & Souza, 2013). This approach was successfully applied on identification of a model for the estimation of the flour concentration in the effluent of a real-world wastewater treatment system. Adaptive neuro fuzzy inference strategies was used to control input displacement of a new adaptive compliant gripper (Petković, Issa, Pavlović, Zentner, & Ćojbašić, 2012; Petković, Pavlović, Ćojbašić, & Pavlović, 2013). An adaptive charged system search (ACSS) algorithm for the optimal tuning of Takagi–Sugeno proportional–integral fuzzy controllers is proposed for the position control of a nonlinear servo system (Precup, David, Petriu, Preitl, & Rădac, 2014). In order to control a heating, ventilating and air-conditioning (HVAC) system, conventional PID control was implemented and fuzzy adaptive control was performed to tune the PID controller gains to maximize the performance of the system (Soyguder & Alli, 2010). An indirect adaptive interval type-2 fuzzy PI sliding mode controller is presented by Ghaemi and Akbarzadeh-Totonchi (2014). Although this system achieves good performance in terms of stability and asymptotic convergence, especially when human expert knowledge is used to initialize its parameters, the controller is computationally expensive. A robust stable controller based on indirect adaptive fuzzy sliding mode for stabilizations of power systems is reported as able to eliminate chattering (Saoudi & Harmas, 2014). Simulation results illustrate the good performance of observer-based fuzzy indirect adaptive controllers (Boulkroune, Bounar, M'Saad, & Farza, 2014; Li, Li, & Jing, 2014). Three model-free indirect adaptive controllers are proposed to control the tip displacement of a conducting polymer actuator, which has an unknown behavior (Beyhan & Itik, 2015). The control methods are based on convention indirect adaptive fuzzy, Chebychev functional-link network, and a hybrid solution of the two previous methods. All of the control methods present satisfactory performance with the hybrid controller providing better results in terms of root-mean-squared error, required input signal power, and settling time. However, the hybrid controller is extremely noisy which prevents its use in many applications.

The above referred literature proved that a controller based on indirect adaptive fuzzy control may provide a stable and robust solution capable to cope with plant disturbances. However, these solutions are neither easy to implement nor in many cases computationally viable. Thus, a purpose of this study is cope with both these challenges providing a systematic procedure to implement an effective controller. A hybrid force/motion control system is proposed to cope with contact issues when industrial robots are involved. The proposed control system is composed by a force control loop and a motion control loop. It is highlighted the force control loop which is based on an indirect adaptive fuzzy control. The great advantage of this system is the on-line generation of the fuzzy rules without previous knowledge about the plant or without rigorous previous knowledge about the plant. Furthermore, the uncertainties of the plant are learned on-line and adaptively compensated for.

2. Architecture

This study is taking into consideration two common scenarios in industrial robotics field:

- There is contact between the robot end-effector and the surrounding environment;
- The robot is programmed off-line.

These two points contribute to the appearance of end-effector positional errors. Since robots are subjected to positional errors from several sources (see below), it becomes important to develop a controller to reduce/eliminate the effect of the positional errors. A hybrid force/motion control system is proposed to cope with positional errors.

2.1. Robot positional error

Within the mechanical robot structure two categories of errors can be distinguished: geometrical errors and non-geometrical errors (Mustafa, Tao, Yang, & Chen, 2010). The former encompasses all the deviation due to imperfect geometries, mating or assembly errors. These errors exist whether the robot is moving or not. The latter include all the error sources related to the dynamical behavior of the robot. In addition, unlike the former, they are time-varying and change in magnitude during manipulator operations. The main effect of both of these error sources is causing discrepancies between the real robot and its kinetostatic and dynamic model from which its characteristics are derived (Legnani, Tosi, Fassi, Giberti, & Cinquemani, 2010) and on which control is based (Dietz et al., 2012).

Geometrical errors, which are generally compensated by calibration, arise from manufacturing or machining tolerances of robot components. Non-geometric errors also occur in a local environment and therefore, cannot be compensated by calibration. They arise from structural deformations of load-transmitting components, links and energy-transforming devices as well as from wear and nonlinear effects such as nonlinear stiffness, stick-slip motion and hysteresis in servo drives (Gong, Yuan, & Ni, 2000; Ruderman, Hoffmann, & Bertram, 2009). The compliance errors are due to the compliance of the links and joints under inertial and external load. In particular, joint compliance results from the torsional stiffness of the gearbox and the output drive shaft actuating the joint. Besides, the masses of the links cause an additional torque on the gears due to gravity effects. Especially during contact tasks, forces add on the load of the gears and cause additional deflection. Link and joint compliance, causing the deflection of the links and finally the end-effector, contribute up to 8–10% of the position and orientation errors of the end-effector (Mustafa, Tao, Yang, & Chen, 2010).

2.2. Programming

The programming process starts with the definition of the nominal robot paths that during the process will be adjusted according to the forces being exerted on the end-effector. The robot is pre-programmed (nominal paths) by off-line programming as described in previous studies in which target points are extracted from CAD (Neto & Mendes, 2013). In order to integrate the force control loop with the motion control loop the methods presented in (Mendes, Neto, Norberto Pires, & Loureiro, 2013) are implemented. During the movement of the robot the forces and torques measured by the force/torque (F/T) sensor and the current pose of the robot end-effector serve as input to the force/motion control system that outputs adjustments for the nominal path. This is done to keep a given set force between the end-effector and the surface (environment).

2.3. Hybrid force/motion controller

In a traditional hybrid force/motion control system applied to a robot manipulator, some robot directions are controlled in motion control and others are controlled in force control. Nevertheless, this study proposes the use of two control loops, an external control loop based on force and torque and an internal control loop based on motion. In this new hybrid force/motion control system, all directions are

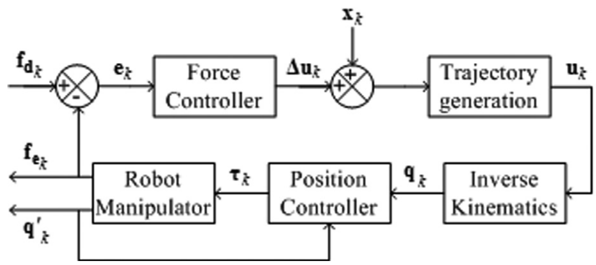

Fig. 1. Hybrid force/motion control system.

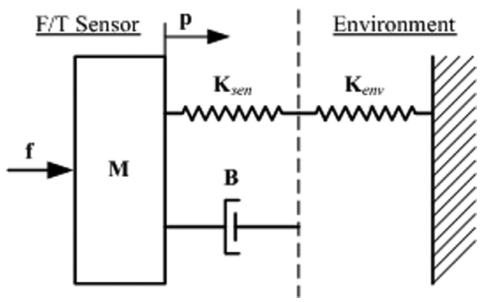

Fig. 2. Contact model.

controlled in motion, through internal control loop, and in some desired directions is applied force control, external control loop, which is superimposed over the internal control loop. The external control loop is used to compensate the deflection of the robot, avoid the undesired obstacles and high forces, and minimize the effect of the robot programming errors. The strategy to operate with the external force/torque controller starts by acquiring information (forces and torques) from the F/T sensor attached to the robot tool and measuring directly the contact between the end-effector and the environment. After that, the external control loop processes the information through an adaptive fuzzy control approach and sends position displacements and orientations corrections to the internal motion control loop in order to correct pre-programmed paths. This one in turn directly controls the servomotors of the robot. A schematic block diagram with the hybrid force/motion controller is shown in Fig. 1 in which $\boldsymbol{\tau}$ is the vector of applied joint torques, $\mathbf{q}$ is the vector of joint positions, $\mathbf{q}'$ is the vector of actual joint positions, $\boldsymbol{\Delta}\mathbf{u}$ is the vector of correction of displacements and orientations in Cartesian space, $\mathbf{u}$ is the robot displacement in Cartesian space, $\mathbf{x}$ is the nominal path, $\mathbf{f_d}$ is the desired force (set force) and $\mathbf{f_e}$ is the actual force.

2.4. Contact modeling

A full dynamic model of an end-effector plus F/T sensor in contact with a given environment is a complex system to model (Eppinger & Seering, 1986). However, the dynamic behavior of this system can be modeled approximately by a well-known mass-spring-damper as shown in Fig. 2 and described by the differential equation:

$$\mathbf{f}(t) = \mathbf{M}\ddot{\mathbf{p}}(t) + \mathbf{B}\dot{\mathbf{p}}(t) + \mathbf{K}_e\mathbf{p}(t) \tag{1}$$

Where $\mathbf{p}(t)$ is the $m \times 1$ end-effector position/orientation vector, $\mathbf{M}$ is the symmetric positive/definite $m \times m$ generalized mass matrix, $\mathbf{B}$ is the $m \times m$ generalized stiffness matrix, $\mathbf{f}(t)$ is the $m \times 1$ force vector applied to the end-effector in the force subspace $\{P\}$ and t is the time variable. The elements of $\mathbf{K}_e$ are the equivalent translation (force) and rotational (torque) coefficients of elasticity (stiffness) of the system in various directions in $\{P\}$. The equivalent stiffness k_e of F/T sensor with stiffness k_{sen} and environment with stiffness k_{env} is given by:

$$k_e = \left({k_{sen}}^{-1} + {k_{env}}^{-1}\right)^{-1} \tag{2}$$

3. Adaptive fuzzy control

Consider the nonlinear system in the following form:

$$x^{(n)} = f(x, \dot{x}, \ldots, x^{(n-1)}) + g(x, \dot{x}, \ldots, x^{(n-1)})u \tag{3}$$

$$y = x \tag{4}$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T = (x, \dot{x}, \ldots, x^{(n-1)})^T \in \Re^n$ is the state vector of the system, $f(\mathbf{x})$ is the unknown continuous function, $g(\mathbf{x})$ is the unknown continuous function control gain and $g(\mathbf{x}) \geq g_{\min} > 0$, u is the control input and y is the plant output.

The control objective is to design an adaptive fuzzy controller such that:

- The plant output y follows the ideal output y_d as close as possible;
- All signals of the closed-loop system are bounded.

Considering that the system has no disturbance, we propose the use of the following control law:

$$u = \frac{1}{g(\mathbf{x})}\left(-f(\mathbf{x}) + y_d^{(n)} + \mathbf{k}^T\mathbf{e}\right) \tag{5}$$

where $e = y_m - y = y_m - x$, $\mathbf{e} = [e, \dot{e}, \ldots, e^{(n-1)}]^T$ and $\mathbf{k} = [k_n, \ldots, k_1]^T$. Since $f(\mathbf{x})$ and $g(\mathbf{x})$ are unknown, these functions are replaced by fuzzy systems $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$, respectively.

In order to design the fuzzy systems $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$, more than one scenario can be considered for each fuzzy system. The different scenarios can vary in the kind of membership function, limits, fuzzy prepositions, number of rules, etc. Let $F_i^{k_i}, k_i = 1, \ldots, p_j$ be the fuzzy sets defined on the ith input and jth scenario. The fuzzy logic system for one scenario is characterized by a set of simplified IF-THEN rules expressed in the following form:

$$\begin{aligned} R^k\!: &\text{ If } x_1 \text{ is } F_1^{k_1} \text{ and} \ldots \text{and } x_n \text{ is } F_n^{k_n} \\ &\quad \text{Then } y \text{ is } y^k (k = 1, \ldots, p_j) \end{aligned} \tag{6}$$

where p_j is the number of rules for the jth scenario, $P = \sum_{j=1}^{m} p_j$ is the total number of rules (m is the number of scenarios), and y^k is the crisp output for the kth rule. The final output of the fuzzy system is calculated as follows:

$$y(\mathbf{x}) = \frac{\sum_{j=1}^{m}\left(\sum_{k=1}^{p_j}\left[\left(\prod_{i=1}^{n}\mu_{F_i}^{k_i}(x_i)\right)y^k\right]\right)}{\sum_{j=1}^{m}\left(\sum_{k=1}^{p_j}\left[\prod_{i=1}^{n}\mu_{F_i}^{k_i}(x_i)\right]\right)} \tag{7}$$

where $\mu_{F_i^{k_i}}(x_i)$ is the membership function of the fuzzy set $F_i^{k_i}$. However, the rules that compose the fuzzy systems $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$ provide only rough information about $f(\mathbf{x})$ and $g(\mathbf{x})$, the constructed fuzzy system $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$ may not approximate $f(\mathbf{x})$ and $g(\mathbf{x})$ well enough. To improve the accuracy of $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$, one idea is to leave some parameters in $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$ free to change during online operation so that the approximation accuracy improves over time. Let $\theta_f \in \Re^{P_f}$ and $\theta_g \in \Re^{P_g}$ be the free parameters in $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$, respectively, so we denote $\hat{f}(\mathbf{x}) = \hat{f}(\mathbf{x}|\theta_f)$ and $\hat{g}(\mathbf{x}) = \hat{g}(\mathbf{x}|\theta_g)$. They can be calculated by:

$$\hat{f}(\mathbf{x}|\theta_f) = \theta_f^T\xi(\mathbf{x}) \tag{8}$$

$$\hat{g}(\mathbf{x}|\theta_g) = \theta_g^T\eta(\mathbf{x}) \tag{9}$$

The parameters θ_f and θ_g are bounded by known positive values, i.e., $\theta_f \leq m_f$ and $\theta_g \leq m_g$, where m_f and m_g are given constants. From (7)–(9):

$$\xi(\mathbf{x}) = \frac{\prod_{i=1}^{n}\mu_{F_i}^{k_i}(x_i)}{\sum_{j=1}^{m}\left(\sum_{k=1}^{p_j}\left[\prod_{i=1}^{n}\mu_{F_i}^{k_i}(x_i)\right]\right)},\ k = i, \ldots, P_f \tag{10}$$

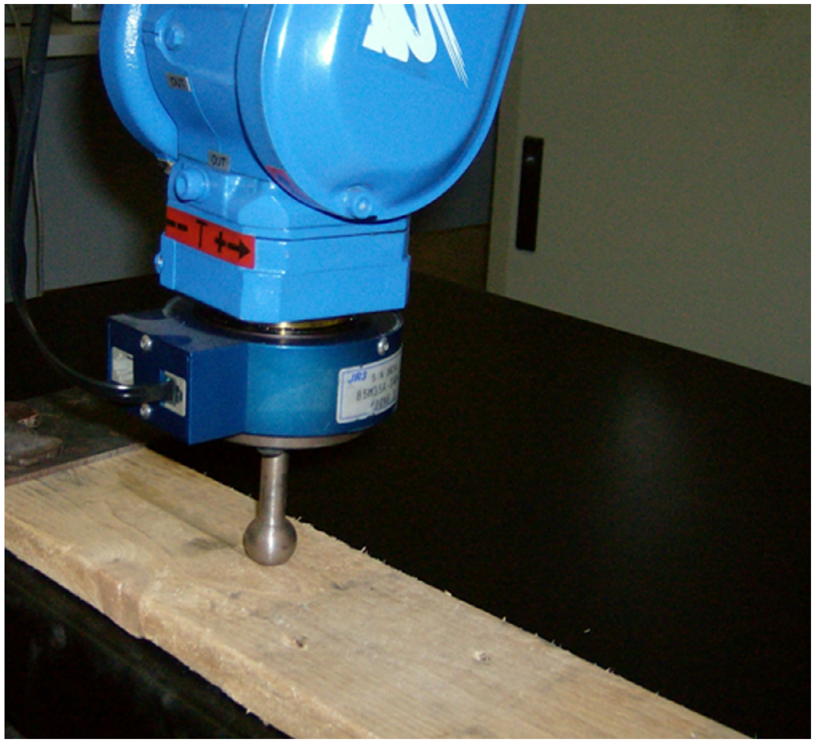

Fig. 3. Robot end-effector in contact with a pine wood work piece.

$$\eta(\mathbf{x}) = \frac{\prod_{i=1}^{h} \mu_{F_i}^{k_i}(x_i)}{\sum_{j=1}^{q}\left(\sum_{k=1}^{r_j}\left[\prod_{i=1}^{h} \mu_{F_i}^{k_i}(x_i)\right]\right)}, k = 1, \ldots, P_g \tag{11}$$

$$\theta_f = \left[y_{f_1}, \ldots, y_{f_n}\right]^T \tag{12}$$

$$\theta_g = \left[y_{g_1}, \ldots, y_{g_h}\right]^T \tag{13}$$

where *q*, *r* and *h* are the number of scenarios, the number of rules in each scenario and the number of input variables, respectively, for the fuzzy system $\hat{g}(\mathbf{x})$. Thus, we obtain the fuzzy controller:

$$u = \frac{1}{\hat{g}(\mathbf{x}|\theta_g)}\left(-\hat{f}(\mathbf{x}|\theta_f) + y_d^{(n)} + \mathbf{k}^T\mathbf{e}\right) \tag{14}$$

Taking (1), (14) and the Lyapunov equation:

$$\mathbf{\Lambda}^T\mathbf{P} + \mathbf{P\Lambda} = -\mathbf{Q} \tag{15}$$

where:

$$\mathbf{\Lambda} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & \ldots & 0 \\ 0 & 0 & 1 & 0 & 0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & 0 \\ 0 & 0 & 0 & 0 & 0 & \ldots & 1 \\ -k_n & -k_{n-1} & \ldots & \ldots & \ldots & \ldots & -k_1 \end{bmatrix} \tag{16}$$

And $\mathbf{Q}$ is an arbitrary $n \times n$ positive definite matrix, and $\mathbf{P}$ is a positive definite matrix satisfying the Lyapunov Eq. (15). After some manipulation, the adaptation law becomes:

$$\dot{\theta}_f = -\gamma_1\mathbf{e}^T\mathbf{Pb}\xi(\mathbf{x}) \tag{17}$$

$$\dot{\theta}_g = -\gamma_2\mathbf{e}^T\mathbf{Pb}\eta(\mathbf{x})u_I \tag{18}$$

Where γ_1 and γ_2 are positive constants, $\mathbf{b} = [0\ldots0\ 1]^T$ and u_I is previous control output (i.e. $u_I = u$). The plant knowledge (fuzzy IF-THEN rules) is incorporated through the initial parameters $\theta_f(0)$ and $\theta_g(0)$ to calculate $\hat{f}(\mathbf{x})$ and $\hat{g}(\mathbf{x})$.

The adaptive control law generates the fuzzy rules on-line. Furthermore, the uncertainties are learned on-line and adaptively compensated for. It should be emphasized that, the developed adaptive laws learn the fuzzy rules and uncertainties.

4. Case study

Increasingly, industrial robots are in contact with its surrounding environment in several applications like deburring and polishing. In this context, they need to keep a given contact force to perform the technological process with success. The proposed adaptive controller was embedded into a robotic system to assess its validity and effectiveness. The system (hardware) is composed by a robotic arm Motoman HP6 equipped with the NX100 controller, a F/T sensor JR3 85M35A-I40 and a common computer. The behavior of the robot plus the proposed controller are observed in two tests involving contact:

- The first test is performed by creating contact between the end-effector (sphere made of steel, Fig. 3) and a pine wood surface.
- The second test is performed by creating contact between the robot end-effector and a surface made of acrylonitrile butadiene styrene (ABS).

Both surfaces are flat and slightly sloped. The pine wood surface presents some irregularities. During the tests the robot end-effector moves through the surfaces trying to keep a given/desired contact force (a set force of -50 (N) for all tests). The displacement adjustments are performed by the robot on a direction normal to the surface. The controller version without plant knowledge has $\theta_f(0)$ and $\theta_g(0)$ initialized with value zero, while the controller version with plant knowledge has $\theta_f(0)$ and $\theta_g(0)$ with values established from previous contact tests (knowledge about the plant). These controllers are composed by just one scenario and two input variable: error (e) and error derivative ($\dot{e}$) which are expressed by five membership functions (NL, NS, ZR, PS and PL), as illustrated in Fig. 4. All the other parameters also are common to both controllers, namely $\mathbf{b} = [0\ 1]^T$, $\gamma_1 = 1$, $\gamma_2 = 10,000$, choosing $k_1 = 0.2$ and $k_2 = 0.07$ so

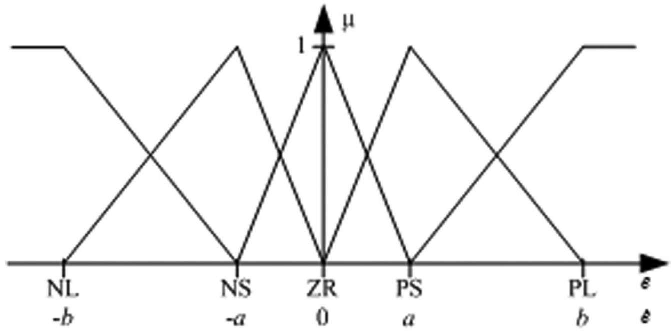

Fig. 4. Membership functions for the input variables with $a = 0.3$ and $b = 1$.

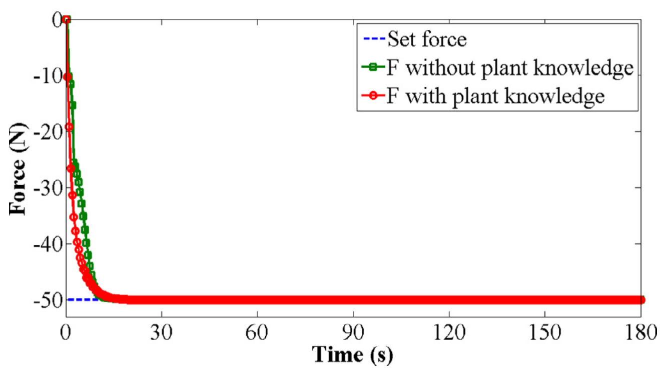

Fig. 5. Simulation results.

that $s^2 + k_1 s + k_2$ is stable, $\mathbf{Q} = diag(10, 10)$ and solving the Lyapunov Eq. (15) $\mathbf{P}$is obtained as $\mathbf{P} = \begin{bmatrix} 4.10357 & 7.14286 \\ 7.14286 & 38.21429 \end{bmatrix}$.

4.1. Simulation results

Fig. 5 shows the simulation results for both versions of the controller (with and without plant knowledge) in a scenario of contact between the robot end-effector and a pine wood surface. These simulations were performed without disturbances and the contact surface is assumed to be perfectly flat and with no slope.

4.2. Experimental results

Fig. 6 shows the behavior of the proposed controllers in a real scenario involving contact between the robot end-effector and a pine wood surface. The end-effector displacement adjustment for this test is illustrated in Fig. 7. In this figure it is visible the slope angle of the surface as well as the irregularities of the surface.

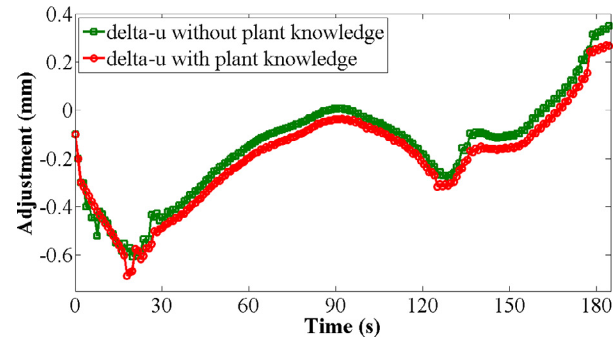

Fig. 7. Displacement adjustment (end-effector – pine wood surface).

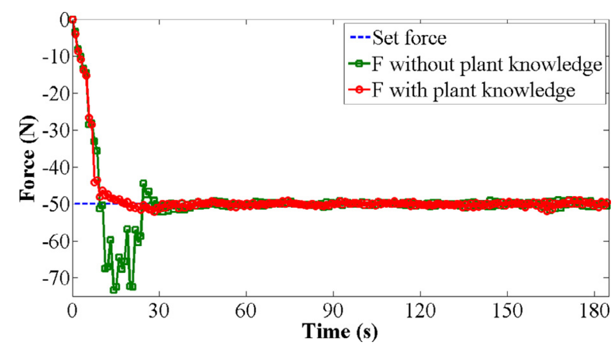

Fig. 8. Measured contact forces (end-effector – ABS surface).

Fig. 8 shows the system behavior for the contact between the end-effector and a surface made of ABS. Fig. 9 shows the displacement adjustment for this test in which the slope is clearly visible. Comparing Fig. 7 with Fig. 9 it can be concluded that in the second test the ABS surface does not present any irregularity.

4.3. Discussion

Simulation results indicate that the plant responses for both versions of the controller (with and without plant knowledge) are very similar. Both of them are asymptotic convergent and the settling time is the same, Fig. 5. However, the plant response of the controller with plant knowledge is smoother during the rising time. In either controllers there is no offset, overshoot or undershoot. Summarizing, the proposed controller can attain the control objective. Comparing these results with the results presented by Beyhan & Itik (2015) it can be stated that the controller presented in this study provides reduced

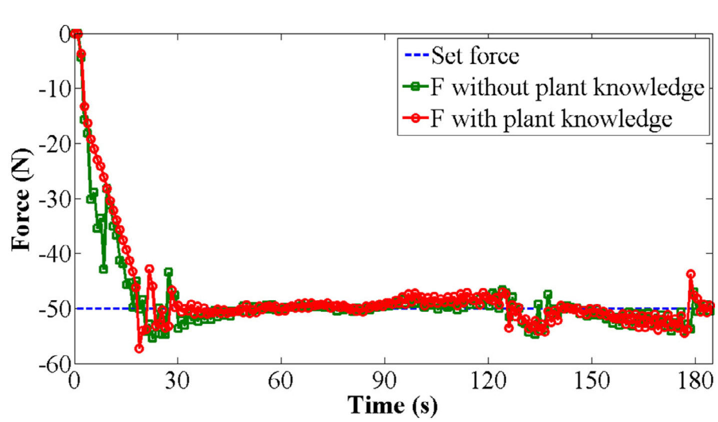

Fig. 6. Measured contact forces (end-effector – pine wood surface).

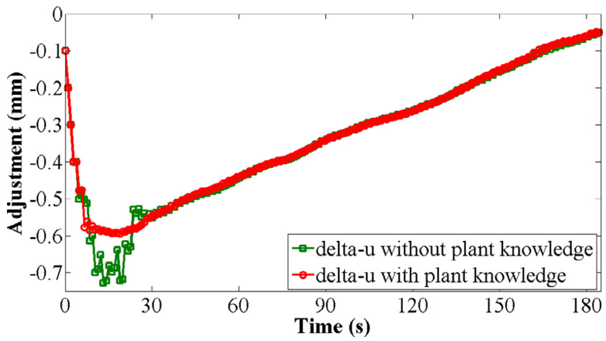

Fig. 9. Displacement adjustment (end-effector – ABS surface).

noise improving the control actuation. This is particularly important for a robotic application like the one presented in this study.

In experimental tests, there is not a clear difference on the plant responses, Figs. 6 and 8. Both responses are asymptotically convergent. There is not a strong difference between the behaviors of the two versions of the control system.

In the first test, both control versions present similar results: the overshoot and undershoot are residual and there is no offset. However, during the rising time the control version with plant knowledge presents a smoother behavior, Figs. 6 and 7. The control output $\mathbf{\Delta u}$ of the adaptive force loop for both control versions, illustrated in Fig. 6, presents a smooth behavior (without oscillation) in steady conditions and in the presence of disturbances.

In the second test, Figs. 8 and 9, once more, both control versions present similar results, there is no offset and the undershoot is residual. However, the control version without plant knowledge presents an overshoot and takes more time to converge to the set force (settling time). This can be explained by the fact that in this initial phase the adaptable parameters (non-suitable parameters) had not converged yet. Moreover, it can be seen that the controller deals with the disturbances of the plant in a suitable way. Taking into account the two tests, a conclusion can be drawn when the surfaces in contact present higher stiffness the controller version without plant knowledge tends to exhibit higher overshoots.

The proposed controller allows tracking a set force, even if the plant is unknown. Results compare favorably in terms of stability and robustness over similar control approaches (less offset and oscillation around the set force) (Blomdell et al., 2005; Petrovskaya, Park, & Khatib, 2007; Saoudi & Harmas, 2014). Similar performance is presented by the controller proposed by Mendes, Neto, Pires, & Loureiro, (2013), but in that case all the fuzzy rules had to be well designed knowing perfectly the plant. This is a clear limitation for unknown plants and also for plants with very distinctive and changeable behaviors along the time.

Summarizing, it can be stated that the proposed control scheme has the following advantages:

- Does not require the system model;
- Guarantees the stability of the closed loop system;
- Uses a simple rule base.

On the other hand, this control scheme may present low performance during the settling time when the plant is unknown. In this case the parameter settling time can achieve longer times as well as higher peaks of overshoot and undershoot.

5. Conclusions

This paper approaches the behavior of an indirect adaptive fuzzy controller used as force controller in a hybrid force/motion solution. The major contributions of the presented adaptive controller are the initialization to zero of the parameters of the fuzzy system, the mathematical model of the plant which is not required, and the convergence of the controlled variable which is ensure. Additionally, the proposed architecture allows the control system to discard previews knowledge about upper bounds for error and disturbance.

Simulation and experimental results show the effectiveness of the overall closed loop system performance. Two versions of the adaptive controller are tested: one without plant knowledge and the other with plant knowledge. Experimental results demonstrate that the former takes more time to converge to the desired set force and has a slight overshoot; the latter practically does not present overshoot and/or undershoot. The plant response is different in the two versions of the adaptive controller because the controller takes more time (settling time) till learn the uncertainties of the plant. This system could be used in industrial applications where contact is involved such as robotic operations of friction stir welding, deburring, polishing and assembly applications.

As a future work, we intend to extend the results of the paper to a multi-input multi-output (MIMO) nonlinear system which will allow to make it more stable by adding vibration input signals from accelerometers attached to the robot end-effector.

Acknowledgments

This research was supported by FEDER funds through the program COMPETE (Programa Operacional Factores de Competitividade), under the project CENTRO-07-0224-FEDER-002001(MT4MOBI) and by national funds through FCT (Fundação para a Ciência e a Tecnologia) under the project PEst-C/EME/UI0285/2013. The authors are grateful to Yaskawa Ibérica for the equipment and support provided.

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