CILAP-Architecture for Simultaneous Position- and Force-Control in Constrained Manufacturing Tasks

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Keywords: Parallel Control, Simultaneous Position- and Force-Control, Constrained Manufacturing, Bio-inspired.

Abstract: This paper presents a parallel control concept for automated constrained manufacturing tasks, i.e. for simultaneous position- and force-control of industrial robotic manipulators. The manipulator's interaction with its environment results in a constrained non-linear switched system. In combination with internal and external uncertainties and in the presence of friction, the stable system performance is impaired. The aim is to mimic a human worker's behaviour encoded as lists of successive desired positions and forces obtained from the records of a human performing the considered task operating the lightweight robot arm in gravity compensation mode. The suggested parallel control concept combines a model-free position- and a model-free torque-controller. These separate controllers combine conventional PID- and PI-control with adaptive neuro-inspired algorithms. The latter use concepts of a reward-like incentive, a learning system and an actuator-inhibitor-interplay. The elements Conventional controller, Incentive, Learning system and Actuator-Preventer interaction form the CILAP-concept. The main contribution of this work is a biologically inspired parallel control architecture for simultaneous position- and force-control of continuous in contrast to discrete manufacturing tasks without having recourse to visual inputs. The proposed control-method is validated on a surface finishing process-simulation. It is shown that it outperforms a conventional combination of PID- and PI-controllers.

1 INTRODUCTION

Automation of contact-based manufacturing processes is of significant interest to the industrial as well as to the scientific community. Humans being highly proficient at manufacturing tasks requiring compliance and force control, high number of research works in the field aim to mimic the human workers' behaviour and to translate its capabilities into robot skills.

(Rozo et al., 2013) used Programming by Demonstration, PbD which teaches a robot by showing the desired behaviour rather than by writing commands in a programming language. Based on Gaussian mixture theory, a single model encompasses both, desired positions and forces. (Abu-Dakka et al., 2015) presented a concept for learning and adaptation of contact-based manipulation tasks. The authors suggested a scheme for online modifications to match desired reference position- and force-profiles. The latter were obtained from programming by demonstration and encoded with dynamic movement primitives. (Oba et al., 2016) discussed the acquisition and replication of polishing skills of a human worker represented as tool trajectory, tool posture and polishing force. These variables which were to be controlled independently and simultaneously formed the input to the controller.

As far as the considered processes are concerned, most manufacturing tasks require the robotic manipulator to interact with its environment which results in contact situations and constrained movements, i.e. the robot arm cannot move freely in all directions. Constraints include natural constraints due to the specificities of the environment as well as artificial constraints due to and characteristic of the desired task. Varying or switching constraints are due to successive discrete or continuous phases in a task. By their nature, the control of constrained tasks requires the simultaneous control of pose and force. Pure position control cannot cope with these complex tasks because already slight deviations from the desired trajectory can lead to errors in the desired forces and torques (Abu-Dakka et al., 2015). Pure

Klecker, S., Hichri, B. and Plapper, P.
CILAP-Architecture for Simultaneous Position- and Force-Control in Constrained Manufacturing Tasks.
DOI: 10.5220/0006828902440251
In *Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2018) - Volume 2*, pages 244-251
ISBN: 978-989-758-321-6

force control on the other hand can lead to contact instabilities at an increased speed (Newman et al., 1999). A promising approach for simultaneous position- and force-control is parallel control, i.e. two controllers acting in parallel. Both independent controllers yield control torque commands which are summed up. In contrast to other state-of-the-art hybrid control methods, parallel control allows for the simultaneous and independent control of position- and force-signals. Parallel control has been the subject of repeated research efforts over the past decades. Based on the interactions of controller, robot arm and environment, (Chiaverini and Sciavicco, 1993) developed a dynamic parallel force-/position-control for constrained motions with an elastic environment. (Ferguene et al., 2009) extended a conventional parallel force-/position-controller with a 3-layer feed-forward neural network to compensate for uncertain or varying robot dynamics and environments. The intended application areas ranged from elastic environments over curved surfaces to unknown environmental stiffness. (Karayiannidis and Doulgeri, 2010) suggested adaptive concepts for position-/force-control in compliant and frictional contacts in the presence of uncertainties in models, end effector-orientation and environment. (Yin et al., 2012) based his tracking controller on a human analogy, i.e. on the human's approach to finger tracking in the absence of visual feedback. For the tracking of an unknown surface, the authors relied on the concepts of moving frames and vector-variations. (Lange et al., 2013) presented a parallel position-based force-/torque-control scheme taking into account couplings between forces and torques, constrained configurations, compliances in robot, sensor and environment as well as the effects due to impact forces. An experimental validation completed the work. The cited contributions present some drawbacks for the here considered automated manufacturing task. The majority of the state-of-the-art controllers are model-based and based only on conventional concepts, not taking advantage of gains in robustness and adaptability offered by intelligent control-extensions.

Over the past decades, some research has also been done separately on control-algorithms. Since their introduction in 1940, model-free PID-controllers have been predominant in industrial settings (Adar and Kozan, 2016). This is due to their key-advantages: robustness and simple design. Their constant fixed parameters as well as their linearity however, make it hard to cope with either nonlinear, time-varying systems or disturbances. The lack of flexible adaptability and the impossibility to increase gains arbitrarily due to actuator limitations as well as the occurrence of instabilities and noise sensitivity (Kuc and Han, 2000) (Siciliano and Khatib, 2008) limit the application areas. Conventional controllers are therefore not suited for controlling manufacturing processes automated with highly nonlinear, coupled robotic systems (Adar and Kozan, 2016) (Kuc and Han, 2000) (Siciliano and Khatib, 2008).

With the aim to take advantage of the conventional controller's trumps while overcoming its drawbacks, biomimetic extensions imitating the learning behaviour of the human brain are presented. Due to the complex nature of this biological system only a concise selection of its key-aspects has been retained for the development of control concepts. (Lucas et al., 2004) presented BELBIC (Brain Emotional Learning-Based Intelligent Control) on the base of the work by (Balkenius and Morén, 2001) on a computational model of the abstracted human amygdalo-orbitofrontal cortex system. The suggested controller mimics the natural interplay of actuating amygdala and inhibiting orbitofrontal cortex. The implementation of an emotional signal can be interpreted as a reward or incentive to guide the system's learning behaviour. (Yi, 2015) combined robust sliding mode control with an intelligent control element comprising an actuator and a preventer inspired on the mammalian limbic system. (Frank et al., 2014)'s work focussed on reinforcement learning allowing an agent to learn a policy with the goal to maximize a reward-signal. The authors combined a low-level, reactive controller with a high-level curious agent. Artificial curiosity contributes to the learning process by guiding exploration to areas where the agent can efficiently learn. The work was validated by a real-time motion planning task on a humanoid robot. (Merrick, 2012) implemented a goal-lifecycle and introspection for reinforcement learning. The aim was to make the system aware of when to learn what as well as of which acquired skills to keep either active, ignored or erased.

The aim of this work is to combine freeform trajectory tracking with force control, i.e. to develop a model-free control strategy enabling an industrial robot-arm to follow a desired freeform-path and simultaneously apply specified adequate joint-torques at the appropriate moment and position. The desired position- and force-signals are to be learned from kinesthetic teaching and introduced as independent lists of successive joint-angles and -torques. This work combines elements of PbD, parallel control and neuro-inspired control-extensions. Compared with related work cited above, the main differences in this paper are: 1) no visual

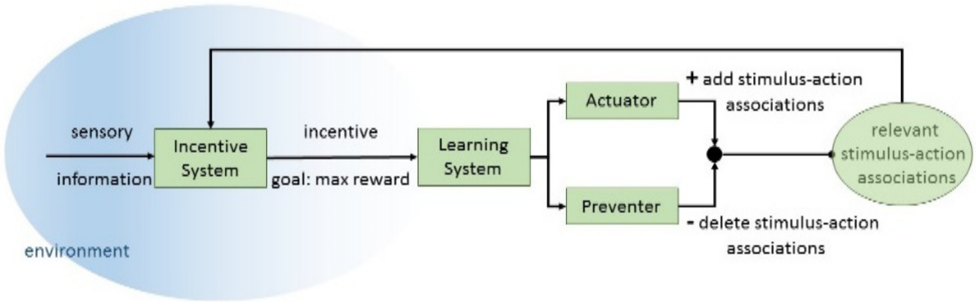

Figure 1: Inspiration for the CILAP-architecture.

information, i.e. no camera is used and 2) the considered tasks are continuous movements instead of discrete contact state formations. The input for the controller is a list of desired successive joint-specific positions and torques which are obtained from the records of a human performing the considered task operating the lightweight robot arm in gravity compensation mode. 3) Further, a parallel control concept composed of a model-free position-controller and a model-free force-controller is designed. These separate controllers combine conventional PID- or PI-control with adaptive neuro-inspired algorithms. The latter make use of an incentive and a learning system as well as of the interaction of an actuator and a preventer to improve the controller performance. The elements Conventional controller, Incentive, Learning system and Actuator-Preventer interplay form the CILAP-concept. The suggested method is validated on a manufacturing process simulation. For the control objectives, the main focus is put on precision. As the considered tasks are not time critical, minimal mean errors of position- and force-signals are the objective.

The rest of the paper is structured as follows: It follows the description of the challenge, i.e. section 2 'Problem Statement'. Section 3 describes the used concepts. In Section 4, the suggested parallel control concept CILAP (conventional-incentive-learning-actuator-preventer) is developed and in section 5 the results of the simulation are presented and discussed. The paper ends with a conclusion.

2 PROBLEM STATEMENT

The robot-arm considered in this work has n links and its dynamics in the presence of uncertainties, disturbances and switching constraints are expressed:

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{G}(\boldsymbol{q}) = \boldsymbol{d} + \boldsymbol{f} + \boldsymbol{Q}_i + \boldsymbol{u} \quad (1)$$

with $\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}} \in R^n$ link position, velocity and acceleration with index d for the desired reference values. $\boldsymbol{M}(\boldsymbol{q}) \in R^{nxn}$ is the inertia matrix, $\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}}) \in R^{nxn}$ the centripetal/Coriolis terms, $\boldsymbol{G}(\boldsymbol{q}) \in R^n$ the gravitational torque-vector. External disturbances are represented by the bounded term $\boldsymbol{d} \in R^n$ while internal uncertainties are implemented as variations in $\boldsymbol{M}(\boldsymbol{q})$, $\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})$ and $\boldsymbol{G}(\boldsymbol{q})$. $\boldsymbol{f} \in R^n$ stands for the friction between end-effector and environment or surface. The friction is a function of the applied torque and the robot link velocity: $\boldsymbol{f} = \gamma \boldsymbol{\tau}_d{}^T \dot{\boldsymbol{q}}_{measured}$ with γ a constant factor. $\boldsymbol{Q}_i \in R^n$ is the global constraint force, $\boldsymbol{Q}_i = \boldsymbol{J}^T(\boldsymbol{q})\boldsymbol{D}_i^T(\boldsymbol{\vartheta})\boldsymbol{\lambda}$ where $\boldsymbol{J}(\boldsymbol{q}) \in R^{nx6}$ is the manipulator's Jacobian, $\boldsymbol{\lambda} \in R^m$ is the vector of Lagrange multipliers and $\boldsymbol{D}_i(\boldsymbol{\vartheta}) = \frac{\delta \boldsymbol{\phi}_i(\boldsymbol{\vartheta})}{\delta \boldsymbol{\vartheta}}$ is the gradient of the task space constraints with $\emptyset_i(\boldsymbol{\vartheta}) \in R^6$ the i^{th} kinematic constraint. $\boldsymbol{\vartheta} \in R^6$ stands for the Cartesian pose and $i = 1,2, \dots m$ denotes the index of constraints for the case of multiple switching constraints with m the total number of constraints.

The considered application is a contact-based manufacturing task, i.e. freeform trajectory tracking with the application of specified forces at specific positions. Manual work is current state-of-the-art for these tasks. Not only the fact that these processes were designed by and for humans but also humans' capabilities make them the most appropriate performers for these complex tasks. The challenge in this work is to mimic the human's approach to perform the considered task by translating his capabilities into robot skills and by including the worker's expertise in the control algorithm. The input for the controller is a .csv-file with desired successive positions and torques which are obtained from the records of a human operating a lightweight robot arm in gravity compensation mode. $\boldsymbol{u} \in R^n$ is the applied input torque. It is the sum of the outputs of the pose-controller and the force-controller, i.e. $\boldsymbol{u}_q + \boldsymbol{u}_\tau$. The control action consists in adapting both robot joint positions and the applied forces to match the desired poses and forces. The goal is to keep the error between desired and measured signals minimal at all times, i.e. the mean error signal over the whole process-period should be minimized.

3 USED CONCEPTS

The concepts used in this work are biologically inspired, similar to the related work cited in section 1. Despite the control concepts being inspired on the functioning of the human brain, they do not attempt to accurately model its structure. Rather than presenting a true-to-life computational model of the mammalian learning behaviour, the aim is to improve conventional model-free PID-control through the implementation of neuro-inspired concepts.

An incentive system transforms sensory information into an incentive, i.e. a reward-based extrinsic motivational stimulus. Depending on the environment, the stimulus to the agent, i.e. how to maximize the reward for the system is changed. This adaptive incentive then forms the input to a learning system which feeds both an actuator and a preventer. The interplay of the latter is inspired on the interplay of the amygdala and the orbitofrontal cortex in the mammalian brain during emotional learning. While the actuator establishes stimulus-action associations, the preventer erases associations which are no longer needed. The removal of no longer relevant stimulus-action association is essential for a successful learning and to reduce the amount of data in the system. The latter is similar to the phenomenon of synaptic plasticity in the human brain. The described structure is schematically represented in Figure 1.

4 THE PARALLEL CILAP-ARCHITECTURE

A parallel control concept is developed to simultaneously control joint angular positions and torques. The complex constrained control task is broken down into two independent subsystems. The suggested concept is composed of a model-free position-controller and a model-free force-controller. Both independent controllers consist of a conventional model-free controller and a model-free controller extension. The former C combines with the Incentive-Learning-Actuator-Preventer to form the CILAP-architecture. The suggested method attempts to combine robustness, simplicity and intuitiveness and is depicted in Figure 2.

The input to the controller is a .csv-file, i.e. a list containing a succession of desired joint positions $\boldsymbol{q}_d$ and joint torques $\boldsymbol{\tau}_d$.

4.1 Position-Control

The conventional PID-controller-output $\boldsymbol{u}_{q_c}$ as in Equation (2)

$$\boldsymbol{u}_{q_c} = K_{pq}\boldsymbol{q}_{error} + K_{dq}\dot{\boldsymbol{q}}_{error} + K_{iq}\int \boldsymbol{q}_{error}\ dt \quad (2)$$

with the error-signal, i.e. the difference between measured and desired signal as in Equation (3)

$$\boldsymbol{q}_{error} = \boldsymbol{q} - \boldsymbol{q}_d \quad (3)$$

where K_{pq}, K_{dq} and K_{iq} are constant gain factors.

For the controller extension, the appreciation, i.e. the value of the current state is defined as the error-signal (Equation (4)). As the only way to collect information about the environment is to interact with it, a feedback-loop is implemented in this controller-part.

$$\boldsymbol{state}_v = \boldsymbol{q} - \boldsymbol{q}_d = \boldsymbol{q}_{error} \quad (4)$$

The reward, i.e. incentive $\boldsymbol{i} \in R^{\boldsymbol{n}}$ is defined in Equation (5).

$$\boldsymbol{i} = (sign(\boldsymbol{state}_v)' \cdot \dot{\boldsymbol{state}}_v)(\boldsymbol{state}_v - \boldsymbol{o}) \quad (5)$$

where $'$ indicates the vector-transpose. $\boldsymbol{o} \in R^n$ represents the interplay of actuator and preventer. $\boldsymbol{o}$ is defined as the difference between their respective outputs (Equations (8) and (9)) which guarantees only relevant connections are kept. Mimicking synaptic plasticity, this law allows to limit the number of active learned connections.

The incentive is the input to the learning system. Its outputs are the learning rates for both the actuator (Equation (6)) and the preventer (Equation (7)).

$$w_a = \alpha \dot{\boldsymbol{state}}_v \cdot \max(\boldsymbol{0}, \boldsymbol{i}) \quad (6)$$

$$w_p = \alpha \dot{\boldsymbol{state}}_v \cdot (\boldsymbol{o} - \boldsymbol{i}) \quad (7)$$

with $\alpha > 0$ a constant factor.

The main part of this half of the control algorithm consists in the interaction between an actuator and an inhibitor. The actuator-output $\boldsymbol{a} \in R^n$ and the preventer-output $\boldsymbol{p} \in R^n$ are defined in Equations (8) and (9).

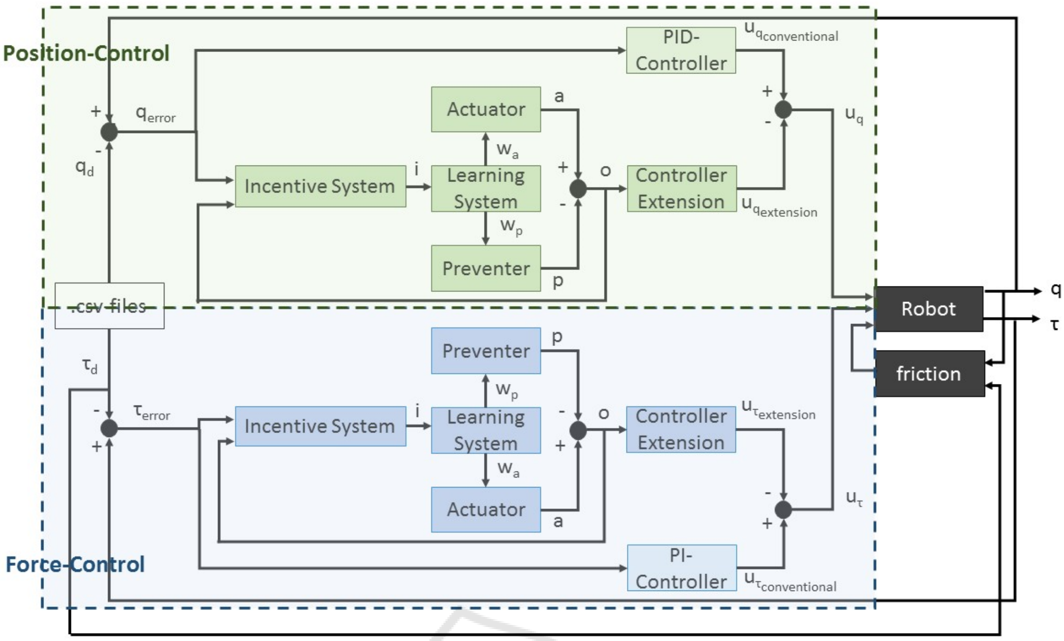

Figure 2: CILAP-architecture.

$$\boldsymbol{a} = \alpha \boldsymbol{state}_v \, w_a \quad (8)$$

$$\boldsymbol{p} = \alpha \boldsymbol{state}_v \, w_p \quad (9)$$

The controller-extension-output is defined in Equation (10), the integration over time mimicking experience.

$$\boldsymbol{u}_{q_e} = \beta \boldsymbol{state}_v - \int \boldsymbol{o} \quad (10)$$

with $\beta > 0$ being a constant gain-factor.

The final position-controller output combines the outputs of the conventional controller and of the extension.

$$\boldsymbol{u}_q = \boldsymbol{u}_{q_c} - \boldsymbol{u}_{q_e} \quad (11)$$

4.2 Force-Control

Parallel to the position-controller, a force-controller is implemented to make sure the desired force-torques from the reference .csv-file are applied.

The conventional PI-controller-output $\boldsymbol{u}_{\tau_c}$ is defined in Equation (12)

$$\boldsymbol{u}_{\tau_c} = K_{p\tau} \boldsymbol{\tau}_{error} + K_{i\tau} \int \boldsymbol{\tau}_{error} \quad (12)$$

where $K_{p\tau}$ and $K_{i\tau}$ are constant gain-matrices and the error-signal

$$\boldsymbol{\tau}_{error} = \boldsymbol{\tau} - \boldsymbol{\tau}_d \quad (13)$$

with $\boldsymbol{\tau} = \boldsymbol{u}_\tau + \boldsymbol{f}$.

For the controller-extension the state-value $\boldsymbol{state}_v$ is defined as the error-signal (Equation (13)). The incentive is defined as follows

$$\boldsymbol{i} = (sign(\boldsymbol{state}_v)' \cdot \dot{\boldsymbol{state}}_v)\,(\boldsymbol{state}_v - \boldsymbol{o}) \quad (14)$$

For the output of the actuator-preventer-system, its constituents and their learning rates the formulas defined in Equations (6)-(9) apply. The controller-extension-output follows Equation (15).

$$\boldsymbol{u}_{\tau_e} = -\beta \boldsymbol{state}_v + \int \boldsymbol{o} \quad (15)$$

The final force-torque-controller output combines the outputs of the conventional controller and of the extension.

$$\boldsymbol{u}_\tau = \boldsymbol{u}_{\tau_c} - \boldsymbol{u}_{\tau_e} \quad (16)$$

5 RESULTS

5.1 Simulation

The proposed control concept is validated on a surface finishing task, i.e. the robot-arm successively follows desired positions and applies desired torques at specified positions. The controller is implemented on a 2D-RR planar robot in the Matlab/Simulink-environment. The parameters of the robotic arm with two rotational joints are described in set of Equation (17).

$$\boldsymbol{M} = \begin{bmatrix} j_1 + m_2 {l_1}^2 & m_2 l_1 lc_2 \cos(q_2 - q_1) \\ m_2 l_1 lc_2 \cos(q_2 - q_1) & j_2 + m_2 {lc_2}^2 \end{bmatrix}$$

$$\boldsymbol{C} = \begin{bmatrix} 0 & -m_2 l_1 lc_2 \sin(q_2 - q_1) \\ m_2 l_1 lc_2 \sin(q_2 - q_1) & 0 \end{bmatrix}$$

$$\boldsymbol{G} = \begin{bmatrix} m_1 g lc_1 \cos(q_1) + m_2 g l_1 \cos(q_1) \\ m_2 g lc_2 \cos(q_2) \end{bmatrix} \quad (17)$$

with link masses $m_1 = m_2 = 1kg$, link lengths $l_1 = l_2 = 1m$, gravitational acceleration $g = 9.8\frac{m}{s^2}$, distances from the link source end to its centre of mass $lc_1 = lc_2$ and link moments of inertia $j_1 = j_2$. The system-inputs are extracted from .csv-files containing a succession of desired reference joint angular positions and torques. The controller-parameters introduced in Equations (2)-(16) are chosen and optimized by trial-and-error-procedure as follows: $\alpha = 5, \beta = 30, \gamma = 1, K_{pq} = -5, K_{dq} = -20, K_{iq} = -20, K_{p\tau} = 5, K_{i\tau} = 35$.

The performance-results are illustrated in Figures 3-8. While Figures 3 and 4 show the trajectory-tracking performance of the suggested controller scheme, Figures 5 and 6 depict its velocity-tracking and Figures 7 and 8 show the force-tracking of link 1 and 2, respectively.

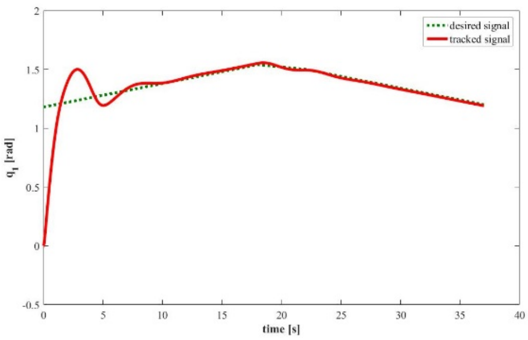

Figure 3: Trajectory tracking of link 1.

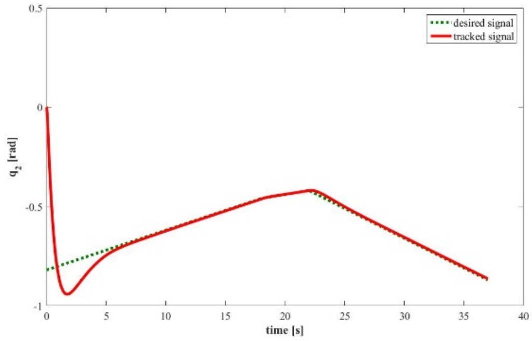

Figure 4: Trajectory tracking of link 2.

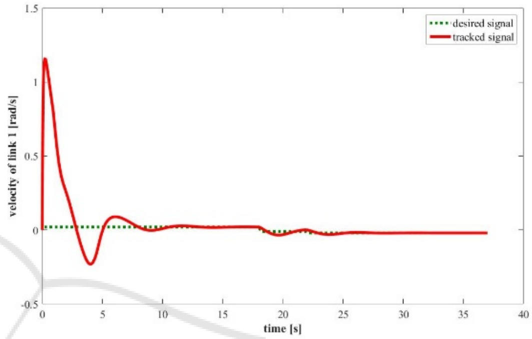

Figure 5: Velocity tracking of link 1.

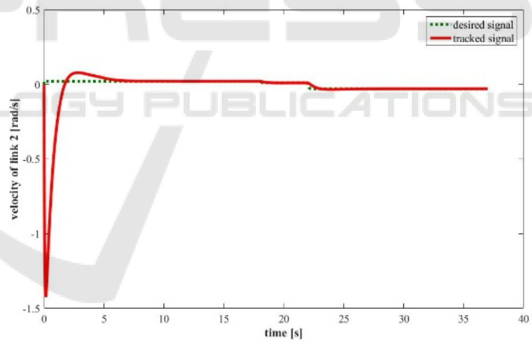

Figure 6: Velocity tracking of link 2.

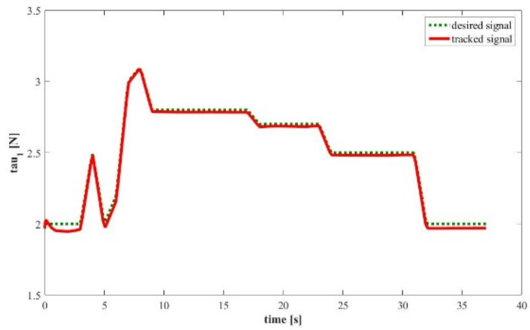

Figure 7: Force tracking of link 1.

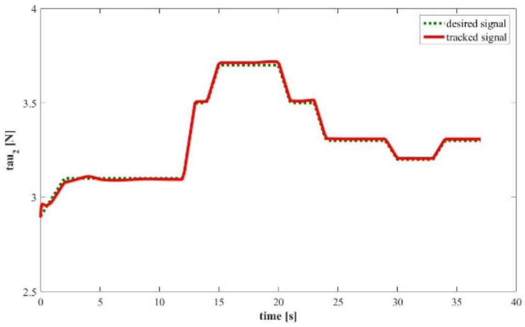

Figure 8: Force tracking of link 2.

5.2 Analysis and Discussion

The simulation-results present good tracking results for all considered signals: joint torques, angular joint positions and velocities. This is illustrated qualitatively in Figures 3-8 as well as quantitatively in Table 1 and Table 2.

The added value of the controller-extension is illustrated in Tables 1-3. In Table 3, the improvement from the parallel controller without the neuro-inspired extension to the suggested CILAP-architecture is given in percentages. It is proven that the latter outperforms a parallel controller with PID-position- and PI-force-control. The main focus in this work was put on the mean error signals.

The industrial applications of the presented work are contact-based manufacturing in general and surface finishing in specific. Manual work being current industrial state-of-the-art, surface finishing processes are the bottleneck of the concerned industry due to their time- and cost-intensive nature. Different studies suggest shares of up to 30-50% of the entire manufacturing time and up to 40% of the total cost. (Dardouri et al., 2017) (Dieste et al., 2013) (Pagilla and Yu, 2001) (Robertsson et al., 2006) (Roswell et al., 2006) (Wilbert et al., 2012). From the scientific point of view, the automation of these contact-based manufacturing processes is highly complex as it requires tackling freeform trajectory tracking and force control simultaneously while mimicking the robust and adaptive behaviour a human provides on a nonlinear system. Additional challenges arising in industrial practice and taken into account here are the absence of visual information from a camera and the application involving continuous movements, e.g. path following rather than discrete contact state formations, e.g. gripping.

As the shown work presents promising results for the automation of the considered continuous manufacturing processes, future work will involve the experimental validation on a KUKA LWR4+ robot-arm with a variety of processes, e.g. grinding or polishing tasks. Comparisons with state-of-the-art controllers will be performed to demonstrate the outperformance of the suggested concept. Also, its real-time capabilities will be proven.

Table 1: Maximum, minimum and mean absolute positional errors for both manipulator-links [rad] for the experiment with (a) the parallel architecture with PID- and PI-controllers and (b) the CILAP-architecture.

	a- q_{error_1}	a- q_{error_2}	b- q_{error_1}	b- q_{error_2}
Max	3.16	0.82	1.18	0.82
Min	9.70e-4	2.25e-5	2.07e-4	2.95e-5
Mean	1.64	0.09	0.13	0.08

Table 2: Maximum, minimum and mean absolute force-errors for both manipulator-links [N/m^2] for the experiment with (a) the parallel architecture with PID- and PI-controllers and (b) the CILAP-architecture.

	a- τ_{error_1}	a- τ_{error_2}	b- τ_{error_1}	b- τ_{error_2}
Max	2.41	2.45	0.05	0.05
Min	0.003	0.001	0.002	1.41e-5
Mean	1.56	1.62	0.02	0.01

Table 3: Average improvement-rate [%] from the parallel architecture with PID- and PI-controllers to the CILAP-architecture for position- and force-tracking.

Position-Control	35 %
Force-Control	87 %

6 CONCLUDING REMARKS

In this paper, the control problem of automated constrained manufacturing tasks was addressed. A parallel control concept composed of two model-free controller-halves is developed. One half controls the position while the other half controls the applied torque of the robot manipulator performing a freeform trajectory tracking application with the application of manufacturing-forces at specified positions in the presence of uncertainties and friction. Both controller-halves combine conventional control with biomimetic adaptive control. The latter is inspired on the human learning behaviour making use of an actuator-inhibitor-system and a reward-like incentive. The elements Conventional controller, Incentive, Learning system and Actuator-Preventer interplay form the CILAP-concept. The developed model-free control concept combines PbD, parallel control and neuro-inspired control-extensions. A surface finishing application-simulation illustrates the suggested scheme outperforms a combination of conventional PID- and PI-controllers.

ACKNOWLEDGEMENTS

This work has been done in the framework of the European Union supported INTERREG GR-project "ROBOTIX-Academy". (http://robotix.academy/)

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