Adaptive Neural-Network Control of a Human-Robot Cooperation

Masoud Pourghavam, Reza Bidari

***Abstract*—Autonomous robots and human–robot cooperation are becoming more personalized, interactive, and engaging than ever, providing assistance from daily life to manufacturing, healthcare, and transportation. In these applications, robots are desired to be capable of handling tasks autonomously in different environments and interacting with humans safely. In this research, an adaptive neural-network controller for trajectory tracking is used for a KUKA iiwa manipulator using CoppeliaSim and MATLAB. Finally, the results obtained from simulations will be discussed.**

***Index Terms*— Neural networks, Human-robot cooperation, Impedance, Adaptive.**

I. Introduction

NOWADAYS, a lot of attention has been paid to industrial robots, service robots, special robots, etc. In industry, robotic manipulators play an important role in smart manufacturing and the digital factory. Reliable robotic manipulators are widely used in various industrial sectors, including in handling, welding, grinding, and assembly. Among the numerous research directions of robotic manipulators, positional force tracking potency with high precision, high stability, and high adaptability are particularly important.

In [1] a hierarchical control scheme has been presented that enables an exoskeleton robot to manipulate cooperatively with humans. The control scheme consists of two layers. In the low-level control of the upper limb exoskeleton robot, an admittance control scheme with an adaptive neural network controller based on an asymmetric barrier Lyapunov function is proposed to allow the robot to be driven backward. In [2] Li et al. develop the adaptive impedance control of a robotic upper extremity exoskeleton using biological signals. First, they develop a musculoskeletal reference model of the human upper extremity and experimentally calibrate the model to match the movement behavior of the operator. Then the proposed new impedance algorithm translates the stiffness from the human operator through the surface electromyography (sEMG) signals, which are used to design the optimal reference impedance model. Considering the unknown dead zone effects in the robot joints and the lack of precise knowledge of the robot dynamics, an adaptive neural network control with a high-gain observer is developed to approximate the dead zone effect and robot dynamics and to control the desired robot tracking trajectories without velocity measurements. In [3] an admittance-based human-robot physical interaction (pHRI) controller is presented to perform the coordinated operation in the constrained task space. An admittance model and a soft saturation function are used to generate a differentiable reference trajectory to ensure that the manipulator's end effector motion matches human operation and avoids collision with the environment. Then, an adaptive neural network (NN) controller with an integrated Barrier Lyapunov Function (IBLF) is developed to solve tracking problems. In [4] two upper limbs of an exoskeleton robot are operated within a restricted area of the operating room with the unidentified intent of the human operator's movement and with uncertain dynamics including physical limitations. The new human-cooperative strategies are developed to recognize the movement efforts of human subjects in order to make the robots' behavior flexible and adaptive. The intention to move extracted from the measurement of the subject's muscular effort in relation to the applied forces/torques can be plotted to derive the reference trajectory of his/her limb using a useful impedance model. Then an online adaptive estimation for impedance parameters is used to deal with the non-linear and variable stiffness property of the limb model. In this paper [5] Huang et al. have developed a coordination control method for a two-armed exoskeleton robot based on human impedance transfer capabilities, where the left (master) robotic arm extracts the impedance stiffness and position profiles of human limbs and then transfers the information to the right arm of the exoskeleton. A computationally efficient model of arm endpoint stiffness behavior is developed and a co-contraction index is defined using muscle activities of a dominant antagonistic muscle pair. A reference command consisting of the operator's stiffness and position profiles is calculated and implemented by a robot in real time. Considering the dynamic uncertainties of the robotic exoskeleton, an adaptive-robust impedance controller in the task space is proposed to drive the slave arm following the desired trajectories with convergent errors. In [6] to explain the problems of human-robot security and adaptability to unidentified situations, a human-inspired control with force and impedance adaptation has been presented to cooperate with unknown environments and parade this biological performance on the developed two arms exoskeleton

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TABLE I
COMPARISON OF DIFFERENT STRATEGIES

LBHC = Learning-Based Hierarchical Control Scheme, AIC = Adaptive Impedance Control, ABC = Admittance-Based Controller, HIC = Human-Inspired Control, HRCC = Human-Robot Coordination Control, ABLF = Asymmetric Barrier Lyapunov Function, NN = Neural Networks, sEMG = Surface Electromyography, RBFNN = Radial Basis Function Neural Network, IBLF = Integral Barrier Lyapunov Function, pHRI = Physical Human-Robot Interaction, ST = Skill Transfer.

Authors	Technique	Approach	Interaction task	Platform	Human role	Robot role	Results
[1]	LBHC	ABLF-based adaptive NN controller	Providing the subjects with just enough assistance	Dual-arm exoskeleton	The human hand should display a minimum required impedance for teaching the robot	Receives force feedback information from the force sensor and applied admittance controller	Achieving safe human-robot cooperative manipulation in impedance-based tasks
[2]	AIC	sEMG	Calibrating the model to match the operator's motion behavior	Upper limb exoskeleton platform	The operator does the kinematic and dynamic behavior	To augment the human's muscular force and endurance in carrying heavy loads	Drove the robotic exoskeleton tracking the desired trajectories
[3]	ABC	RBFNN, IBLF, pHRI	To perform the coordinated operation in the constrained task space	Baxter robot	The human operates the manipulator toward constrained boundaries in the XYZ axes orderly	The robotic manipulator interacts with a human operator to perform tasks collaboratively	Approximated dynamic uncertainties
[6]	HIC	sEMG	Execute a skill transfer control	Dual-arm exoskeleton robot	The human would adjust his limb adaptively with the changed interaction force	Interact with unknown environments	Estimated stiffness of human arm and transfer position and stiffness profiles to robot arm in real-time
[8]	HRCC	ST	To adapt limb impedance to stably and properly interact with various environmental forces	Human-robot coordination platform	Human operator transfers the stiffness and exoskeleton robot is tele-operated by the operator	The robotic exoskeleton replicates the impedance of human operator's arm	Maintaining stability and eliminating the effect of external perturbations

robots. First of all, they use a computational model that uses scanned surface electromyogram (sEMG) signals to calculate the end-point stiffness of the human arm and define a co-contraction index to describe the dynamic behavior of muscle activities in the tasks. Then, the obtained human limb impedance stiffness parameters and scanning position information are transmitted in real-time as input variables of the controller to the slave arm of the exoskeleton. In [7] a trajectory deformation algorithm (TDA) is developed as a high-level trajectory planner that can plan the subject's desired trajectory based on the interaction force during physical human-robot interaction (pHRI). A low-level proportional differential position (PD) controller is selected to ensure that the lower limb rehabilitation robot (LLRR) can track the desired trajectory. Then the validity of TDA is verified by simulation and experimental studies. Li et al. in [8] develop a control approach that combines automatic robotic control with impedance control, using the stiffness transmitted by a human operator. Assuming a linear mapping between muscle surface electromyography (sEMG) signal amplitude and human arm stiffness, we use the incremental stiffness extraction method in the operating room with an improved performance by compensating for the residual nonlinear error in the mapping. The teleoperated robotic exoskeleton is able to replicate the impedance of the human operator's arm while compensating for external disturbances through disturbance observer technology. In [9] the physical haptic feedback mechanism is introduced to result in muscle activity that would naturally generate EMG signals to achieve intuitive human impedance transfer through a designed coupling interface. Relevant processing methods are built into the system, including the spectral collaborative representation-based classification method used for hand motion detection; fast smooth envelope, and dimensionality reduction algorithm for arm endpoint stiffness estimation. In [10] the physical human-robot interaction (pHRI) approach is presented for the developed robotic exoskeleton that uses access control to deal with the intentions of the human subject as well as the unknown inertial masses and moments in the robot dynamics. The human subject's intention is represented by the reference trajectory when the robotic exoskeleton conforms to the external interaction force. The online stiffness estimation is used to deal with the variable impedance property of the robotic exoskeleton. Access control is first presented based on the measured force to generate a reference trajectory in interaction tasks. Then an adaptive control is proposed to cope with the uncertain robot dynamics and a stability criterion can be obtained.

As seen, in recent works, different methods have been used to control HRC. But in this research, we controlled the robotic arm using an adaptive neural-network controller for trajectory tracking without pose control in CoppeliaSim simulation software. The comparison of different methods used in recent years is given in Table 1.

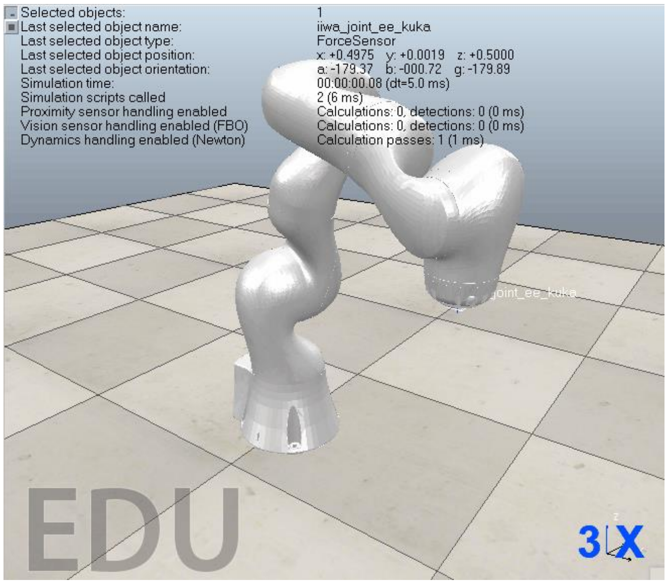

Fig. 1. Simulation of LBR iiwa robotic arm through the CoppeliaSim software.

II. Modeling

This section describes the target and actual rigid body dynamics of the robot manipulator. To use the dynamic surface as a non-linear approach, the actual dynamics of the manipulator are formulated in the state space. A rigid body form that accurately describes the nominal dynamic equations of the n-joint robot manipulator can be considered as follows:

$$H(q)\ddot{q}+V(q,\dot{q})+G(q)+J^{T}(q)\,f_{e}+\tilde{f}=\tau \qquad (1)$$

where $\boldsymbol{q} \in \mathrm{R}^{n\times 1}$ is the joint displacement vector, $\boldsymbol{\tau} \in \mathrm{R}^{n\times 1}$ refers to the applied joint torque or force signal control, $\boldsymbol{H(q)} \in \mathrm{R}^{n\times n}$ denotes the inertia matrix, $\boldsymbol{V(q, \dot{q})} \in \mathrm{R}^{n\times 1}$ shows the Coriolis and centrifugal vector, $\boldsymbol{G(q)} \in \mathrm{R}^{n\times 1}$ illustrates the gravitational vector and $\boldsymbol{J(q)}$ stands for the Jacobin matrix. $\mathbf{f_e}$ is the

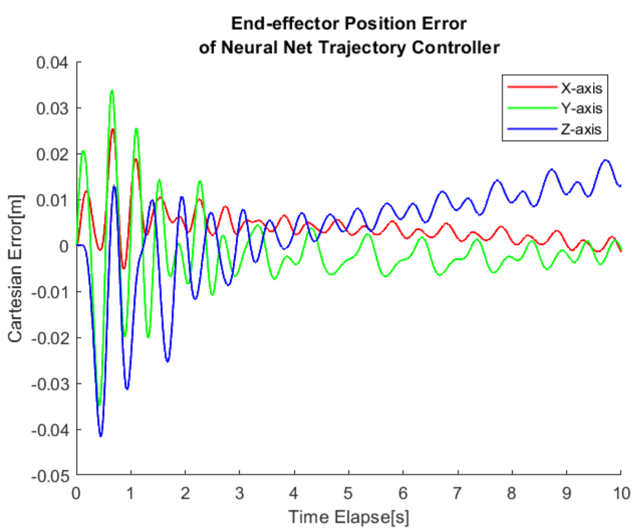

Fig. 2. End-effector position error of neural network trajectory controller.

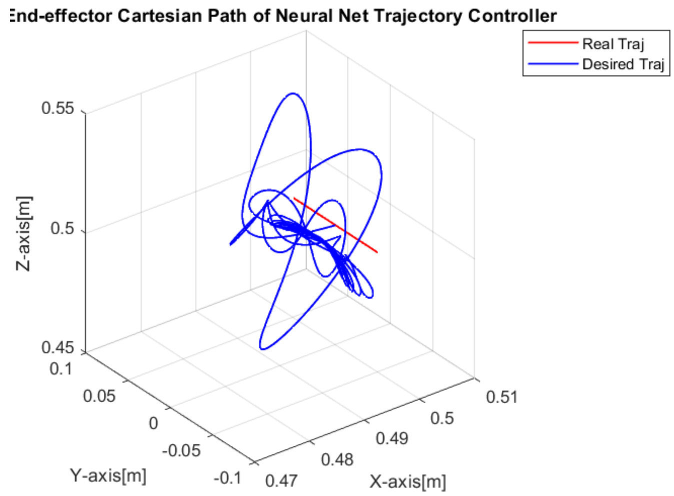

Fig. 3. End-effector cartesian path of neural network trajectory controller.

interaction forces vector and $\tilde{\mathbf{f}}$, as the external disturbances and described in the joint space, introduces uncertainty of the interaction forces. Assuming that the system states $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ and interaction force $\mathbf{f_e}$ are available for feedback. Because of model uncertainty and external disturbance, the nominal values of $\boldsymbol{H(q)}$, $\boldsymbol{V(q, \dot{q})}$ and $\boldsymbol{G(q)}$ are different from the actual values $\boldsymbol{\hat{H}(q)}$, $\boldsymbol{\hat{V}(q, \dot{q})}$ and $\boldsymbol{\hat{G}(q)}$, respectively. Consequently, the nominal values are known and the actual values and $\tilde{\tilde{\mathbf{f}}}$, as the external disturbances, are unknown.

III. Simulation

Simulations in this paper are done using the CoppeliaSim and MATLAB. CoppeliaSim, formerly known as V-REP, is a robot simulator used in industry, education and research. In this simulation, an LBR iiwa robotic arm is used, and you can see the simulation of this robotic arm through the CoppeliaSim in Figure 1. With the LBR iiwa, one of KUKA's lightweight cobots specialized in delicate assembly work, safety fences make way for human-robot-collaboration in the workspace.

IV. Results and Discussion

In this section, the results obtained from the simulation using the neural network are given. In Figure 2, the end-effector position error of neural network trajectory controller has been shown. The end-effector cartesian path of neural network trajectory controller is represented in Figure 3. Where the red line is the real trajectory and the blue line is the desired trajectory. The joint torque of neural network trajectory controller has been shown in Figure 4, where the red and blue lines represent model-based torque and neural network approximation, respectively. The cartesian position of neural network trajectory controller is given in Figure 5, where the red and blue lines represent the model-based torque and neural network approximation, respectively. In Figure 6, the adaptive neural-network controller for trajectory tracking without position control is represented, where the red line is the

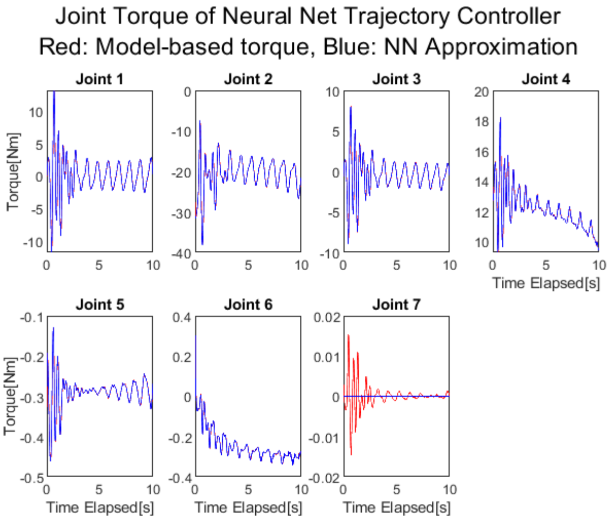

Fig. 4. Joint torque of neural network trajectory controller.

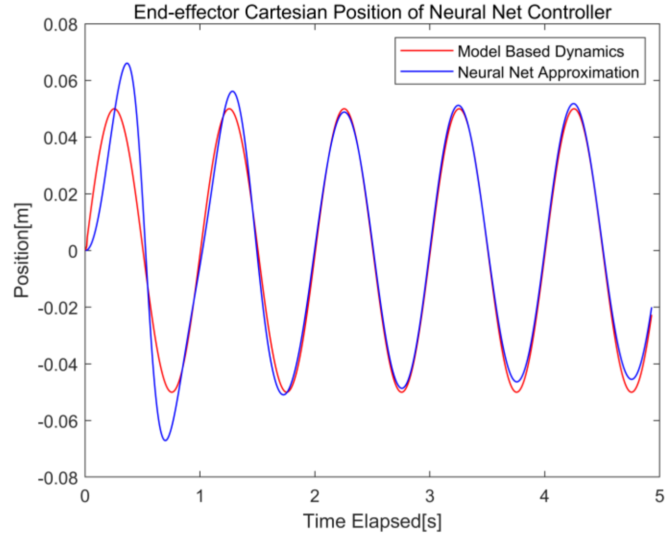

Fig. 6. Adaptive neural-network controller for trajectory tracking without position control.

model-based dynamics and the blue line is the neural network approximation.

V. Conclusion

In this research, an adaptive neural network controller is used for the trajectory tracking of LBR iiwa robot. The adaptive gains are derived by satisfying the condition that the error between the outputs of the actual plant and the reference model asymptotically tends to zero. The parameters of the kinematic controller are determined online via neural networks. Since the parameters are tuned online, the proposed controller can eliminate the disadvantages of the conventional controllers under the influence of model uncertainties and disturbances. Simulation studies with a kinematic and adaptive dynamic controller considering model uncertainties have shown that it does not follow the desired trajectory. However, the proposed controller follows the desired trajectory almost error-free, even in the presence of model uncertainties. Our simulations on CoppeliaSim and MATLAB on the LBR iiwa robot showed the outstanding effectiveness and feasibility of the adaptive neural network controller in terms of accuracy, overall control effort, and robustness compared to other controllers. For future work, we intend to use setpoint PD, feedforward, and nullspace impedance controllers to control the LBR iiwa robotic manipulator for cooperative tasks and compare the results of each controller.

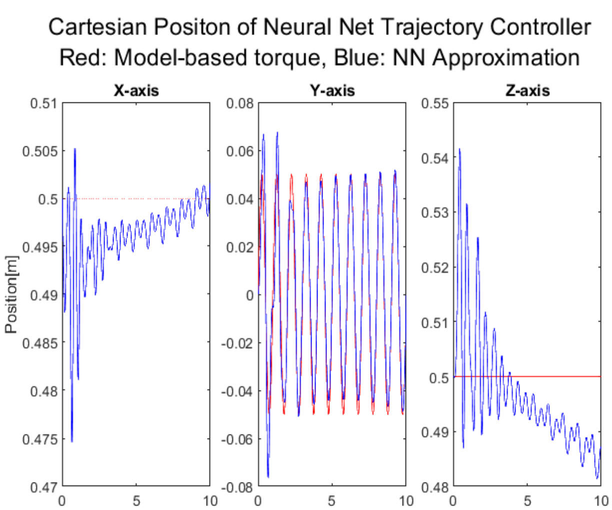

Fig. 5. Cartesian position of neural network trajectory controller.

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