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Improving the Dynamic Accuracy of Industrial Robots by Trajectory Pre-Compensation*

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Abstract

This paper presents a method to improve the path tracking accuracy of an industrial robot without replacing the standard industrial controller. By calculating off-line an appropriate trajectory pre-compensation, the effects of the nonlinear dynamics are compensated. This is realized by filtering the desired trajectory with the inverse dynamic model of the robot and its velocity controller. This compensation is applied as a velocity feed-forward in the standard industrial controller avoiding the need for a torque control interface. The presented method is experimentally validated on a KUKA IR 361 industrial robot. The results show clearly improved path tracking accuracy on circular trajectories.

I Introduction

Industrial robots have become an indispensable means of automation to increase productivity and flexibility of production systems. The ever increasing quality standards and international competition impose higher requirements on reliability and positioning accuracy, and above all on velocity of industrial robots. Moreover, modern applications like laser cutting and welding require an increasing path tracking accuracy.

Path tracking errors mainly originate from kinematic errors, controller performance limitations, and joint flexibility [1]. The kinematic errors can easily be compensated in the path planning, and flexibility is mostly negligible because commercial robots have high transmission stiffness. Although typical industrial controllers are sufficient for simple pick-and-place applications, they don't take into account nonlinearities like centrifugal, gravitation, Coriolis forces, friction, motor dynamics, and dynamic coupling between the axes, resulting in deviations from the desired motion. The inclusion of these nonlinear effects is however necessary for accurate high speed path tracking. Due to the complexity of advanced control algorithms developed in robotics research [2, 3, 4], the classical control techniques are still widely used in industrial robot applications. Nevertheless, there is a growing interest from industry for an improved path tracking accuracy with the current generation of robots and controllers.

Because there is no possibility to change the standard controllers of industrial robots, a compensation of the nonlinear dynamics can only be realized by adding a compensation to the desired trajectory [5]. Lange et al. present an adaptive learning algorithm that reduces the path deviations [6, 7]. The measured deviations are taken into account in the compensation scheme.

This paper presents a model based method that uses a priori knowledge of the robot dynamics to improve the path tracking accuracy by generating an additional velocity feed-forward based on the robot dynamics. The pre-compensation module can be seen as an off-line compensation of the velocity trajectory in such way that after execution the end effector follows the desired position trajectory more accurately.

Section II discusses the different steps of the trajectory pre-compensation method. The implementation of the method on a KUKA IR 361 industrial robot is discussed in section III. Validation of the method is

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performed by means of circular trajectories. The results show clearly the improved path tracking accuracy on these trajectories.

II Trajectory pre-compensation

Figure 1 presents the general idea of pre-compensation. The desired trajectory q_d is first compensated by filtering it using the inverse model of the system. This consists of the controller and robot dynamics in closed loop configuration. The compensated trajectory $q_{d,comp}$ is then applied to the real system, yielding perfect tracking if no disturbances or modelling errors are present.

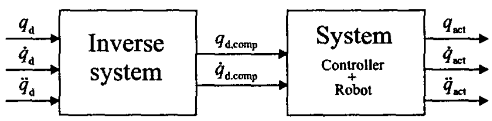

Figure 1: General idea of pre-compensation

To implement the trajectory pre-compensation module, a model of the inverse system has to be identified. The inverse system consists of two main parts: an inverse dynamic model of the robot, and an inverse model of the controller. The two parts of the inverse model and the trajectory pre-compensation are discussed in the following sections. Section A discusses the identification of an inverse dynamic model of the robot which includes the nonlinear dynamic effects. In the second step (section B), a model of the linear robot controller is constructed. Finally, the obtained models are combined to implement the pre-compensation module in section C.

A The dynamic robot model

The dynamic robot model describes the relation between the robot motion and the required actuator torques. It includes nonlinearities like friction, centrifugal, gravitation, and Coriolis forces. The equations of the inverse robot dynamics can be written in the following form

$$\tau = M(q)\ddot{q} + C(q,\dot{q}) + G(q) + F(\dot{q}) \quad (1)$$

where M is the mass matrix, C includes the Coriolis, centrifugal forces, and G the gravitational forces, τ is the vector of the torques applied at the joints by the actuators. The friction term $F(\dot{q})$ consists of viscous and Coulomb friction:

$$F(\dot{q}) = F_c \mathrm{sign}(\dot{q}) + F_v\dot{q}. \quad (2)$$

This is a simple, but appropriate friction model with F_c and F_v the Coulomb and viscous friction coefficient respectively.

Finally, the inverse dynamic robot model can be written in a linear form

$$\tau = \Phi(q,\dot{q},\ddot{q})\theta \quad (3)$$

by combining inertial parameters into barycentric parameters [8]. This model form is the basis of the experimental parameter identification presented in previous work [9]. Swevers et al. [10] present an identification method that is based on a maximum likelihood estimator using data measured during optimized periodic excitation trajectories, yielding accurate inverse dynamic robot models that allow accurate actuator torques predictions for a desired motion.

B Controller dynamics

Next to the robot dynamics, the controller dynamics have to be identified. This includes model structure and parameter identification. This information might be provided by the robot manufacturer or has to be obtained experimentally.

In most practical cases, the controller consists of three cascaded control loops: an analogue motor current controller, an analogue velocity controller, and a digital position controller.

The current controller is the most inner loop, and has a high bandwidth, such that its dynamics may be neglected.

The analogue velocity controller feeds back the measured motor velocity and compares it with the desired velocity. A PI structure with tachometer feedback has been identified as an appropriate model for the analogue velocity controller, represented as G_{contr}. Its estimation will be discussed in section B.

In the outer loop, the position controller is implemented digitally, is completely known, and allows to add a velocity feed-forward to the position controller. This extra input is used to provide the compensation signal.

C The trajectory pre-compensation

Figure 2 shows the global scheme of the robot and its controller with the pre-compensation in the off-line part. Nonlinear pre-compensation uses an inverse model of the closed loop system to filter the desired trajectory. This inverse model consists of the inverse dynamic robot model, describing the rigid body dynamics and joint friction, and the inverse model of the

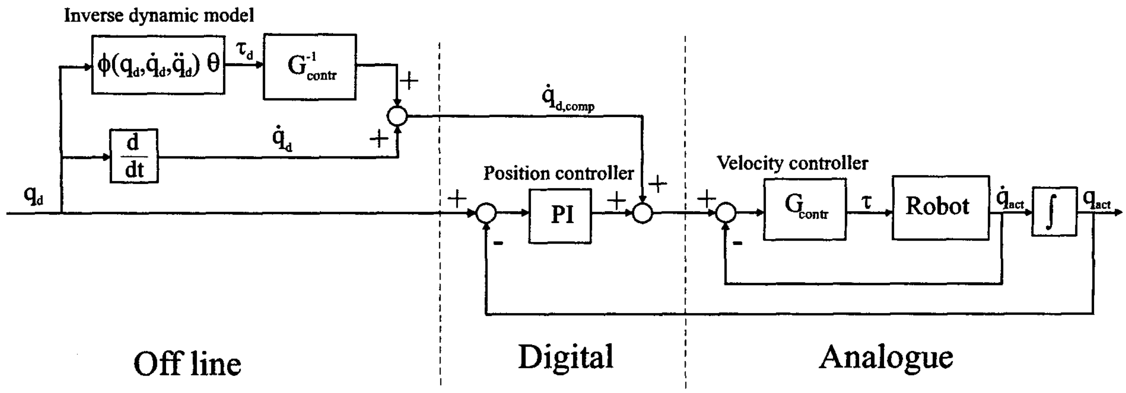

Figure 2: Structure of robot with nonlinear pre-compensation

analogue velocity controller. The current controller dynamics are neglected.

The desired motor torques τ_d required to generate the desired robot motion q_d are calculated in a first step from equations (1) and (2):

$$\begin{aligned}\tau_d &= M(q_d)\ddot{q}_d + C(q_d,\dot{q}_d) + G(q_d) + F(\dot{q}_d) \\ &= \Phi(q_d,\dot{q}_d,\ddot{q}_d)\ \theta. \end{aligned} \tag{4}$$

In a second step, the inverse model of the velocity controller converts the desired motor torques τ_d to compensated desired velocities

$$\begin{aligned} G_{contr}(\dot{q}_{d,comp} - \dot{q}_d) &= \tau_d \\ &\Downarrow \\ \dot{q}_{d,comp} &= G^{-1}_{contr}\tau_d + \dot{q}_d, \end{aligned} \tag{5}$$

which are implemented as a velocity feed-forward (see figure 2). Because the standard industrial controller cannot be changed to provide a computed torque feed-forward, the trajectory pre-compensation is added using the available velocity feed-forward controller input. Equation (5) clearly shows that this feed-forward generation corresponds to a trajectory pre-compensation: the desired velocity trajectory $\dot{q}_d$ is compensated using the inverse controller model G^{-1}_{contr} and the torques τ_d required to generate the desired motion q_d.

This method combines the general idea and advantages of computed-torque with the standard industrial controller. Like computed-torque, the inverse dynamics of the robot are used to calculate the expected motor torques for the desired joint motion. Since there is no torque interface available, the resulting values are converted to a velocity feed-forward using the inverse model of the controller.

It is necessary to preserve a position feedback to control deviations from the nominal trajectory, originating e.g. from inaccuracies in the dynamic model or external disturbances. As desired position we preserve q_d.

The practical implementation of the pre-compensation scheme requires the further tuning of the pre-compensation scheme by identifying additional constants and time delays which can only be determined in a closed loop identification. Section C gives more details about this tuning.

III Experimental verification

This section discusses the experimental application and validation of the presented method on a KUKA IR 361 robot in the PMA lab. Section A presents the test setup. The used robot and controller model are shortly discussed in section B. Section C introduces the reference trajectory, used to tune the pre-compensation scheme, and the validation trajectories. Finally, the results have been validated by using different trajectories (section D). Some performance criteria are used to express the improvement of the path tracking accuracy.

A Description of test case

The considered test case is a KUKA IR 361 robot (figure 3). Only the first three robot axes are considered.

The position controller is digitally implemented in the COMRADE software. This flexible control environment allows to add a velocity feed-forward. The digital controller runs at a sampling rate of 150 Hz.

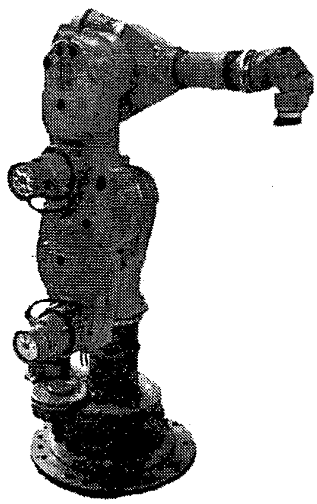

Figure 3: KUKA IR 361 robot

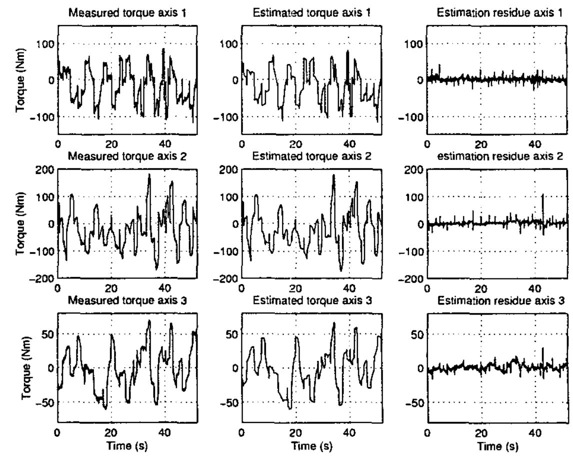

Figure 4: Measured motor torque, predicted torque and the corresponding torque prediction errors for the validation trajectory

The standard industrial controller RC 22/42 is maintained for the analogue control levels.

B Description of the robot model

In previous research [9] an inverse dynamic robot model of the KUKA IR 361 has been identified, which allows accurate prediction of the actuator torques for any given desired motion. The robot model is based on the so-called barycentric parameters [8]. This parameterization guarantees a model that is linear in the unknown parameters, which simplifies the identification [10]. Figure 4 shows the measured and predicted torque, and the corresponding torque prediction errors for a validation trajectory. It goes through 20 points randomly chosen in the workspace of the robot. The robot moves with maximum acceleration and deceleration between these points, and comes to full stop in each point. The prediction errors are small proving the accuracy of the obtained dynamic model.

The velocity controller dynamics are identified by applying multisine trajectories with a bandlimit of 5 Hz [11]. This frequency is far below the bandwidth of the velocity controller, but high enough for the given application. The measured signals that are used in the identification are: the velocity command signal, the tachometer signal and the motor torque. The most appropriate model structure yielding the best correspondence with the ETFE [11] resulting from these measurements is a PI structure with tachometer feedback.

C Reference and validation trajectories

The reference and validation trajectories are circles in vertical and horizontal planes. These trajectories have a simple analytic description in the cartesian space, and yield periodic and continuous joint trajectories. This allows time domain averaging and frequency domain calculations of the velocity and accelerations, which is more accurate than applying numerical differentiation techniques [9].

The reference trajectory is executed 15 times. The measurements of this excitation are averaged over all the measured periods and used to tune the pre-compensation scheme. This tuning is necessary because the identification of the inverse model was executed in separate parts. Scaling factors that exist between these submodels have to be determined using measurements of the closed loop behavior. In order to obtain optimal results, it is also necessary to compensate for the transport delays due to the digital implementation of the position controller. This is done by taking into account a time shift of approximately 3 ms for the desired position signal.

The pre-compensation method is validated using several circular trajectories. These validation trajectories differ from each other in circle diameter, position and orientation in the workspace, and path velocity. The performance of the industrial controller with pre-compensated velocity feed-forward and normal velocity feed-forward are compared.

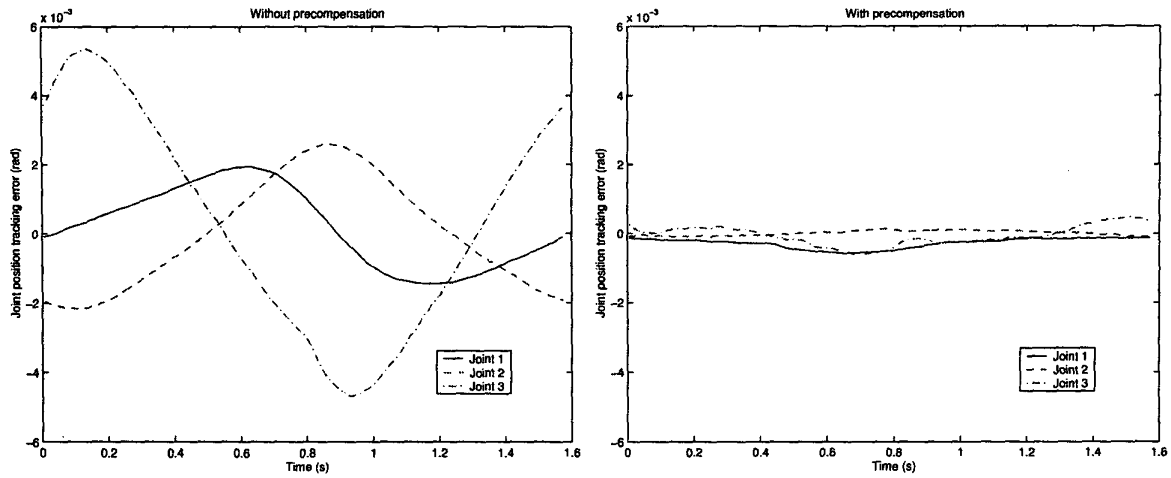

Figure 5: Tracking error for a circle (diameter 40 cm at velocity 0.6 m/s) in a horizontal plane without compensation (left) and with compensation (right) of the nonlinear dynamics

D Experimental results

The results are evaluated both at the joint level and at the cartesian level. At the joint level, the joint position tracking error $q_d - q_{act}$ is used. The tracking error is a measure of the remaining modelling errors and disturbances, and hence the achieved control performance. Figure 5 shows the tracking error $q_d - q_{act}$ with and without compensation of the nonlinear dynamics for a circle with a diameter of 40 cm executed at a velocity of 600 mm/s in a horizontal plane. The corresponding maximum absolute values of the tracking error is listed in table 1. These values show clearly the improved control performance.

	without compensation	with compensation
joint 1	$1.95 \cdot 10^{-3}$ rad	$0.58 \cdot 10^{-3}$ rad
joint 2	$2.60 \cdot 10^{-3}$ rad	$0.13 \cdot 10^{-3}$ rad
joint 3	$5.34 \cdot 10^{-3}$ rad	$0.62 \cdot 10^{-3}$ rad

Table 1: Maximum absolute value of tracking error for circle with diameter 40 cm at a velocity of 0.6 m/s in the horizontal plane

To have a measure of the improvement of the absolute path tracking accuracy, the cartesian positions have been calculated from the measured motor positions using the forward kinematics. Possible deviations due to kinematic errors and joint flexibilities are not considered for simplicity. An external measurement of the absolute end effector accuracy is not available. Figure 6 shows the calculated deviations from the desired trajectory for the given circle.

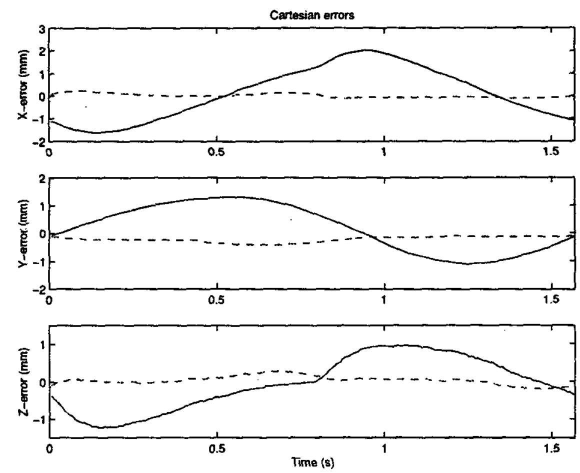

Figure 6: Cartesian error for a circle (diameter 40 cm at velocity 0.6 m/s) in a horizontal plane without (full line) and with compensation (dashed line)

To evaluate the experiments, the following performance criteria are defined:

- $d_{mean} = \frac{1}{N}\sum_{i=1}^{N} d_i$ gives the mean distance between the desired and the corresponding actually measured position, where N is the number of measured points on the trajectory.
- $d_{max} = \max_i d_i$ gives the maximal deviation from

the desired trajectory.

The distance between the measured point (x, y, z) on the trajectory and the corresponding point (x_d, y_d, z_d) on the desired trajectory in Cartesian coordinates is given by the Euclidean distance:

$$d_i = \sqrt{(x_d(i) - x(i))^2 + (y_d(i) - y(i))^2 + (z_d(i) - z(i))^2} \tag{6}$$

Table 2 shows the values for these performance criteria, and confirm the improvement of the path tracking accuracy by using trajectory pre-compensation.

	d_{mean} [mm]	d_{max} [mm]
without compensation	1.422	2.01
with compensation	0.249	0.45

Table 2: Performance criteria for circle with diameter 40 cm at velocity 0.6 m/s

The experiments have been repeated with other diameters of the circle, with different velocities and for other positions of the circle in an horizontal and vertical plane, yielding similar results. Some of these results are summarized in table 3.

	d_{mean} [mm]	d_{max} [mm]
diameter 30 cm at velocity 600 mm/s		
without compensation	1.017	1.72
with compensation	0.062	0.16
diameter 40 cm at velocity 300 mm/s		
without compensation	0.260	0.67
with compensation	0.042	0.19

Table 3: Performance criteria for circles with an other diameter and a different velocity in a vertical plane

IV Conclusion

This paper presents a method to compensate offline the nonlinear robot dynamics. A trajectory pre-compensation is calculated by filtering the desired trajectory with an inverse dynamic robot model including the controller dynamics yielding an improved velocity feed-forward signal. First experimental results of this trajectory pre-compensation approach show that it is possible to achieve an significant improvement of the path tracking accuracy. In future work, the method will be extended to arbitrary continuous trajectories, and an online implementation of this scheme will be developed.

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