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Lifted system iterative learning control applied to an industrial robot

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Abstract

This paper proposes a model-based iterative learning control algorithm for time-varying systems with a high convergence speed. The convergence of components of the tracking error can be controlled individually with the algorithm. The convergence speed of each error component can be maximised unless robustness for noise or unmodelled dynamics is needed. The learning control algorithm is applied to the industrial Stäubli RX90 robot. A linear time-varying model of the robot dynamics is obtained by linearisation of the non-linear dynamic equations. Experiments show that the tracking error of the robot joints can be reduced to the desired level in a few iterations.

Keywords: Learning control; Robot dynamics; Linearisation; Time-varying systems; Singular value decomposition; Convergence analyses

1. Introduction

Laser welding has several advantages over conventional welding, e.g., the high depth-to-width ratio of the weld, the relatively small heat input and the high processing speed. To obtain defect free welds, the laser beam should typically track the weld seam with an accuracy in the order of 0.1 mm (Duley, 1998) at speeds beyond 100 mm/s. The demands on the orientation of the laser beam with respect to the weld seam are in the order of several degrees and not as restrictive as the demands on the linear tracking accuracy. Nevertheless, the required linear tracking accuracy puts high demands on the manipulator that moves the laser beam with respect to the weld seam. The industrial applicability of laser welding will be increased considerably by the use of commercially available six-axes industrial robots, as these robots can access complicated three-dimensional seam geometries. However, using standard industrial controllers the tracking accuracy of these robots appears to be insufficient for laser welding at high speeds. Since the (dynamic) repeatability of the robots is much better than their tracking accuracy it is expected that the tracking performance of these robots can be improved considerably with iterative learning control (ILC).

ILC is a learning control technique for systems making repetitive movements. Each trial a feedforward is computed based on measurements of the error in the previous trials, such that the error converges to a small value. Since the pioneering work of Arimoto, Kawamura, and Miyazaki (1984) a vast amount of applications and implementations of ILC have been proposed. An overview of the work until 1998 is given by Moore (1998).

From the beginning ILC has been used to improve the tracking accuracy of robotic manipulators. Two main approaches can be distinguished. The first approach, applied by, e.g., Arimoto et al. (1984), Arimoto, Nguyen, and Naniwa (2000), Elci, Longman, Phan, Juang, and Ugoletti (2002), Guglielmo and Sadegh (1996), Longman (2000), is to use a feedforward that is proportional to the error in the previous run, its time derivative or its time integral (PID-like ILC). Thus no explicit model of the robot is used to compute the feedforward with this type of ILC. Convergence of the error, for a certain choice of the learning gains, is proven by, e.g., passivity analyses (Arimoto et al., 2000) or Lyaponov analysis (Guglielmo &

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Sadegh, 1996). Although the computation of the feedforward is straightforward, the convergence speed of these algorithms is often limited, i.e., the reduction of the tracking error requires many iterations. The other approach, applied by, e.g., Gunnarsson, Norrlöf, Rahic, and Özbek (2004), Kavli (1993), Norrlöf and Gunnarsson (2002), Poo, Lim, and Ma (1996), is to use some kind of model of the robot dynamics in the ILC algorithm (model-based ILC). An approximate inverse of the dynamics is used to compute the feedforward from the error measured in the previous run. Although the model-based algorithms require a model of the robot, the convergence rate of the error is generally much higher than for the PID-like ILC algorithms.

In this paper the goal is to achieve the tracking error required for laser welding. Furthermore, the number of iterations to achieve this error should be limited, i.e., a high convergence speed is required. For this reason the model-based approach is adopted. The dynamics of an industrial robot are non-linear and since industrial robot feedback controllers are often simple PID-controllers, the closed-loop dynamics are non-linear as well. Using a linear time-invariant (LTI) approximation of the dynamics (Gunnarsson et al., 2004; Kavli, 1993; Norrlöf & Gunnarsson, 2002) or only information on the mass matrix (Poo et al., 1996) in the ILC algorithms results in a converging error, but it is expected that the convergence speed can be increased by including more information on the robot dynamics. Therefore, the well-known non-linear equations of the rigid robot-dynamics are used for model-based ILC in this paper. This model information is used to increase the convergence speed of ILC. To avoid the use of the complicated non-linear model for ILC, the model is linearised for small deviations from a reference trajectory. The resulting linear-time variant (LTV) robot model is combined with the known controller dynamics to obtain an LTV closed-loop dynamic model. These linearised equations of motion were previously used by Arimoto et al. (1984) for convergence analyses of ILC, but to the authors knowledge these equations have not been used for model-based ILC so far.

The ILC algorithm proposed in this paper is formulated in the lifted system description that is very well suited for analyses and design of ILC for LTV systems. In the lifted system description all time samples of a signal are stacked into a single vector and a linear (time-varying) system is represented by the system matrix that maps the input vector to the output vector. Likewise ILC maps the measured error vector to the feedforward vector in the subsequent trial. The term "lifted" is taken from the work of Dijkstra (2004), Tousain (2001). Equivalent formulations were used by many others (Elci et al., 2002; Gunnarsson et al., 2004; Longman, 2000; Norrlöf & Gunnarsson, 2002). The lifted system description is often combined with an optimisation based approach to ILC (Q-ILC). In this approach the applied feedforward minimises a weighted norm of the predicted error and the feedforward (see, e.g., Dijkstra, 2004; Gunnarsson et al., 2004; Kim, Chin, Lee, & Choi, 2000; Norrlöf & Gunnarsson, 2002; Tousain, 2001).

In this paper a slightly different approach is adopted. The singular value decomposition of the system matrix is used. The tracking error is projected on the left singular vectors of the system matrix to decouple the system dynamics. The evolution of each of the projected error components from trial to trial can be controlled individually. It is shown that the control of each error component is a trade-off between convergence speed and robustness for unmodelled dynamics and noise. A learning control algorithm is proposed to maximise convergence speed of each error component unless it has to be reduced to guarantee robustness for noise or unmodelled dynamics. The advantage of the approach in this paper over Q-ILC is that the robustness needed for error components affected by noise or unmodelled dynamics does not limit the convergence speed of the other error components. Kim et al. (2000) used the singular value decomposition of the lifted system matrix to analyse the properties of Q-ILC and to reduce the size of the optimisation problem. However, the singular value decomposition was not used to be able to control each error component individually.

The learning controller that is proposed in this paper is applied to an industrial robot. The error components that are affected by noise or unmodelled robot dynamics are not compensated by ILC, while the remaining components are eliminated in one trial. Experiments show reduction of the tacking error and the convergence speed that result from the application of the learning controller on the joint tracking error of an industrial robot, the Stäubli RX90 robot.

In the first section lifted system ILC is introduced, a learning control algorithm is proposed and its convergence and robustness properties are analysed. In the second section a linearised model of the dynamics of the industrial Stäubli RX90 robot is derived. Experimental results of the application of the proposed learning controller to the Stäubli RX90 robot are presented in the third section.

2. Lifted system ILC

An ILC algorithm based on the lifted system description is proposed in this section. The first subsection introduces the lifted system description. The second subsection discusses lifted system ILC (LSILC) and shows the analogy with conventional feedback control. In the third subsection the system dynamics are decoupled using SVD and a learning algorithm is proposed based on the decoupled system equations. Robustness of the proposed learning algorithm is analysed in the subsequent subsections. The last subsection gives guidelines for tuning the proposed ILC algorithm for specific applications.