Arm side evaluation of ILC applied to a six degrees of freedom industrial robot

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Abstract

Experimental results from a first order P-type ILC algorithm applied to a large size six degrees of freedom commercial industrial robot are presented. The ILC algorithm is based on measurements of the motor angles, but in addition to the conventional evaluation of the ILC algorithm based on the control error on the motor side, the tool path error on the arm side is evaluated using a laser tracker. Experiments have been carried out in three different operating points using movements that represent typical paths in a laser cutting application, and different choices of algorithm design parameters have been studied. The motor angle error is reduced substantially in all experiments, and the tool path error is reduced in most of the cases. In one operating point, however, the error does not decrease as much and an oscillatory tool behaviour is observed. Changed filter variables can give worse error reduction in all operating points. To achieve even better performance, especially in difficult operating points, it is concluded that an arm side measurement, from for example an accelerometer, needs to be included in the learning.

Keywords: Iterative methods, Learning control, Control applications, Industrial robots, Position control

Arm side evaluation of ILC applied to a six degrees of freedom industrial robot ⋆

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1. INTRODUCTION

In many applications industrial robots usually repeat the same desired trajectory over and over again, and in such cases the *Iterative Learning Control (ILC)* method is a way to compensate for repetitive errors. The origin of ILC can be traced back to a US patent accepted in 1971 on “Learning control of actuators in control systems” Garden (1971). The first academic contribution to what today is called ILC is Uchiyama (1978), but from an academic perspective it was not until 1984 that ILC started to become an active research area. Arimoto et al. (1984), Casalino and Bartolini (1984), and Craig (1984) were independently describing a method that iteratively compensated for model errors and disturbances. The development of ILC stems originally from the robotics area, and examples of contributions where ILC is applied in robotics are Arimoto et al. (1984), Bondi et al. (1988), Guglielmo and Sadegh (1996), Horowitz et al. (1991), Lange and Hirzinger (1999) and Elci et al. (2002). Examples of surveys on ILC are Moore (1999), Chen and Wen (1999), Bien and Xu (1998) and Bristow et al. (2006). In Longman (2000) and Elci et al. (2002) ILC is applied to a seven degrees of freedom robot arm, however smaller than the one used here, and the type of trajectories used in these experiments are not motivated by any particular application.

The results presented in this paper concern a relevant problem in laser cutting, and the purpose of this paper is to present results from experiments carried out on all six motors of a large size commercial industrial robot. The experiments are performed using an ABB robot with an experimental controller, accomplishing a small circular movement in three different operating points. A commercial robot with similar load capacity (175 kg) is shown in Fig. 1. The robot positions used in the experiments are relevant for the application and they are chosen to avoid singularities, where the accuracy degrades.

Fig. 1. Example of a large size commercial industrial robot from ABB (2007) with similar size as the robot used in the experiments.

The ILC algorithm applied to the robot is simple; the same parameters are used for all six motors, and the learning is stopped after only five iterations. In practise there is little time for algorithm tuning, and a small effort that gives a substantial error reduction after only a few iterations is often sufficient. Among the large number of publications dealing with various aspects of ILC, there are

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very few publications presenting results of this kind, *i.e.*, experimental evaluation using a large size commercial industrial robot where ILC is applied to all six motors and is stopped after only a few iterations.

2. PROBLEM DESCRIPTION

The main purpose of the paper is to illustrate the difficulties that arise when the robot is subject to mechanical flexibilities and the ILC algorithm is based on motor angle measurements only. This line of reasoning is motivated by a two mass model of the dynamics of a single joint. Convergence of the ILC algorithm, presented in Sec. 2.2, does not necessarily mean good performance on the arm side, *i.e.*, the position and orientation of the robot tool.

2.1 ILC applied to the robot system

Assuming that the mechanical flexibilities are concentrated to the joints of the robot, the simplified model of a single joint, shown in Fig. 2, can be used to explain the problem. The variable q_m denotes the motor angle, which, in industrial robots is the only variable that can be measured. This variable is also used in the ILC algorithm when computing the update signal. The robot performance on the arm side is, however, determined by the arm angle q_a, which is not measured in conventional robot systems.

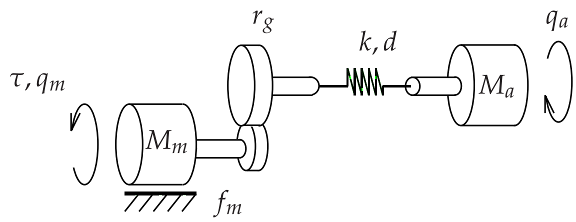

Fig. 2. A two mass model of the dynamics in one joint of an industrial robot. It is characterised by spring k, damper d, friction f_m, gear ratio r_g, moments of inertia M_m, $M_a(q_a)$, torque τ and angles q_m, q_a.

It will be illustrated below that convergence of the ILC algorithm (see Sec. 2.2) and good performance when considering the error, calculated by the difference between motor angle reference and measured motor angle signal, does not necessarily imply high accuracy of the movement of the tool. Assuming that a correct kinematic and dynamic model is available, the position and orientation of the tool could theoretically be derived from the motor angles. This is however not realistic, since this would require exact descriptions of phenomena like friction, backlash and nonlinear stiffness in the gear, together with a complete model of the mechanical flexibilities. A remedy for handling this situation could be to use additional sensors and estimate the position and orientation of the tool. In the experiments presented below the performance of the tool is measured using a laser measurement system of the type Leica LTD800, see Leica Geosystems (2007), but since this is an expensive equipment it is not realistic to use it in conventional operation. A more realistic alternative is to use low cost sensors, like for example accelerometers, in combination with signal processing algorithms to obtain accurate estimates of the relevant signals. These estimates are then used in the ILC algorithm, presented below.

2.2 General first order ILC algorithm

The update equation for a general first order ILC algorithm with iteration independent operators is given by

$$u_{k+1}(t) = Q(q)\big(u_k(t) + L(q)e_k(t)\big), \quad (1)$$

where the subscript k denotes iteration number and q is the time shift operator. The error

$$e_k(t) = r(t) - y_k(t) \quad (2)$$

is the difference between motor angle reference signal and measured motor angle at iteration k. The update equation (1) implies the standard frequency domain convergence criterion, see, *e.g.*, Norrlöf and Gunnarsson (2002a),

$$|1 - L(e^{i\omega})T_u(e^{i\omega})| < |Q^{-1}(e^{i\omega})|, \quad \forall\omega, \quad (3)$$

where T_u denotes the transfer function from the applied ILC input $u_k(t)$ to the measured output $y_k(t)$. The criterion shows that the filter Q can be used to improve the robustness of the ILC algorithm. The inequality (3) can be satisfied by choosing the magnitude of the Q filter small enough, and it is well known that this will prevent the final error, after the ILC algorithm has converged, to be zero.

3. EXPERIMENTS

The ILC algorithm used in the experiments and the experimental conditions are described more extensively. Thereafter the performance measures on the motor side and the arm side used in this paper are explained.

3.1 Experimental conditions

The robot is a multivariate system, but for simplicity the joints will be treated individually with a separate ILC algorithm for each joint. The algorithm is based on an heuristic design procedure, described in Norrlöf and Gunnarsson (2002b), with a linear low-pass discrete time Q filter and a linear discrete time filter $L(q) = \gamma q^{\delta}$. Note that both filters can be non-causal. The general ILC algorithm (1) now implies the ILC update equation

$$u_{k+1}(t) = Q(q)\big(u_k(t) + \gamma e_k(t + \delta)\big), \quad (4)$$

with k denoting the iteration number. The design variables in the ILC algorithm are

- Type and order of Q filter.
- Q filter cutoff frequency ω_n.
- Learning gain γ, with $0.0 < \gamma \leq 1.0$.
- Time shift δ.

In this paper the design variables ω_n and δ and their influence of the ILC algorithm performance are investigated, while the other design variables remain constant during the experiments. Q is chosen as a second order Butterworth filter, which is applied using the Matlab function `filtfilt` in order to get a zero phase behaviour. The L filter learning gain γ is 0.9, motivated by the tradeoff between convergence rate and robustness.

During the experiments the robot controller works in parallel with the ILC algorithm, *i.e.*, ILC works as a complement to the conventional system and can be implemented without modifying the robot controller. The update $u_k(t)$ from the ILC algorithm in (4) is added to the reference signal of the control system. The same ILC design variables are applied to all motors and the learning is stopped after five iterations, because an approach as simple as possible is desirable, see also Wallén et al. (2007).

The experiments are performed in the robot positions

$$\begin{aligned} p_1 &= (1.3166\ 0.0014\ 1.5992) \\ p_2 &= (1.8000\ 0.1000\ 1.5992) \\ p_3 &= (2.2000\ 0.2000\ 1.5992)\,, \end{aligned} \tag{5}$$

which correspond to the tool center point position in meters, expressed in the robot base frame. The positions are relevant for the laser cutting application because they are chosen to avoid singularities in the workspace of the robot, and chosen not too far away from the zero pose in order to achieve good accuracy. The robot configurations for the three positions (5) can be seen in Fig. 3. The quaternion describing the orientation of the tool is identical in all three positions and is given by

$$q = (0.6322\ 0.0353\ 0.7732\ 0.0353)\,. \tag{6}$$

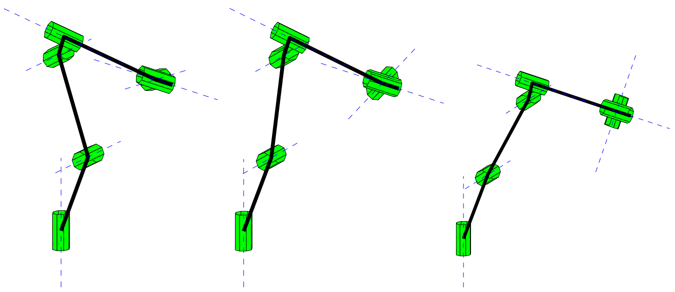

Fig. 3. The robot tool center point positions p_1 (left), p_2 (center), and p_3 (right) used in the experiments.

In each experiment the robot makes a circle of radius 5 mm in xy direction. The operating conditions of the robot in the experiments are velocity $v = 40$ mm/s, positions (5) and quaternion (6). The design variables varying in the experiments are cutoff frequency ω_n of the Q filter and time shift δ of the L filter, as mentioned before. In Wallén et al. (2007) similar experiments are performed and evaluated on the motor side of the robot. Even though a fairly simple ILC algorithm is applied, it is shown in Wallén et al. (2007) that the error reduction measured on the motor angles is substantial after only five iterations and the algorithm shows good robustness properties on the motor side.

3.2 Performance measures

Motor side The results on the motor side are evaluated by the norm of the control errors for each iteration, normalised with respect to the largest control error without ILC (for all motors and the compared experiments), as in

$$J_{k,i,j} = \frac{\|e_{k,i,j}\|}{\max_{l,m} \|e_{0,l,m}\|}. \tag{7}$$

The motor angle error (2) is denoted e, and the subscripts $i = 1, \ldots, 6$ is motor number, j is experiment number and k denotes the iteration. One experiment means that one combination of operating conditions (position) of the robot and ILC design variables (δ, ω_n) is studied. The error measure (7) is studied using both 2-norm and ∞-norm.

Arm side The root mean square (RMS) error on the arm side at iteration k is calculated as

$$\text{RMS}_k = \sqrt{\frac{1}{N}\sum_n \left(r_{ref} - r_{meas,k}(n)\right)^2}, \tag{8}$$

where $r_{meas,k}(n)$ denotes the radius of the measured circle at each sample n, and N is the total number of samples along the circle. The maximum deviation (maxdev) from the reference circle r_{ref} at iteration k is defined as

$$\text{maxdev}_k = \max_n \left(|r_{ref} - r_{meas,k}(n)|\right). \tag{9}$$

4. EXPERIMENTAL RESULTS

First the results for the "nominal" case, *i.e.*, time shift $\delta = 3$ and cutoff frequency $\omega_n = 10$ Hz, are shown for the operating positions (5). They are then compared to the resulting robot performance in experiments with $[\delta = 6, \omega_n = 10\,\text{Hz}]$ and $[\delta = 3, \omega_n = 15\,\text{Hz}]$, respectively.

4.1 Performance with respect to operating points

Experiments are performed in the three positions (5) with the ILC design variables $\delta = 3$ and $\omega_n = 10$ Hz. First, the result from experiments in p_1 is shown. This position gives a good learning, as can be seen in Fig. 4, where the circle measured on the arm side at each iteration is compared to an ideal reference circle with radius 5 mm. The errors are compensated for by the ILC algorithm and the measured circle is close to the reference circle after five iterations.

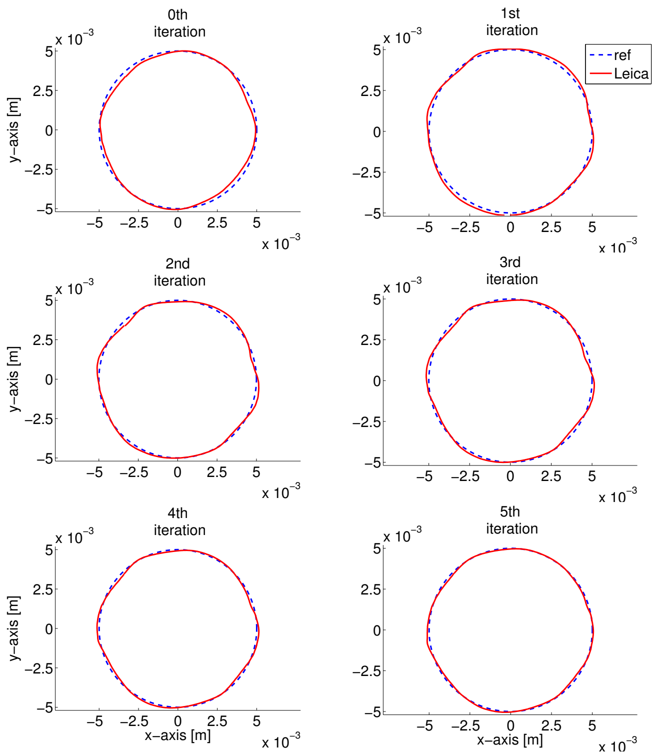

Fig. 4. Measured circles on the arm side at every iteration, compared to an ideal circle with radius 5 mm. The experiment is performed in position p_1 and with ILC design variables $\omega_n = 10$ Hz and $\delta = 3$. The experiment shows a good behaviour and the measured circle is close to the reference circle after five iterations.

In Fig. 5 the behaviour in the positions (5) on the motor side is evaluated, using the error measure (7) expressed in ∞-norm. The error measure (7) expressed in 2-norm shows a similar appearance, see Wallén et al. (2007). It is interesting to note that the errors, *i.e.*, the difference between desired and measured motor angles, are reduced in all three positions compared to the 0th iteration (no ILC algorithm applied) seen from the motor side. The only exception is motor 2 in position p_2, where a slightly increasing behaviour can be noticed after a few iterations. However, the conclusion in Fig. 5 is, viewed on the whole, a decreasing error for all positions in all iterations.

As a comparison, Fig. 6 shows the RMS error (8) and maximum deviation (9) of the error on the arm side for the three positions. The error measure (7) in 2-norm on the motor side corresponds to the RMS error on the arm side. The error measure (7) in ∞-norm on the motor side, seen in Fig. 5, corresponds to the maximum deviation of the error on the arm side. Position p_1 gives the best behaviour in Fig. 6, with a decreasing trend in both RMS error and maximum deviation of the error, which corresponds well to the result on the motor side. Position p_2 shows an increasing trend of the errors, and for position p_3, the errors are even as large as or even larger as the errors in

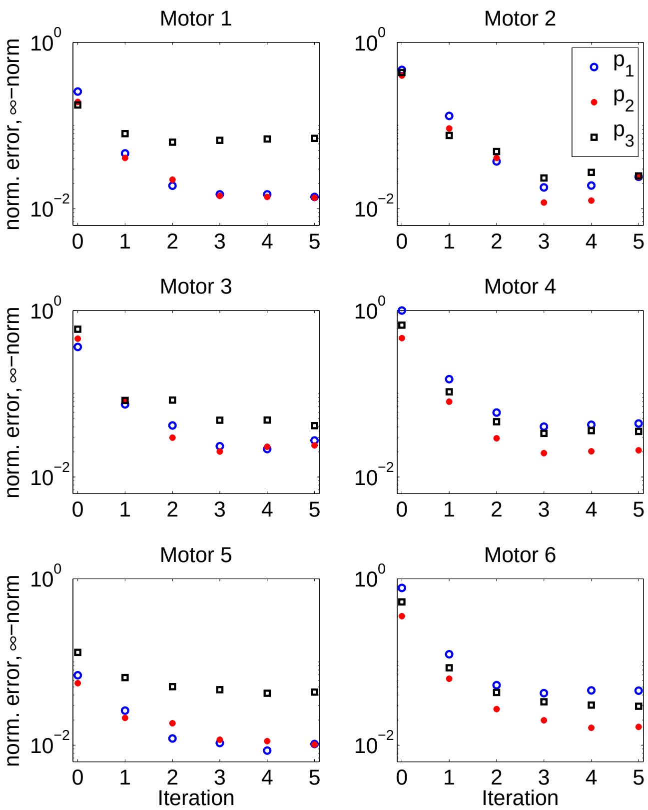

Fig. 5. The error measure $J_{k,i,j}$, see (7), on motor side expressed in ∞-norm for all motors $i = 1, \ldots, 6$, three positions $j = p_1, p_2, p_3$ and iterations $k = 0, \ldots, 5$. The experiments are performed with the ILC design variables $\omega_n = 10\,\text{Hz}$ and $\delta = 3$ and shows a decreasing error.

0th iteration, when no ILC algorithm is applied. Changing the filter parameters can give a worse error reduction also in the other positions. These results show that even though the result on the motor side is good, it is no guarantee that the errors on the arm side – the position of the tool – are decreasing. There are a number of possible explanations for the observed behaviour. First, the operating point plays an important role. A more extended robot makes the problem harder, because mechanical flexibilities become more pronounced in a more extended position. The fact that the arm side error in point p_3 grows during the initial iteration can be a result of the externally injected ILC signal, which can excite the flexibilities.

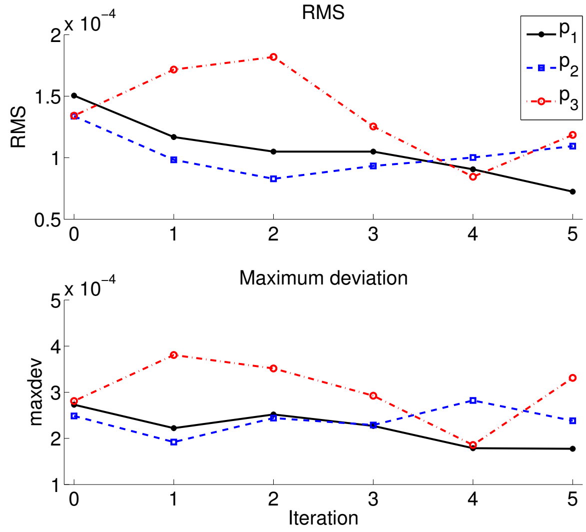

Fig. 6. The error measures on the arm side, see (8)–(9); RMS error and maximum deviation of the error for positions p_1, p_2 and p_3. In the experiment the ILC design variables $\omega_n = 10\,\text{Hz}$ and $\delta = 3$ are used.

4.2 Performance with respect to δ of L

In order to investigate the robot performance with respect to the time shift of the L filter, experiments were performed with $\delta = 3, 6$ in positions p_1 and p_2. The cutoff frequency of the Q filter is still $\omega_n = 10\,\text{Hz}$. In Fig. 7 it is seen that $\delta = 6$ gives lower RMS error (8) and maximum deviation (9) of the error on the arm side, which can be explained by decreasing energy content in the ILC update signal u_k, and thereby decreasing excitation of the flexibilities. The corresponding behaviour can also be seen on the motor side, see Wallén et al. (2007), explained by the fact that $\delta = 3$ theoretically gives a faster convergence.

4.3 Performance with respect to ω_n

The robot performance with respect to the cutoff frequencies $\omega_n = 10, 15\,\text{Hz}$ has also been investigated. The experiments have been carried out with $\delta = 3$ in positions p_1 and p_2. The same behaviour can be noticed for both position p_1 and p_2, and therefore only the results for p_1 are shown. When studying the error measure (7) on the motor side expressed in ∞-norm, see Fig. 8, the errors are reduced when $\omega_n = 15\,\text{Hz}$ is used, compared to $\omega_n = 10\,\text{Hz}$. It

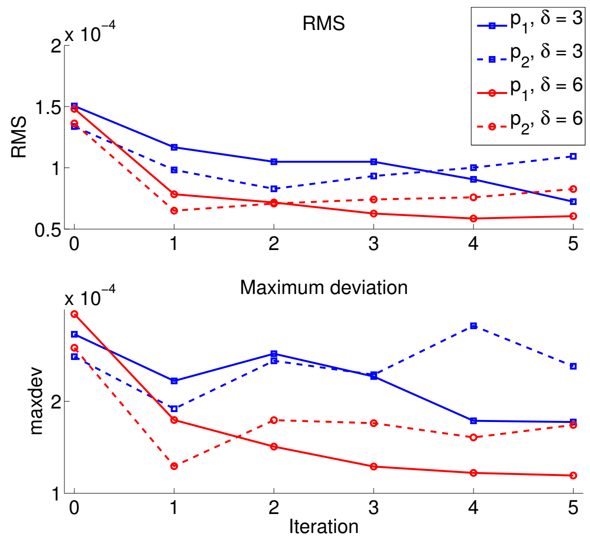

Fig. 7. The error measures on the arm side, see (8)–(9); RMS error and maximum deviation of the error for positions p_1 and p_2. The experiments are performed with the ILC design variables $\omega_n = 10\,\text{Hz}$ and $\delta = 3, 6$. Higher δ gives lower errors, this can be explained by decreasing energy content in the ILC update signal.

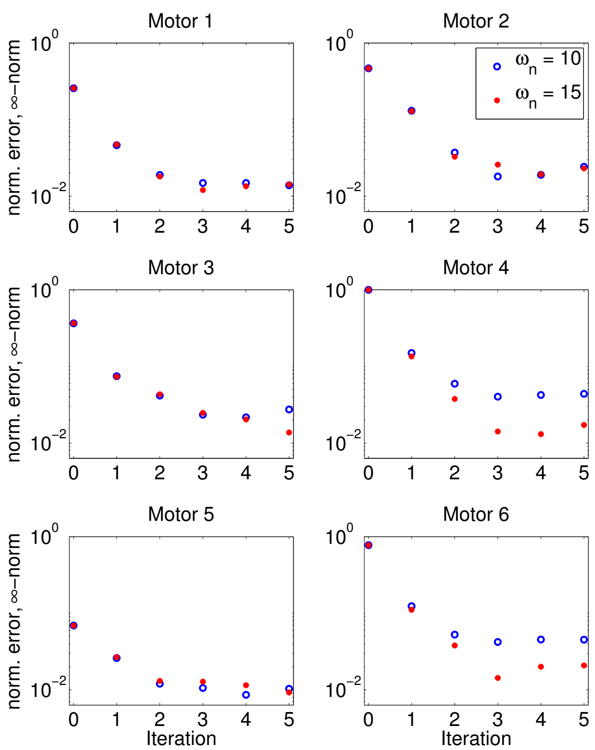

Fig. 8. The error measure $J_{k,i,j}$, see (7), on motor side expressed in ∞-norm for all motors $i = 1, \ldots, 6$, cutoff frequencies $\omega_n = 10, 15\,\text{Hz}$ and iterations $k = 0, \ldots, 5$. The experiments are performed in position p_1 with $\delta = 3$. A higher cutoff frequency gives a better reduction of the control error, but the error is no longer monotonically decreasing as a function of iteration.

can be explained by the fact that with a larger cutoff frequency of the Q filter, a larger part of the error signal is taken into account in the ILC update equation (4), and less information is lost. However, the corresponding error measures (8)–(9) on the arm side, shown in Fig. 9, concludes that the actual tool path error is increased for $\omega_n = 15\,\text{Hz}$ compared to $\omega_n = 10\,\text{Hz}$. This is an opposite result compared to Fig. 8, and will be discussed next.

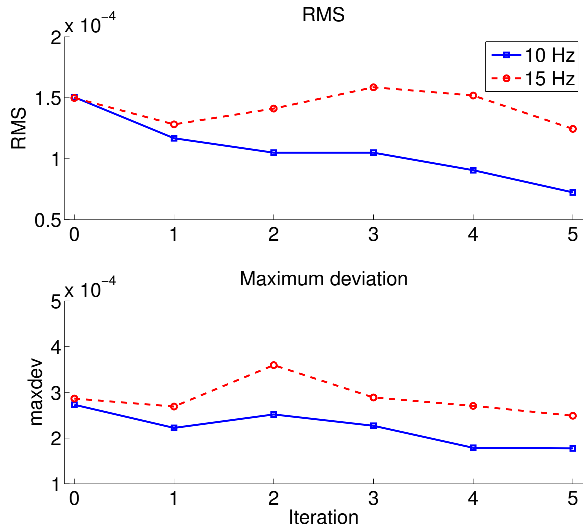

Fig. 9. The error measures on the arm side, see (8)–(9); RMS error and maximum deviation of the error for position p_1. The experiments are performed with the ILC design variables $\omega_n = 10, 15\,\text{Hz}$ and $\delta = 3$. As can be seen, higher ω gives larger errors.

An oscillatory behaviour on the arm side is also noticed, as can be seen in Fig. 10, where the results from the 0th and 5th iteration are compared. The only difference between the system without/with the ILC algorithm applied, is the ILC control signal added. When oscillations occur on the arm side after a few iterations, they originate from the ILC update signal u_{k+1}, applied at iteration $k + 1$, see (1). In Fig. 11, the frequency content of this signal is shown for the ILC update signals u_1, u_3, u_5, which are added to the reference signal of the conventional control system at the iterations $k = 1, 3, 5$. As can be seen, the frequencies around 6–7 Hz are amplified when u_3 and u_5 are compared to the first update signal u_1. This gives rise to the oscillative behaviour on the arm side seen in Fig. 10, and thereby also the increasing errors in Fig. 9.

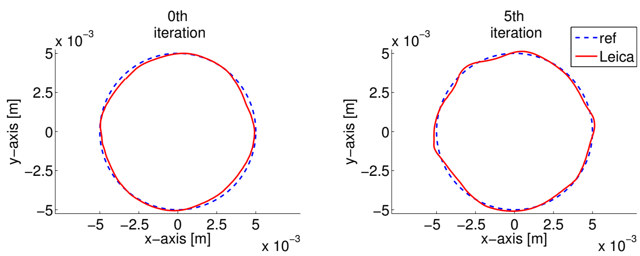

Fig. 10. Measured circle on the arm side when the experiment is performed in position p_1, with the ILC design variables $\delta = 3$ and $\omega_n = 15\,\text{Hz}$. Iteration 0 and 5 are compared and an oscillatory behaviour is noticed.

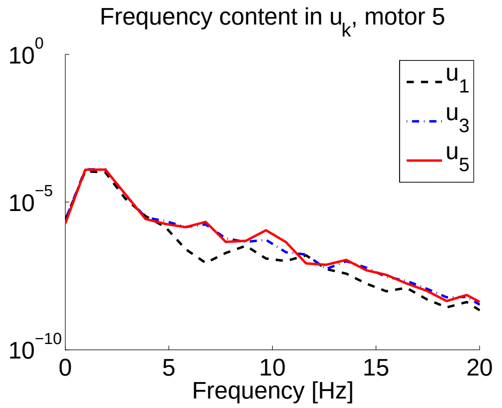

Fig. 11. Frequency content in the ILC update signal u_k, $k = 1, 3, 5$ for motor 5. The experiment is performed in position p_1, with $\delta = 3$ and $\omega_n = 15$ Hz.

The message in this example with varying cutoff frequencies of the Q filter, is that one has to be very careful when dealing with resonant systems. The ILC algorithm can increase the oscillations in the system, in particular when the controlled variable, here the tool position, is not directly measured and included in the algorithm. It motivates the need of additional sensors, like accelerometers, to obtain accurate estimates of the actual position and use this information in the algorithm.

5. CONCLUSIONS AND FUTURE WORK

A first order P-type ILC algorithm has been applied on a large size six degrees of freedom commercial industrial robot. An heuristic ILC algorithm is used, the same design parameters are used for all six motors for simplicity reasons, and the motor angles are used in the algorithm. The operating points represents typical robot configurations in a laser cutting application. The performance on the arm side is evaluated by a laser tracker LTD800, Leica Geosystems (2007), and compared to the motor side errors. It can be concluded that the tool path error is reduced in most cases, but the ILC algorithm can increase the oscillations in the resonant system because the motor angles are used in the algorithm, and not actual tool position. Therefore additional sensors are needed in difficult operating conditions in order to estimate the tool position. Future work includes arm side measurements from low cost sensors like accelerometers, combined with signal processing algorithms to obtain accurate estimates. Some works in this direction are presented in, *e.g.*, Gunnarsson et al. (2007) and Norrlöf and Karlsson (2005).

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Sammanfattning
Abstract

Experimental results from a first order P-type ILC algorithm applied to a large size six degrees of freedom commercial industrial robot are presented. The ILC algorithm is based on measurements of the motor angles, but in addition to the conventional evaluation of the ILC algorithm based on the control error on the motor side, the tool path error on the arm side is evaluated using a laser tracker. Experiments have been carried out in three different operating points using movements that represent typical paths in a laser cutting application, and different choices of algorithm design parameters have been studied. The motor angle error is reduced substantially in all experiments, and the tool path error is reduced in most of the cases. In one operating point, however, the error does not decrease as much and an oscillatory tool behaviour is observed. Changed filter variables can give worse error reduction in all operating points. To achieve even better performance, especially in difficult operating points, it is concluded that an arm side measurement, from for example an accelerometer, needs to be included in the learning.

Nyckelord
Keywords

Iterative methods, Learning control, Control applications, Industrial robots, Position control