TITLE:

Iterative Learning Control for variable setpoints, applied to a motion system

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ABSTRACT

Iterative Learning Control (ILC) is a known technique for improving the performance of systems or processes that operate repetitively over a fixed time interval. ILC generates a feed-forward signal effective for providing good tracking control. However, there still exist a number of problems which hinder extensions of ILC schemes. The major obstacle is perhaps the requirement that the trajectory (or repetitive disturbance) must be strictly repeatable over operations. ILC has also liability to deal with stochastic effects.
This paper presents the design and the implementation of a *time-frequency adaptive ILC* that is applicable for motion systems which execute the same kind of repetitive tasks. For the motion system, we show that the adaptive algorithm we propose leads to design *one* (learned) feed-forward signal suitable for different setpoints. We demonstrate that, when implementing time-frequency adaptive ILC, very good time performance (tracking errors) is obtained. The proposed algorithm converges faster than standard ILC. With time-frequency adaptive ILC noise amplification is reduced.

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Iterative Learning Control for variable setpoints, applied to a motion system

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1 Introduction

Iterative Learning Control (ILC) is a effective technique for improving the transient response and tracking performance of processes or systems that execute the same trajectory, motion or operation over and over. The ILC method overcomes some of the traditional difficulties associated with the design of feedback control systems [4]. However, there still exist a number of problems which hinder extensions of ILC schemes. The major obstacle is perhaps the requirement that the trajectory (or repetitive disturbance) must be strictly repeatable over operations. If any change occurs due to the variations of control objectives or task specifications the control system has to start the learning process from the very beginning and the previously learned control input profiles can no longer be used, in order to have negligible control errors again.

Generally speaking, there are two kinds of non-repeatable problems encountered in learning control [1]: non-repeatability of a task or disturbance and non-repeatability of a process. In this paper we will focus on non-repeatability of a task, in particular for (scanning) motion systems where the point-to-point motion contains a constant velocity phase with variable length. Hence, the acceleration and deceleration part of trajectory are fixed and only the scan length (where accurate positioning and settling are specified) varies. Different trajectories, (see Fig. 1), require the learning process to be performed again. Redesigning the learned feed-forward signal and iterating to converge takes time.

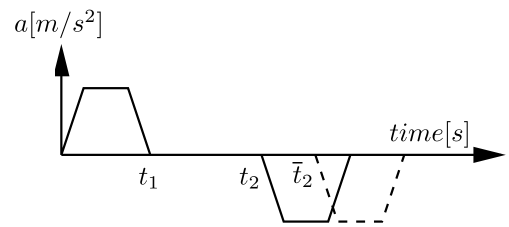

Figure 1: Different scanning profiles.

Therefore, the throughput of such a motion system is obstructed. Finding a technique that leads to a scan length independent learning feed-forward is attractive, since this requires to learn only once for a variety of scans with different lengths.

This paper presents *a time-frequency adaptive ILC* that is applicable for motion systems which execute the same kind of repetitive tasks. The control scheme is the same as for standard ILC [5], the only difference being that the fixed robustness filter $Q(j\omega)$, $\omega \in \mathbf{R}$ becomes $Q_k(j\omega, \tilde{t}, \sigma_k(\tilde{t}))$, where $k \in \mathbf{N}$ gives the trial index, the parameter σ_k can vary throughout the length of each trial k as function of time $\tilde{t}$, $\tilde{t} \in [t_{0(k)}, t_{0(k)} + T]$, where $t_{0(k)}$ is the starting time of the trial k and T is the trajectory length. We remark that throughout this paper the time $\tilde{t}$ is given (time instants where measurements are performed). $\tilde{t}$ might be seen as a time instant within the interval $[t_{0(k)}, t_{0(k)} + T]$ or as a time vector including all given time instants within the same interval. Depending on choice, the equations which contain the parameter $\tilde{t}$ will be scalar respectively vectorial.

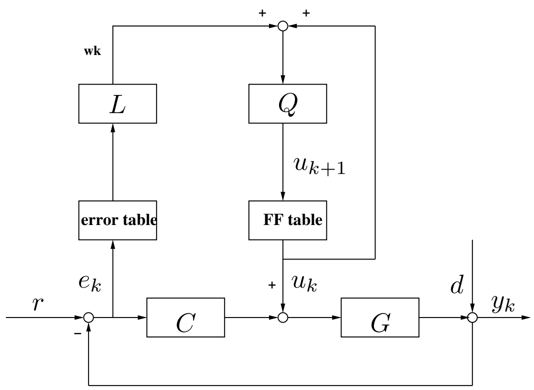

Figure 2: Closed-loop LC configuration.

The Q-filter changes not only within one trial as a function of time, but also over trials. The learning filter L and the convergence criterion remain the same as in the case of standard ILC [5].

This paper focuses on the design and implementation of the time-frequency adaptive ILC. For the motion system, we show that the adaptive algorithm we propose leads to design *one* (learned) feed-forward signal suitable for different setpoints (see Fig. 1). We demonstrate that, using the time-frequency adaptive Q-filter, very good time performance (tracking errors) is obtained. The proposed time-frequency adaptive ILC converges faster than standard ILC. With time-frequency adaptive ILC noise amplification is reduced.

The paper is organized as follows: Section 2 introduces the concept of adaptive ILC. Section 3 presents the time-frequency adaptive filter design. Section 4 addresses the implementation of the adaptive ILC on the motion system test rig and presents the time domain performance. Section 5 focuses on the design of the (learned) feed-forward signal suitable for different scanlengths. The last section summarizes conclusions and recommendations.

2 Adaptive ILC

ILC is based on the principle of using the tracking error of a system in order to obtain an ideal input to reduce the tracking error of the system ([5], [1]). Fig. 2 shows the "standard" ILC loop. We restrict the study to the case where the plant is a causal, LTI dynamical system G. C is a feedback controller which insures the stability of the closed loop system.

We suppose that the desired response r is defined on the interval $(t_0, t_0 + T)$, where $T < \infty$ and the initial conditions are the same at the beginning of each trial.

The goal of ILC design is to produce the signal u^* (the feed-forward signal) such that $r = Gu^*$. We seek a sequence of inputs u_k with the property that $\lim_{k\to\infty} u_k = u^*$, where the index k is the iteration trial. A prototype update law that implements ILC by updating the past iteration input u_k on the basis of the past error is [5]

$$u_{k+1} = Q(u_k + w_k), \tag{1}$$

where

$$w_k = Le_k. \tag{2}$$

The learning filter L has to approximate the inverse of the modeled process sensitivity function $P_s(s)$ ($P_s = \frac{G}{1+GC}$) [5]. For a proper minimum phase modeled process sensitivity function, one can compute and implement its inverse without any problems. For non-minimum phase plants, a stable approximation of the real inverse is used. When applying standard ILC, the robustness filter Q is a low-pass filter which is equal to identity in the frequency band where the inverse of the process sensitivity function approximates the real inverse well enough and has small values for the remaining frequencies.

Remark 1. When applying standard ILC to the motion system for a given scanning trajectory the cut-off frequency has to be adapted such that the learned servo error is convergent overall along the scanning trajectory, i.e., the fixed cut-off frequency is reduced such that one accounts for position dependent dynamics whithin the scanning trajectory. The Q-filter is also used in order to increase the robustness of the ILC against high-frequent noise amplification and plant/model mismatch.

Next we introduce the time-frequency adaptive Q-filter. With the same learning filter as for standard ILC, we replace the fixed Q-filter with a time-varying Q-filter $Q_k(s, \tilde{t}, \sigma_k(\tilde{t}))$, namely a zero-phase Butterworth filter of a generic order n and cut-off frequency $\sigma_k(\tilde{t})$, whose magnitude is given by the following formula

$$Q_k(s, \tilde{t}, \sigma_k(\tilde{t})) = \sqrt{\frac{1}{1 + \left(\frac{\omega}{\sigma_k(\tilde{t})}\right)^{2n}}}. \tag{3}$$

where $\tilde{t} \in [t_{0(k)}, t_{0(k)} + T]$, $t_{0(k)}$ is the initial time of the k-th cycle, T is the time required to perform the trajectory. The cut-off frequency $\sigma_k = \sigma_k(\tilde{t})$ may vary throughout the length of each trial. Therefore, at each time instant $\tilde{t}$, the Q-filter might change its cut-off frequency. In what follows, we denote by $\Gamma(t, \tilde{t}, \sigma_k(\tilde{t}))$ the inverse Fourier transform of the Butterworth type filter $Q_k(s, \tilde{t}, \sigma_k(\tilde{t}))$:

$$Q_k(s, \tilde{t}, \sigma_k(\tilde{t})) \xrightarrow{\mathcal{F}^{-1}} \Gamma(t, \tilde{t}, \sigma_k(\tilde{t})). \qquad (4)$$

Therefore, by (4), the ILC law (1) can be written as

$$u_{k+1}(\tilde{t}) = \Gamma(t, \tilde{t}, \sigma_k(\tilde{t})) * (u_k(t) + w_k(t)), \qquad (5)$$

where * denotes the convolution operator of two signals.

We shall apply the adaptation mechanism along the whole trajectory length time-interval. First, the design of the time-frequency Q-filter comprehends the use of the Wigner distribution. Using Wigner distribution we identify the high and low frequency components of the control signals (namely, the signals $u_k + w_k$) as well as their energy levels so that one could determine if there is deterministic (low or high frequency) system dynamics at a particular time instant (for a given setpoint, time is equivalent to position) or just measurement noise. The stochastic definition of the Wigner distribution allows us to identify the *stochastic effects* presented in the control signals (implicitely in the servo errors) and to consider these effects in the control strategy.

The Q-filter bandwidth (cut-off frequency of the Butterworth type filter σ_k) varies according to the current frequency contents present in the system signals. The filter effectively changes its bandwidth (cutoff frequency) as a function of time and the *high frequency dynamics will enter into the learning feed-forward controlled process at the appropriate time instants.* Also, the bandwidth of the filter is reduced when the system dynamics do not exhibit high frequency components and therefore, it *avoids noise amplification when applying learning feed-forward control.* Therefore, the adaptation algorithm will adjust the bandwidth frequency as a function of time to maximize the tracking performance while still maintaining a good noise performance.

The use of the time-frequency adaptive filter Q is, at this moment intuitively speaking, a solution to better optimize the trade-off motivated in *Remark 1.*

3 The time-frequency adaptive Q-filter design

In this section we design a time-frequency adaptive Q-filter which is going to be implemented in the closed-loop LC configuration (see Fig.2). The following steps are followed:

- Implement a feed-forward signal u_k. We denote the obtained servo error with e_k. The first feed-forward signal considered for implementation is the acceleration feed-forward signal u_0. The corresponding obtained servo error is e_0.
- Using time-frequency analysis (Wigner distribution), one identifies the high and low frequency components of the control signal $u_k + w_k$ as well as their energy levels so that one could determine if there is deterministic (low or high frequency) system dynamics at a particular time instant or just measurement noise.
- Write an algorithm which designs the cut-off frequency of a time-frequency adaptive filter (a low-pass filter whose cut-off frequency varies according to the current frequency contents present in the system signals).

Next we describe the main steps of the adaptation algorithm for an arbitrary fixed iteration trial k:

The bandwidth profile $F_k(\tilde{t})$. We are interested to find high-energy frequency components of the control signal which is going to be Q-filtered, namely the signal $u_k + w_k$ defined in (2). Using the Wigner distribution the energy corresponding to a certain time and frequency is computed. We remember here that the Wigner distribution of a signal w at time $\tilde{t}$ [s] and frequency Ω [Hz] is defined as follows:

$$W(\tilde{t}, \Omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} w^*(\tilde{t} - \frac{1}{2}\tau) w(\tilde{t} + \frac{1}{2}\tau) e^{-j\tau 2\pi\Omega} d\tau \qquad (6)$$

where w^* is the conjugate of the signal w (identical to w for real signals).

Remark 2. Because of its quadratic non-linear form, the Wigner distribution puts non-zero values at time-instants when the actual signal is zero [6]. Also, the noise around one time instant could be spread all over the time frequency plane. As in [8], we expect that for the system noise occurs with much lower energy than determistic dynamics. The appearance of non-zero or noise terms at times or frequencies where they do not exist is called *interference or cross terms*. In the case of servo errors (when applying acceleration feed-forward or ILC), this problem is solved by dividing the compact time-interval of the signals to be analyzed in four pieces such that almost no cross terms will appear [6]. For the discussed system, we consider the acceleration profile given in Fig. 1, with $t_1 = 0.1$ [s], $t_2 = 0.2$ [s]. The Wigner distribution of the control signal $u_0 + w_0$ is depicted in the three-dimensional image shown in Fig. 3.

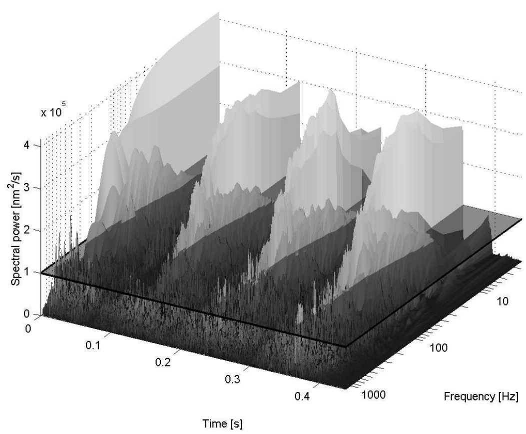

Figure 3: The 3-D Wigner distribution on the TF plane of typical control signal $u_k + w_k$.

We choose a plane of height c_e parallel with time-frequency (TF) plane (Fig. 3). This plane should enclose the frequency components having enough energy to be picked up at this energy level. We denote the crossing contour which results by intersecting the three-dimensional energy distribution plot with the c_e height plane by $\omega_k(\tilde{t})$. The constant c_e has to be chosen large enough to identify no noise but small enough to consider all deterministic dynamics frequencies. Also, the parameter c_e is selected to be large enough to eliminate the possible remained cross terms of the Wigner distribution. We remark that the obtained contour $\omega_k(\tilde{t})$ is not a function in mathematical sense, may have the form depicted in Fig. 4, left. We consider the highest frequency-time profile (envelope), as shown in Fig. 4, right, i.e.,

$$F_k(\tilde{t}) = max(\omega_k(\tilde{t})), \text{ for } W_k(\tilde{t}, \omega_k) = c_e. \quad (7)$$

Based on the contour $F_k(\tilde{t})$, the Q-filter bandwidth profile at any time instant is going to be

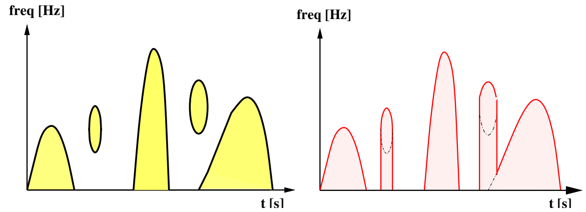

Figure 4: Use contour of TF graph to identify different frequency components along time scale.

designed.

Compute the Q-filter bandwidth $\Omega_{Q_k}(\tilde{t})$. Consider the windowed least mean square norm of the tracking error at trial k

$$S_k(\tilde{t}) = \sum_{i=\tilde{t}-T_w/2}^{\tilde{t}+T_w/2} (e_k(i))^2, \quad (8)$$

where T_w is the length of the moving window, $e_k(i)$ is the tracking error during the $k-th$ trial, at a certain time instant $i \in [\tilde{t} - T_w/2, \tilde{t} + T_w/2]$, $\tilde{t} \in [t_{0(k)}, t_{0(k)} + T]$.

Consider the difference between the least mean square norms corresponding to the iterations k and k-1.

$$\Delta S_k(\tilde{t}) = S_k(\tilde{t}) - S_{k-1}(\tilde{t}). \quad (9)$$

Update the Q-filter bandwidth $\Omega_{Q_k}(\tilde{t})$ using iterative learning and the windowed error norm change $\Delta S_k(\tilde{t})$.

$$\begin{aligned} \Omega_{Q_k}(\tilde{t}) &= \Omega_{Q_{k-1}}(\tilde{t}) + \Delta\Omega_{Q_k}(\tilde{t}) \quad (10) \\ \Delta\Omega_{Q_k}(\tilde{t}) &= -F_k(\tilde{t}) \cdot \Delta S_k(\tilde{t}) \cdot \mathrm{sign}(\Delta\Omega_{Q_{k-1}}(\tilde{t})) \end{aligned}$$

For the first trial we choose $\Omega_{Q_1}(\tilde{t}) = 10\ [Hz]$.

Compute the relationship between the filter bandwidth $\Omega_{Q_k}(\tilde{t})$ and $\sigma_k(\tilde{t})$. We consider the time vector $\tilde{t} = (\tilde{t}_i)_{i\in\overline{1,N}}$, $N \in \mathbf{N}$ corresponding to the scanning interval. For any time instant $\tilde{t}_i$, $i \in \overline{1,N}$ we compute the Q-filter bandwidth $\Omega_{Q_k}(\tilde{t}_i)$ [Hz]. We denote by $s_i = j2\pi\Omega_{Q_k}(\tilde{t}_i)$. The parameter $\sigma_k = \sigma_k(\tilde{t}_i)$ is found when solving the following equation

$$\text{bandwidth}(Q_k(s, \tilde{t}_i, \sigma_k(\tilde{t}_i))) = \Omega_{Q_k}(\tilde{t}_i). \quad (11)$$

For any time instant $\tilde{t}_i$, $i \in \overline{1,N}$, the relationship (11) between the computed Q-filter bandwidth $\Omega_{Q_k}(\tilde{t}_i)$ and the parameter $\sigma_k = \sigma_k(\tilde{t}_i)$ is non linear. For computations, different linear approximations might be considered.

Remark 3. The time-frequency adaptive Q-filter can be seen as a time-varying low-pass filter. The filter might change very fast (the motion control considered has a sampling rate of 0.125 [ms]). The fast switching between the cut-off frequency of different Q-filters which correspond to different time instants is a major issue in switching control and hybrid system area. For stability results for switched systems, which can indicate a way to handle with the Q-filter, we refer to [3]. In case of the considered motion system, the cut-off frequencies are changing smoothly enough from one time instant to another. The switching control law does not affect the stability of the system.

4 Implementation on the motion test rig

In this section we apply the procedure described in previous sections to the motion system, see Fig. 5.

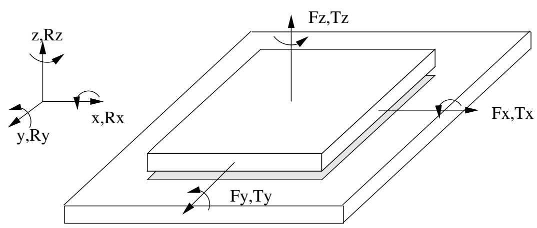

Figure 5: Schematic view of a 3 DOF linear motion system.

It is an electromechanical servo system with scan speeds and accelerations of respectively 0.5 m/s and 10 m/s^2. The positioning accuracy is in terms of nanometers and microradians.

The time-frequency ILC is applied for a representative scan of velocity 0.5 [m/s], acceleration of 5 [m/ s^2], jerk of 1000 [m/s^3] over 0.1 [m] in y direction . The scanning trajectory starts at $(x, y) = (0, -0.05)$ [m^2] and ends up at $(x, y) = (0, 0.05)$ [m^2].

In what follows we describe the implementation procedure and related results. We first implement the acceleration feed-forward signal u_0.
As reference point for the time-frequency analysis of the (learned) servo errors, we consider the Wigner distribution of the standstill error (Fig. 6). In this case, the Wigner distribution describes the time-frequency behaviour of the standstill error: it measures how much of the signal energy at a certain time [s] is concentrated at a certain frequency [Hz] or, in other words, the frequency contents is plotted as a function of time.

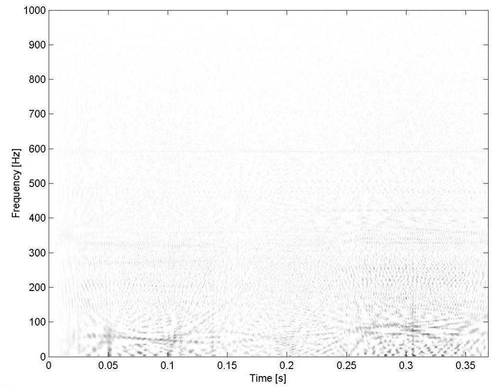

Figure 6: Wigner distribution of the standstill servo error.

The Wigner distribution of the servo error e_0 (when acceleration feed-forward is applied) shows high-energy low-frequency dynamics (where the acceleration profile changes), and higher frequency dynamics overall in time (Fig. 7).

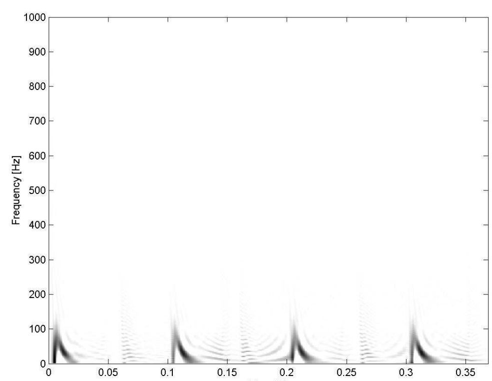

Figure 7: Wigner distribution of the servo error when acceleration feed-forward control is applied.

Using time-frequency analysis (Fig. 3), one identifies the high and low frequency components of the control signal $u_0 + w_0$ (see Fig. 2) as well as their energy levels so that one could determine if there is deterministic (low or high frequency) system dynamics at a particular time instant or just measurement noise.
As shown in Section 3, the time-varying cut-off frequency of the Q-filter is designed. The signal $u_0 + w_0$ is filtered (see (5)) with the time-varying Q-filter resulting in the first learned feed-forward u_1. Implementing the feed-forward signal u_1 on the system, we obtain the first learned tracking error e_1. In order to compute the feed-forward signal u_2, the same L-

and Q-filter as in the previous trial, the past feed-forward signal u_1 and the past servo error e_1 are employed in the update law (5).
The same process can be iterated resulting in better tracking errors. The servo error depicted in Fig. 8 is obtained only after two iterations.

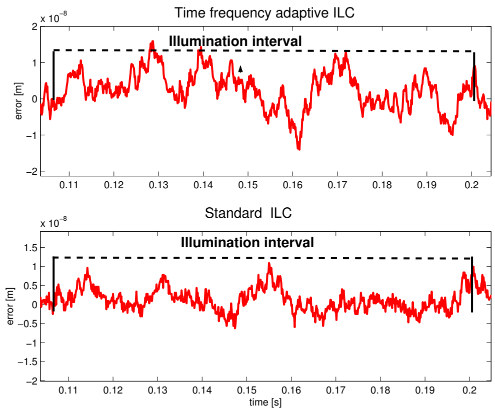

Figure 8: Servo errors in the y direction, adaptive ILC and standard ILC.

Remark 4. The algorithm explained in Section 3 is adaptive not only over the time interval within a considered trial, but over iterations also. In this paper we show the time domain performance results when implement the same time-frequency adaptive filter for all trials. Therefore, the bandwidth of the Q-filter changes in time within one trial, but does not adapt it's profile from one iteration to another one. Adaptive tuning of the Q-filter bandwidth profile over iterations will be shown in a future paper.

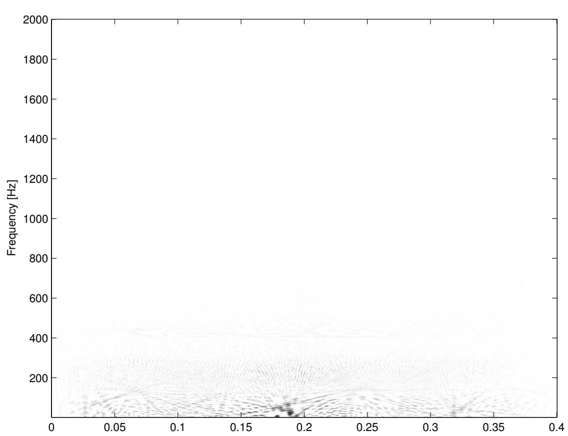

Figure 9: Wigner distribution of the servo error when adaptive ILC is applied.

When applying adaptive ILC, a comparable time domain performance with standard ILC performance is achieved (see Fig. 8). All repetitive deterministic components of the tracking errors are eliminated. The non-repetitive and the stochastic effects (up to about 250 [Hz]) presented in the servo errors are not amplified when applying ILC. The performance of the adaptive ILC from deterministic/stochastic point of view is very good: the Wigner distributions of the learned errors (Fig. 9) are comparable with the Wigner distribution of the standstill error (Fig. 6).

5 Scan-length independent feed-forward signal

The motion system considered exhibits high-energy repetitive deterministic system dynamics in the beginning and at the end of the scanning interval (Fig. 3 and 7). This system property was a sufficient reason to explore the possibility to design one learned feed-forward signal suitable for different scan lengths.

The Q-filter bandwidth varies from about 500 [Hz] in the beginning and at the end of scanning interval to 50 [Hz] arround the middle of the constant speed interval. This means that around the points $t_1 = 0.1$ $[s]$ and $t_2 = 0.2$ $[s]$, the Q-filter is active and the determinstic repetitive dynamics is suppressed up to 500 [Hz]. In the vicinity of the middle point of the constant speed interval, the ILC is almost not active.
Remark 5. The Q-filter cut-off frequencies overall in time are given by the choice of the c_e in the adaptive alghorithm (see Section 3). Chosing a lower c_e means that we learn up to higher frequencies around the points t_0, t_1, but the c_e-level plane encloses more noise, which means that the noise would be amplified by the learning process. Increasing the value c_e implies that in the beginning and at the end of scanning interval the learning process is active up to lower frequencies than in the first case, but the noise will not be amplified. The time domain performance of the adaptive ILC with fine-tuning of the algorithm introduced in Section 2 (especially tuning of the parameter c_e) will be considered in another paper.

When applying the adaptive ILC, we obtain the learning feed-forward signal depicted in Fig. 10. In comparison to the standard ILC feed-forward signal, it displays dynamics only in the beginning and at the end of the scanning interval. Between these intervals the adaptive learned feed-forward signal has zero values.

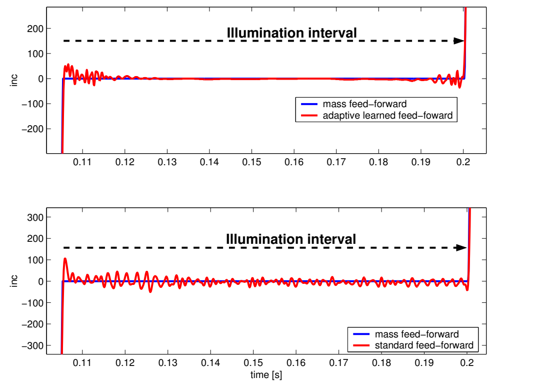

Figure 10: Feed-forward signals in the y direction, adaptive ILC and standard ILC.

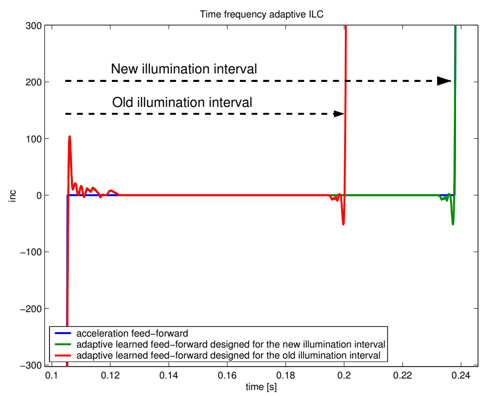

Figure 11: The design of the adaptive learned feed-forward signal for different scan-length.

Therefore, when the scan-length changes we do not have to perform learning again: we prolong the old learned feed-forward signal inserting zeros such that the exposure length of the new feed-forward signal corresponds to the required scan-length (Fig.11). Implementing the lengthened learning feed-forward signal for a corresponding (longer) scanning interval, good time-domain performance is achieved.

6 Conclusions

When implement time-frequency adaptive ILC, we conclude the following:

- Good tracking error along the entire scanning pattern is achieved.
- For a given scanning trajectory, one accounts for position-dependent dynamics. Understanding and controlling position-dependent dynamics while tracking movements on different (x, y) positions (Fig. 5) is still an issue.
- Design ONE learned feed-forwards signal suitable for different setpoints (see Fig.1).
- Does not amplify stochastic and non-repetitive effects.

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