Iterative Learning Control and Decoupling of Lorentz Force Based Actuator Systems for Turbulence Research

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Abstract— **This work discusses classic feedback control (PD) and Iterative Learning Control (ILC) applied to a Lorentz force based actuator system for turbulence research. The goal is precise and reliable generation of transversal waves on an aluminum surface in wind tunnel experiments. For research on unsteady inflow conditions wave parameters have to be adjustable quickly within given ranges (50 to 135 Hz frequency, 260 to 500 µm amplitude, 80 to 160 mm wavelength). We present results of simultaneous control of individual actuators as well as decoupling steering. Using Finite Element simulations the observed unwanted tilting oscillations could be explained.**

I. Introduction

Turbulent drag is an important economic and ecological issue throughout most of modern transportation. The research group FOR 1779, funded by the DFG (German research foundation) [1], studies active drag reduction via wavy surface oscillations. The participating researchers perform numerical simulations [2] as well as wind tunnel experiments [3] to develop robust methods for the reduction of turbulent friction drag.

In wind tunnel experiments at low Reynolds numbers a traveling transversal aluminum surface wave shall be enabled with parameter ranges as shown in Table 1. For this, we developed a Lorentz force actuator system. Each of the up to 20 actuators is realized as a linear electric motor with one coil (see fig. 1). The parallel arranged actuators are glued to the surface in an equidistant spacing. Hence to produce a traveling wave they need to move on sine trajectories with evenly increasing phase shift. We control this movement via the voltage applied to the coils.

Research on unsteady inflow conditions requires the ability to quickly and reliably react to the new condition by changing the parameters of the surface wave. We focus on facilitating such transitions and stabilizing our most recent actuator system, while other researchers within FOR 1779 focus on flow control (e.g. [4]). We will discuss control methods for our current 20 actuator, 10 mm spacing system in the following.

The second section will describe the plant and its special properties in more detail. The following section, section three, describes results obtained using classic control implemented on a test system. The fourth section introduces the idea of improving over PD using an Iterative Learning Control (ILC), which has been studied in simulation, and deals with implementation of ILC. The following, fifth section addresses the issue of decoupling, which is essential to further improve control. Tilting of the actuators is one of the main obstacles to be overcome in order to achieve the desired control and is discussed in the sixth section. The work closes with an outlook to our future research on control.

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II. Plant Dynamics and Model

The actuators are coupled via the 0.3 mm aluminum surface. Within the desired range of wavelength and amplitude this coupling requires the application of a control system to ensure accurate and reliable waves.

Strong beating oscillations and uneven amplitude distribution along the direction of propagation of the wave would disturb wind-tunnel measurements to an unacceptable level. Therefore feedback and feed-forward control techniques are under development to overcome these problems. In addition we pursue the goal of quickly and smoothly changing important wave parameters such as amplitude, wavelength and frequency (Table 1).

TABLE I. Wave Parameter Ranges

Wave parameter	Frequency in Hz	Amplitude in µm	Wavelength in mm
Target range	50–135	260–500	80–160

As shown in fig. 1 we use two types of sensors to detect the position of each actuator bar and from this we determine the shape of the wave, which is the controlled variable. The laser triangulation sensors cannot be used during wind tunnel experiments as they would disturb the airflow. We use them to calibrate analog light barrier sensors, which are capable of detecting the position of the actuator bar with high accuracy (in the range of 10 µm) and bandwidth (> 1 kHz, further detail in section VI and [12]).

A model capturing the main dynamics of the system is based on the actuators behaving like coupled linear harmonic oscillators. The differential equations describing the system also contain its electromagnetic dynamics (inductivity, back electromotive force). We find the force equilibrium:

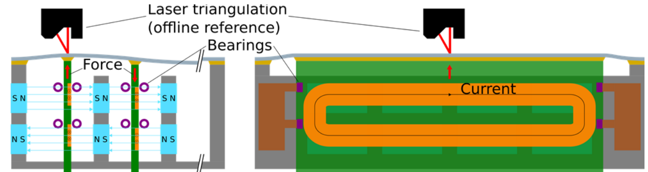

Figure 1. Cross sections of the actuator system.

$$F_{Mech} = F_{Lorentz} \tag{1}$$

$$F_{Mech} = m_i\ddot{x}_i + f_i\dot{x}_i + c_i \cdot x_i + c_{i,i-1} \cdot (x_i - x_{i-1}) + c_{i,i+1}(x_i - x_{i+1}) \tag{2}$$

$$F_{Lorentz} = \frac{lnB}{R} \cdot \left(U - L\dot{I} - lnB\dot{x}_i\right) \tag{3}$$

Here x_i denotes the position of the ith actuator bar, m_i its mass, f_i its friction coefficient, c the spring constants between actuators denoted by the indices, l length of the conductor in the magnetic flux B for a coil with n turns, inductivity L, resistance R and input voltage U, which is the manipulated variable. However measurements show that electromagnetic dynamics have no significant impact at our operating frequencies so approximately $F_{Lorentz} \propto U$.

Of course there are some limitations to this model. As elongation increases reset force becomes significantly non-linear. Based on our measurements this is not a significant issue within our current wave parameters and surface thickness. Non-linear friction might also severely limit the linear model but has not been studied in detail so far.

The key disturbances include: above mentioned non-linearity, forces due to unpredictable actuator movement imposed by the moving surface or asymmetries due to manufacturing margins which may directly impact up-down movement or lead to varying friction. As a preliminary measure we also treat coupling of the actuators as disturbance and use single input single output controllers starting with proportional-differential (PD) control.

III. Classic Control

As a first approach PD control was used on a testbed system having 3 actuators at the same 10 mm spacing as the target system [7]. Its success lies primarily in showing that feedback control works on the system in principle. However, it can only produce a limited phase difference of approximately 15° between the actuators, resulting in a minimum wavelength of 240 mm.

Integral action is not used as it is not necessary while impacting stability adversely. The steady state (zero) position of the actuators is mostly fixed by the close boundaries in this test system and does not require adjustment.

The 3 actuator system is strongly influenced by boundary effects. The boundary actuators are most closely coupled to their only moving next neighbor. Therefore they tend to oscillate in phase with that neighbor. The coupling of a freely moving actuator between two phase shifted neighbors to the neighbors is roughly equal. This leads to its phase shift also lying roughly in the middle between the neighbors. Additional issues (discussed in section V) also hinder the use of pure PD control further away from boundaries.

IV. Iterative Learning Control

A. Suitability of Iterative Learning Control

To overcome the PD control limitations concerning maximum phase shift we applied Iterative Learning Control (ILC) which is an attractive approach for periodic references and plants with inherently periodic disturbances (e.g. [5]). The key disturbances (as described in sec. II) in our application are

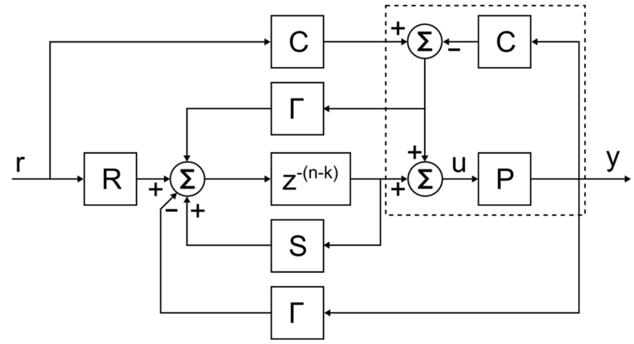

Figure 2. ILC with underlying classic feedback control (in dotted frame) block diagram based on [11]. The Plant is P, Γ is the learning filter, S is a steering filter, R filters the reference and is usually chosen R = Γ (nominal-actual comparison). C is the classic feedback loop filter, a PD with filtered differential part in our case.

dependent on the collective position and dynamical state of the actuators which is highly periodic in the fully settled traveling wave (fixed frequency, wavelength traveling wave). These sources might also produce transient disturbances when transitioning to another set of wave parameters. However, these transitions are expected to occur with sufficient time spacing to accommodate ILC convergence to the new parameter set. In addition this problem can be alleviated by smoothing the transition [6]. Other transient disturbances act slowly (gravity, temperature changes) and are therefore not as relevant.

B. General Scheme for Implementation

Previously we developed a gain switching PD-Type ILC, which showed promising results in simulation study based on the geometric parameters of our 10 actuator system with 20 mm actuator spacing [8].

For implementation we altered the control scheme slightly to a so called Repetitive Control configuration. Within a more general mathematical framework it can be shown that Iterative Learning Control and Repetitive Control (RC) are the same [9].

C. Model based learning

To reduce convergence time we furthermore use model based ILC. Of course we have to assume some model mismatch especially as we do not take coupling into account at first. In practice it is therefore necessary to add a low pass iteration filter S for stability [10] [11] (see fig. 2). It suppresses feedback at frequencies where model mismatch would lead to instability.

The learning filter Γ is based on aforementioned linear model of the actuator. Not all parameters are well known or easy to measure independently. Therefore we generate a grey box state space model from the differential equations (1) to (3). Using the Matlab System Identification Toolbox we fit the unknown model parameters. We now denote the true plant with P and the model with $\tilde{P}$. To find a good learning filter we follow the internal model principle and use the inverted model

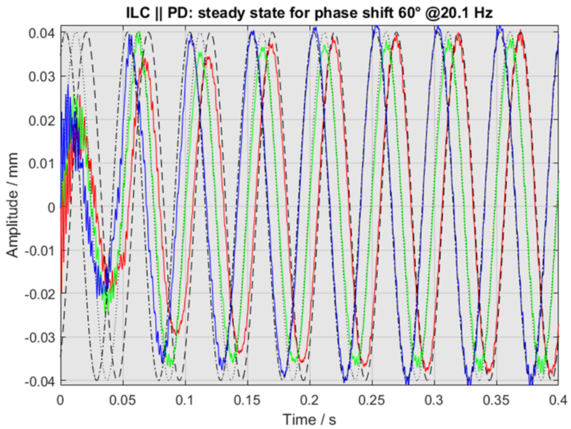

Figure 3. Convergence of ILC with underlying PD after switching on.

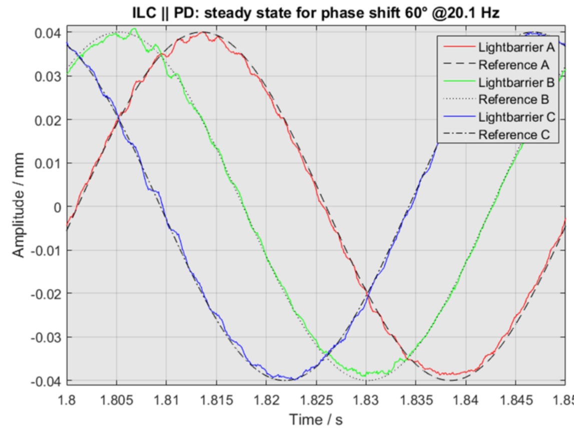

Figure 4. Converged tracking by ILC with underlying PD.

as base, which is modified with a low pass filter S (same as the iteration filter) leading to the learning Filter Γ.

This avoids excessive amplification of high frequency sensor noise. In addition robustness can be increased by carefully reducing the absolute value of the learning gain, multiplying with a factor $g < 1$ [13], which comes at the price of slower convergence towards the reference waveform. We therefore have the learning filter:

$$\Gamma = g \cdot \tilde{P}^{-1} \cdot S \tag{4}$$

This parameter and the corner frequency of the digital low pass filter used for the steering filter and as part for the synthesis of the learning filter have been extensively tuned for best results.

D. Zero Phase Filtering

Based on similar approaches in related applications [10], we implemented the learning filter as a zero-phase (hence non-causal) filter. This is done by manipulating the delay which lies at the heart of the ILC ($z^{-(n-k)}$ in fig. 2). The learning filter and the steering filter S are designed as $2 \cdot k$ tap symmetric Finite Impulse Response (FIR) filters with linear phase and constant group delay. Reducing the delay by k samples exactly compensates for the phase of the filters. They then appear as zero phase filters cascaded with an n sample delay. This delay, the ILC period, needs to be changed with the adjustable actuation frequency to match the actuation period. Therefore the largest possible k equals $f_{sample}/f_{actuation,max}$, with $f_{sample} = 10$ kSps and $f_{actuation,max}$ the largest possible actuation frequency. For the implementation shown here $k = 50$ is chosen, which allows for a maximum actuation frequency of 200 Hz.

E. Experimental Results

Combining these methods results in stable control at frequencies up to 20 Hz. To improve transient response and suppression of non-periodic disturbances the ILC is combined with classical PD feedback control. This can be done in series or in parallel. Since the serial approach usually is chosen only in combination with a preexisting, working feedback control, we choose the parallel configuration shown in fig. 2 (derived from [11]).

As shown in fig. 3, convergence is fast (approx. 0.4 s) and phase error after convergence (fig. 4) is minimal, although this test was done on the 3 actuator setup, which has proven to be difficult in this regard (see above). Also overall error is sufficiently small (< 5 %).

V. Combining Iterative Learning Control with Decoupling

To achieve stable control in the desired frequency range (see Table 1) we combine ILC with decoupling. Similar to the learning filter decoupling is derived from a model. The simplest way to do this is to use the model inverse (if it exists like in our case) for feedforward. For this purpose our previous model was too inaccurate. To avoid the complex task of modeling and inverting a system with potentially multiple resonances in the frequency range of interest, the model for decoupling only takes one frequency into account. In successive experiments the actuators are each excited with a 100 Hz sine voltage individually and the response of all actuators is measured. Using Hilbert transform to determine instantaneous phase and amplitude of the responses and averaging over multiple periods, gain and phase of each actuator with respect to the input signal are determined. Entering these results as complex valued coefficients in a 20x20 matrix yields a system description for the specific frequency. Assuming a linear time invariant system, the inverse of this matrix should then decouple the system at the specific frequency. As an example results for actuator 7 are shown in fig. 5 and 6.

Although the measurements indicate decoupling is not perfect, it severely reduces the impact of coupling as a disturbance, which a SISO ILC has to overcome. This should improve the convergence time of the ILC which is a major goal of our research. However, the central question remains, if this extends stable operation to the desired frequency range. This is subject of ongoing research.

Large phase delay close to 180° is measured from voltage input to position sensor output for many frequencies between 27 Hz and 135 Hz. This could render classic feedback useless for the 20 actuator setup. Fortunately ILC can deal with such a situation if model mismatch is sufficiently small.

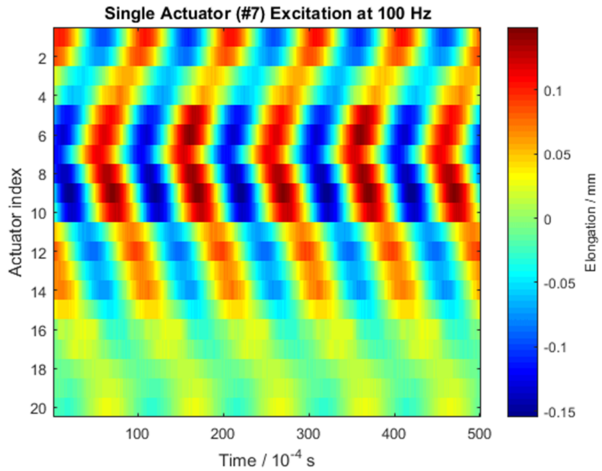

Figure 4. Pseudocolor picture of actuator movement when only actuator 7 is excited with a 100 Hz sine signal.

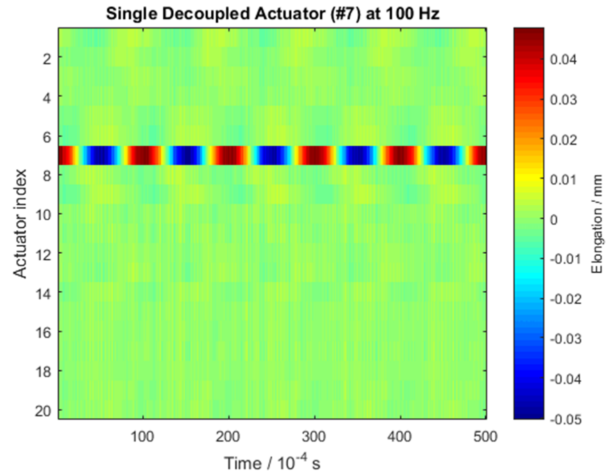

Figure 5. Pseudocolor picture of actuator movement with inversion decoupling on all actuators. Ideally only actuator 7 should move.

Progress towards decoupling was achieved by investigating tilting oscillations of the actuator system which will be described in the following section.

VI. Finite Element Simulation of Actuator Tilting

Loss of stability above 20 Hz and difficulties obtaining an accurate model for decoupling and ILC are closely related to tilting oscillations that can be observed with two reference sensors measuring one actuator. To understand mechanisms behind tilting oscillations, Finite Element (FE) simulations of the mechanical setup have been performed. The simulations identified actuator tilting as an effect of eigenmodes shown in fig. 7 and 8 which are comparable tilting and non- tilting modes. The associated eigenfrequencies are very close to each other. Therefore disturbances from uneven forces acting on the actuators due to uneven spring force (inhomogeneity of surface material, limited manufacturing precision) and dynamic variations of load on the bearings, and accordingly varying friction force, tilting oscillations are easily excited.

This has led to inconsistent sensor readings used for feedback. These sensors are also the only available method for fully capturing the system response. Therefore during system identification errors have been introduced which lead to large model mismatch and in turn to stability problems. As a first approach we redesigned the sensors [12]. The new sensor configuration is capable of measuring the center of mass movement of the actuators and their tilting motion reliably.

Unfortunately, the tilting oscillations cannot be actively counteracted in the current setup. Upgrading the setup with additional coils and amplifiers is an option but would increase the complexity of the control significantly. We also performed FE simulations on the placement of additional bearings. This shifts the eigenfrequency of the tilting oscillations to such high frequencies (>900 Hz) that it should not interfere with actuation at our target frequencies anymore. Experiments on additional bearings are in progress.

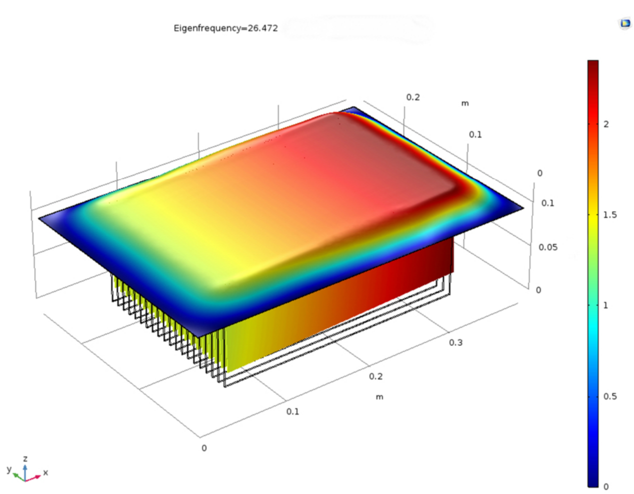

Figure 6. FE simulation of tilting standing wave oscillation. Pseudocolor indicates displacement in arbitrary units.

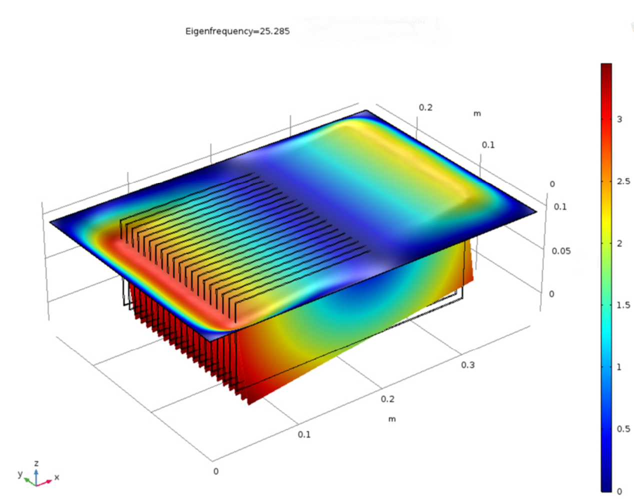

Figure 7. FE simulation of non-tilting standing wave oscillation. Pseudocolor indicates displacement in arbitrary units.

VII. CONCLUSION

We have described various approaches to control a system of strongly mechanically coupled actuators to produce a stable traveling wave. The implementation of classic PD control shows that feedback control is possible in principle but is limited to large wave lengths. Theoretical results show that gain-switching PD-type ILC is a capable tool for dealing with the given problem based on its inherent periodicity (in time). Implementation of loosely model based ILC with underlying PD using zero phase filtering achieves marked improvements over PD control on its own as expected. It also improves over the convergence time of gain switched ILC. The desire to achieve higher frequencies embracing the model based approach leads into decoupling control. This step-wise improvement makes us confident that our present research together with improvements to the hardware to suppress tilting oscillations that hinder control will finally yield a method to achieve stable traveling waves in the desired parameter range with sufficient flexibility.

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