Efficient Model-Free Iterative Learning Control for Massive MIMO Systems using Stochastic Approximation

Leontine Aarnoudse¹, Tom Oomen¹
¹Control Systems Technology, Eindhoven University of Technology, P.O. Box 513, 5600MB Eindhoven, The Netherlands
Email: l.i.m.aarnoudse@tue.nl

1 Background

Iterative learning control (ILC) aims to achieve high performance while providing robustness against model errors. Typical optimization-based ILC approaches use models combined with experimental data [1], and existing data-based methods such as [2] are experimentally expensive. This research aims to develop an efficient model-free ILC approach for massive MIMO systems using an unbiased gradient estimate that is obtained from a single experiment.

2 Problem formulation

Consider a MIMO system \( J \in \mathbb{R}^{n_o \times n_i \times N} \) with \( n_i \) inputs and \( n_o \) outputs, given in lifted form by
\[
e = r - Jf
\]
with input \( f \in \mathbb{R}^{n_i \times N \times 1} \), error \( e \in \mathbb{R}^{n_o \times N \times 1} \) and unknown exogenous disturbance \( r \in \mathbb{R}^{n_o \times N \times 1} \). The criterion
\[
\mathcal{J}(f) = \|e\|^2_W + \|f\|^2_W
\]
with \( \|x\|_W = \sqrt{x^T W x} \) is minimized iteratively using a gradient descent algorithm with parameter update
\[
f_{i+1} = f_i - \varepsilon_i g(f_i)
\]
with step size \( \varepsilon_i \) and gradient
\[
g(f_i) = -2J^T W e_i + 2W_f f_i.
\]

3 Approach

A stochastic approximation adjoint ILC (SAAILC) approach is proposed, in which an unbiased approximation of the gradient is obtained from a single experiment as
\[
\hat{g}(f_i) = -2T^{n_i} A J 1^{n_o} W e_i + 2W_f f_i.
\]
The entries of matrix \( A \) are samples from a symmetric Bernoulli ±1 distribution, and \( T \) is a time-reversal operator, for which it holds that \( T J^{11} T = (J^{11})^T \) for a SISO system \( J^{11} \). Estimate (5) replaces \( g(f_i) \) in (3), and since

\[
E(\hat{g}(f_i)) = g(f_i),
\]
the resulting algorithm can be interpreted as a Robbins-Monro type stochastic gradient descent algorithm, for which convergence can be shown.

The proposed SAAILC approach is experimentally advantageous compared to the deterministic approach in [2], which essentially applies the method by [3] to each subsystem of \( J \) subsequently, thus requiring \( n_i \times n_o \) dedicated experiments to obtain the gradient for a non-symmetric \( n_i \) by \( n_o \) system.

4 Results

In Figure 1, SAAILC is illustrated using a random non-symmetric \( 21 \times 21 \) MIMO system. It is shown that SAAILC achieves the same cost as the deterministic MIMO adjoint ILC algorithm, while reducing the number of required experiments significantly. In addition, it is shown that assuming that the system is symmetric in order to reduce the number of experiments results in a diverging cost.

Figure 1: The cost as a function of the number of experiments in adjoint ILC for a non-symmetric \( 21 \times 21 \) MIMO system. SAAILC (---) requires far fewer experiments to reach the same cost as non-symmetric deterministic adjoint ILC (--), while symmetric deterministic adjoint ILC (---) results in a diverging cost.

References