# Iterative Learning Control with Measurements

## Aaron Trowbridge

# Setup

Given a nominal state trajectory  $\hat{x}(t)$  and control trajectory u(t), we apply the controls to the experimental system and retrieve a set of measurements (abusing notation) y(t) from the (possibly hidden) experimental trajectory  $\bar{x}(t)$ . Schematically we have:

$$u(t) \longrightarrow \bar{x}(u(t), t) \longrightarrow g(\bar{x}(t), t) = \bar{y}(t)$$

which coincides with the simplified model situation:

$$u(t) \longrightarrow \hat{x}(u(t), t) \longrightarrow g(\hat{x}(t), t) = \hat{y}(t)$$

We now have two sets of measurements:

•  $\hat{y}(t)$ : the nominal measurement

•  $\bar{y}(t)$ : the experimental measurement

# **Problem Formulation**

Let us write

$$\bar{x}(t) = \hat{x}(t) + \epsilon(t)$$

where  $\epsilon(t)$  is the error in the experimental trajectory. To correct for this error, we can find a correction term  $\Delta x(t)$  s.t.

$$g(\bar{x} + \Delta x) = g(\hat{x} + \epsilon + \Delta x) = \hat{y}$$

For example, if g(x) = x is the identity function, i.e. we are trying to track the trajectory:

$$\Delta x = -\epsilon$$

The real problem involves finding the corresponding correction to the controls:  $\Delta u(t)$ . This involves setting up a quadratic optimization problem.

## **Quadratic Correction Problem**

The goal is now to go from the measurement error  $\Delta y$  to a state correction  $\Delta x$  and a control correction  $\Delta u$  by simultaneously solving two linear systems. Schematically:

$$\Delta y \xrightarrow{M \cdot \Delta x = \Delta y} \Delta x \xrightarrow{D \cdot \Delta z = 0} \Delta u$$

### Measurement Correction to State Correction

With  $\Delta y \equiv \bar{y} - \hat{y}$ , we have

$$\begin{split} \bar{y} &= g(\bar{x}) \\ &= g(\hat{x} + \epsilon) \\ &\approx g(\hat{x}) + \nabla g(\hat{x}) \cdot \epsilon \\ &= \hat{y} + \nabla g(\hat{x}) \cdot \epsilon \end{split}$$

which, with writing  $\nabla \hat{g} = \nabla g(\hat{x})$  yields

$$\Delta y \approx \nabla \hat{q} \cdot \epsilon$$

and since  $g: \mathbb{R}^n \to \mathbb{R}^m$  where  $m \leq n$ ,  $\nabla g$  is not necessarily invertible, but we can use the Moore-Penrose pseudoinverse here to get a guess for  $\epsilon$ :

$$\epsilon \approx (\nabla \hat{g})^+ \cdot \Delta y \equiv \hat{\epsilon}$$

To tie the experimental measurements to the model measurements we require

$$\hat{y} = g(\bar{x} + \Delta x)$$
$$\approx \bar{y} + \nabla g(\bar{x}) \cdot \Delta x$$

which yields the condition

$$\nabla g(\bar{x}) \cdot \Delta x = -\Delta y \tag{1}$$

where

$$\begin{split} \nabla g(\bar{x})_i^j &= \nabla g(\hat{x} + \epsilon)_i^j \\ &\approx \nabla g(\hat{x} + \hat{\epsilon})_i^j \\ &= \nabla g(\hat{x})_i^j + \sum_k \left(\nabla^2 g(\hat{x})\right)_i^{jk} \, \hat{\epsilon}_k \\ &= \nabla \hat{g}_i^j + \sum_{kl} \left(\nabla^2 \hat{g}\right)_i^{jk} \, \left((\nabla \hat{g})^+\right)_k^l \Delta y_l \end{split}$$

#### **State Correction to Control Correction**

To propagate the state correction to the control correction, we utilize the dynamics constraint,  $f(z_t, z_{t+1}) = 0$ , where we define the *knot point* 

$$z_t = \begin{pmatrix} x_t \\ u_t \end{pmatrix}$$

Let's write  $\mathbf{z}_t = \begin{pmatrix} z_t \\ z_{t+1} \end{pmatrix}$ . Then we have

$$0 = f(\hat{\mathbf{z}}_t + \Delta \mathbf{z}_t)$$
  
 
$$\approx f(\hat{\mathbf{z}}_t) + \nabla f(\hat{\mathbf{z}}_t) \cdot \Delta \mathbf{z}_t$$

which yields

$$\nabla f(\hat{\mathbf{z}}_t) \cdot \Delta \mathbf{z}_t = 0$$

### Putting it all together

We seek to find the solution to

where the  $\tau$ s are the measurement times.

Building the KKT matrix from this problem, we can solve the system and extract  $\Delta u(t)$  and repeat the procedure until convergence.

This problem, which returns  $\Delta Z$  is referred to as

$$\Delta Z = \mathsf{QuadraticProblem}(\hat{Z}, \Delta Y)$$

#### KKT Matrix (for just single quantum state and controls)

Below we use:

- $n = \dim z_t = \dim x_t + \dim u_t$
- $d = \dim x_t = \dim f(z_t, z_{t+1})$
- $c = \dim u_t$
- $m = \dim y_t$
- M = # of measurements

For a trajectory  $Z = \text{vec}(z_{1:T})$ , we need to construct the matrix

$$\begin{pmatrix} H & A^{\top} \\ A & 0 \end{pmatrix}$$

where H is the Hessian of the cost function:

$$H = \bigoplus_{t=1}^{T} (Q \oplus R) = I^{T \times T} \otimes (Q \oplus R)$$

and A is the constraint Jacobian:

$$A = \begin{pmatrix} \nabla F \\ \nabla G \end{pmatrix}$$

with

$$\nabla F = \begin{pmatrix} \nabla f(\hat{\mathbf{z}}_1) & & \\ & \ddots & \\ & & \nabla f(\hat{\mathbf{z}}_{T-1}) \end{pmatrix} \in \mathbb{R}^{d(T-1) \times nT}$$

and

$$\nabla G = \begin{pmatrix} \ddots & & \\ & \nabla g(\bar{x}_{\tau}) \ \mathbf{0}^{m \times (a+c)} & \\ & & \ddots \end{pmatrix} \in \mathbb{R}^{mM \times nT}$$

where  $\tau = t_1, \ldots, t_M$  are the measurement times.

For the constraints we then have

$$\nabla F \cdot \Delta Z = 0$$
 and  $\nabla G \cdot \Delta Z = -\Delta Y$ 

where again

$$\Delta Y = \bar{Y} - \hat{Y}$$

# ILC Algorithm

## Algorithm 1: Iterative Control Learning

```
Data: \hat{Z}^{\text{goal}}, tol > 0, max_iter \gg 0
Result: U
\begin{array}{l} Y^{\mathrm{goal}} \leftarrow \mathsf{measure}(\hat{Z}^{\mathrm{goal}}) = \mathrm{vec}(y_{\tau_1:\tau_M}) \\ \hat{Z} \leftarrow \hat{Z}^{\mathrm{goal}} \end{array}
U \leftarrow \mathsf{controls}(\hat{Z}) = \mathsf{vec}(u_{1:T})
\bar{Y} \leftarrow \mathsf{experiment}(U) = \mathrm{vec}(\bar{y}_{\tau_1:\tau_M})
\Delta Y \leftarrow \dot{\bar{Y}} - Y^{\text{goal}}
k \leftarrow 1
while |\Delta Y| > \textit{tol } \mathbf{do}
        if k > max\_iter then
         break
        \quad \text{end} \quad
        \Delta Z \leftarrow \mathsf{QuadraticProblem}(\hat{Z}, \Delta Y)
       \hat{Z} \leftarrow \hat{Z} + \Delta Z
       U \leftarrow \mathsf{controls}(\hat{Z})
       ar{Y} \leftarrow \operatorname{experiment}(U) \Delta Y \leftarrow ar{Y} - Y^{\operatorname{goal}}
       k \leftarrow k+1
\mathbf{end}
{\bf return}\ U
```