Iterative Learning Control for Precise Aircraft Trajectory Tracking in Continuous Climb Operations

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Overview

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Aircraft dynamics

ILC for trajectory tracking

Experimental setup

Results

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SESAR operational ATM concept

- Trajectory based operations:
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SESAR operational ATM concept

- Trajectory based operations: optimized trajectories based on the preferences of the airlines.
**Introduction**

**SESAR operational ATM concept**

- Trajectory based operations: optimized trajectories based on the preferences of the airlines.
- 4D trajectories:
Introduction

SESAR operational ATM concept

- Trajectory based operations: optimized trajectories based on the preferences of the airlines.
- 4D trajectories: delays must be regarded as a deviation from the planned trajectory as much as a spatial deviation.
Introduction

SESAR operational ATM concept

- Trajectory based operations: optimized trajectories based on the preferences of the airlines.
- 4D trajectories: delays must be regarded as a deviation from the planned trajectory as much as a spatial deviation.

Precision in tracking the planned trajectories is needed.
... but deviations may occur.
... but deviations may occur.

Wind

Storms

Desired trajectory

Actual trajectory

Spatial deviations

Temporal deviations
Introduction

Causes of deviations
Introduction

Causes of deviations

- Modeling errors.
Introduction

Causes of deviations

- Modeling errors.
- Weather conditions (wind and storms).
Introduction

Causes of deviations

▷ Modeling errors.
▷ Weather conditions (wind and storms).

Aircraft trajectory tracking controllers
Introduction

Causes of deviations

- Modeling errors.
- Weather conditions (wind and storms).

Aircraft trajectory tracking controllers

- Cannot predict deviations accurately.
Introduction

Causes of deviations

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Aircraft trajectory tracking controllers

- Cannot predict deviations accurately.
- Compensate for disturbances only after they occur.
Introduction

Causes of deviations

- Modeling errors.
- Weather conditions (wind and storms).

Aircraft trajectory tracking controllers

- Cannot predict deviations accurately.
- Compensate for disturbances only after they occur.

Predictability is of special importance in the TMA.
Introduction

Objective


title

Objective

Precise aircraft trajectory tracking using Iterative Learning Control (ILC):
**Objective**

Precise aircraft trajectory tracking using Iterative Learning Control (ILC):

- Estimate deviations from previous flights.
Introduction

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Precise aircraft trajectory tracking using Iterative Learning Control (ILC):

- Estimate deviations from previous flights.
- Update the reference trajectory to compensate for repetitive disturbances.
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Limitations
In each iteration:
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Objective
Precise aircraft trajectory tracking using Iterative Learning Control (ILC):

- Estimate deviations from previous flights.

- Update the reference trajectory to compensate for repetitive disturbances.

Limitations
In each iteration:

- Same dynamical system (aircraft).
Introduction

Objective
Precise aircraft trajectory tracking using Iterative Learning Control (ILC):

- Estimate deviations from previous flights.
- Update the reference trajectory to compensate for repetitive disturbances.

Limitations
In each iteration:
- Same dynamical system (aircraft).
- Same trajectory.
Information from previous aircraft is needed.
Introduction

Information from previous aircraft is needed.

System-Wide Information Management (SWIM)
Introduction

Information from previous aircraft is needed.

**System-Wide Information Management (SWIM)**

Collaborative ATM processes with exchange of data:
Introduction

Information from previous aircraft is needed.

System-Wide Information Management (SWIM)
Collaborative ATM processes with exchange of data:

- Intended trajectory.
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Information from previous aircraft is needed.

System-Wide Information Management (SWIM)

Collaborative ATM processes with exchange of data:

- Intended trajectory.
- Actually flown trajectory in 4D.
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Information from previous aircraft is needed.

System-Wide Information Management (SWIM)

Collaborative ATM processes with exchange of data:

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- Weather data.
Introduction

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3-DOF model

- Non-rotating flat Earth model.
Aircraft dynamics

3-DOF model

- Non-rotating flat Earth model.
- Symmetric flight.
Aircraft dynamics

3-DOF model

- Non-rotating flat Earth model.
- Symmetric flight.

(j) Top view  (k) Front view  (l) Lateral view
Aircraft dynamics

Longitudinal dynamics
Aircraft dynamics

Longitudinal dynamics

- Constant course and heading angle.
Aircraft dynamics

Longitudinal dynamics

- Constant course and heading angle.
- Leveled wing flight.
Aircraft dynamics

Longitudinal dynamics

- Constant course and heading angle.
- Leveled wing flight.

\[
\dot{V}(t) = \frac{T(t) - D(h_e(t), V(t), C_L(t)) - m(t) \cdot g \cdot \sin \gamma(t)}{m(t)}
\]

\[
\dot{\gamma}(t) = \frac{L(h_e(t), V(t), C_L(t)) - m(t) \cdot g \cdot \cos \gamma(t)}{m(t) \cdot V(t)}
\]

\[
\dot{x}_e(t) = V(t) \cdot \cos \gamma(t)
\]

\[
\dot{h}_e(t) = V(t) \cdot \sin \gamma(t)
\]

\[
\dot{m}(t) = -T(t) \cdot \eta(V(t)).
\]
Aircraft dynamics

Flight envelope and constraints
Aircraft dynamics

Flight envelope and constraints
Performance limitations and parameters obtained from BADA.
Flight envelope and constraints

Performance limitations and parameters obtained from BADA.

\[0 \leq h_e(t) \leq \min[h_{M0}, h_u(t)],\]
\[M(t) \leq M_{M0},\]
\[\dot{V}(t) \leq \bar{a}_l,\]
\[\dot{\gamma}(t)V(t) \leq \bar{a}_n,\]
\[T_{\text{min}}(t) \leq T(t) \leq T_{\text{max}}(t).\]
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Improved performance of a control system
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times by learning from previous executions.
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times by learning from previous executions.

Applications:
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times by learning from previous executions.

Applications:

- robotics,
Iterative Learning Control

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Applications:

- robotics,
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Iterative Learning Control

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Applications:
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Optimization-based ILC method
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times by learning from previous executions.

Applications:

- robotics,
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Optimization-based ILC method

The ILC problem is solved in two steps:
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times by learning from previous executions.

Applications:
- robotics,
- aerial robots.

Optimization-based ILC method

The ILC problem is solved in two steps:
- disturbance estimation, and
Iterative Learning Control

Improved performance of a control system that executes the same task multiple times by learning from previous executions.

Applications:
- robotics,
- aerial robots.

Optimization-based ILC method
The ILC problem is solved in two steps:
- disturbance estimation, and
- control input update.
Iterative Learning Control

input → Dynamical system → output
deviation
→ Estimation

updated input
→ Control
Iterative Learning Control

Starting point
Iterative Learning Control

**Starting point**

Time-varying nonlinear model of a real dynamic system
Iterative Learning Control

**Starting point**

Time-varying nonlinear model of a real dynamic system

\[
\begin{align*}
\dot{x}(t) &= f(x(t), u(t), t) \\
y(t) &= g(x(t), u(t), t)
\end{align*}
\]

\[\iff\]

Aircraft dynamics
Iterative Learning Control

Starting point

Time-varying nonlinear model of a real dynamic system

\[
\begin{align*}
\dot{x}(t) &= f(x(t), u(t), t) \\
y(t) &= g(x(t), u(t), t)
\end{align*}
\]

and constraints

Aircraft dynamics
Starting point

Time-varying nonlinear model of a real dynamic system

\[ \dot{x}(t) = f(x(t), u(t), t) \]
\[ y(t) = g(x(t), u(t), t) \]

and constraints

\[ Z \ q(t) \leq q_{max}, \]
Iterative Learning Control

Starting point

Time-varying nonlinear model of a real dynamic system

\[
\dot{x}(t) = f(x(t), u(t), t) \quad \iff \quad \text{Aircraft dynamics}
\]

\[
y(t) = g(x(t), u(t), t)
\]

and constraints

\[
Z \ q(t) \leq q_{\text{max}}, \quad \iff \quad \text{Flight envelope}
\]

where

\[
q(t) = \left[ x(t), u(t), \dot{x}(t), \ddot{u}(t), \ldots, \frac{d^m}{dt^m}x(t), \frac{d^m}{dt^m}u(t) \right].
\]
Iterative Learning Control

Linearization and discretization
Iterative Learning Control

Linearization and discretization

Deviations from the desired trajectory \((x^*(t), u^*(t), y^*(t))\):
Iterative Learning Control

Linearization and discretization

Deviations from the desired trajectory \((x^*(t), u^*(t), y^*(t))\):

\[
\tilde{x}(t) = x(t) - x^*(t),
\]
Iterative Learning Control

Linearization and discretization
Deviations from the desired trajectory \((x^*(t), u^*(t), y^*(t))\):

\[
\tilde{x}(t) = x(t) - x^*(t), \quad \tilde{u}(t) = u(t) - u^*(t),
\]
Iterative Learning Control

Linearization and discretization

Deviations from the desired trajectory \((x^*(t), u^*(t), y^*(t))\):

\[
\tilde{x}(t) = x(t) - x^*(t), \quad \tilde{u}(t) = u(t) - u^*(t), \quad \tilde{y}(t) = y(t) - y^*(t).
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Iterative Learning Control

Linearization and discretization

Deviations from the desired trajectory \((x^*(t), u^*(t), y^*(t))\):

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\tilde{x}(t) = x(t) - x^*(t), \quad \tilde{u}(t) = u(t) - u^*(t), \quad \tilde{y}(t) = y(t) - y^*(t).
\]

Linear discrete time-varying system:
Iterative Learning Control

Linearization and discretization

Deviations from the desired trajectory \((\mathbf{x}^*(t), \mathbf{u}^*(t), \mathbf{y}^*(t))\):

\[
\tilde{\mathbf{x}}(t) = \mathbf{x}(t) - \mathbf{x}^*(t), \quad \tilde{\mathbf{u}}(t) = \mathbf{u}(t) - \mathbf{u}^*(t), \quad \tilde{\mathbf{y}}(t) = \mathbf{y}(t) - \mathbf{y}^*(t).
\]

Linear discrete time-varying system:

\[
\begin{align*}
\mathbf{x}(k+1) &= A_D(k)\tilde{\mathbf{x}}(k) + B_D(k)\tilde{\mathbf{u}}(k) \\
\tilde{\mathbf{y}}(k) &= C_D(k)\tilde{\mathbf{x}}(k) + D_D(k)\tilde{\mathbf{u}}(k),
\end{align*}
\]
Iterative Learning Control

Linearization and discretization

Deviations from the desired trajectory \((x^*(t), u^*(t), y^*(t))\):

\[
\tilde{x}(t) = x(t) - x^*(t), \quad \tilde{u}(t) = u(t) - u^*(t), \quad \tilde{y}(t) = y(t) - y^*(t).
\]

Linear discrete time-varying system:

\[
\begin{align*}
\tilde{x}(k+1) &= A_D(k)\tilde{x}(k) + B_D(k)\tilde{u}(k) \\
\tilde{y}(k) &= C_D(k)\tilde{x}(k) + D_D(k)\tilde{u}(k),
\end{align*}
\]

\[
Z\tilde{q}(k) \preceq q_{\text{max}}(k).
\]
Iterative Learning Control

Lifted system representation
Iterative Learning Control

**Lifted system representation**

Map of the input time series $\tilde{u}(k)$
Iterative Learning Control

**Lifted system representation**

Map of the input time series $\tilde{u}(k)$ into the output time series $\tilde{y}(k)$. 
Iterative Learning Control

**Lifted system representation**

Map of the input time series $\tilde{u}(k)$ into the output time series $\tilde{y}(k)$. Deviations from the desired trajectory:

$$u = [\tilde{u}(0), \tilde{u}(1), \ldots, \tilde{u}(N - 1)]^T \in \mathbb{R}^{Nn_u}$$
Iterative Learning Control

**Lifted system representation**

Map of the input time series $\tilde{u}(k)$ into the output time series $\tilde{y}(k)$. Deviations from the desired trajectory:

\[
    u = [\tilde{u}(0), \tilde{u}(1), \ldots, \tilde{u}(N - 1)]^T \in \mathbb{R}^{Nn_u}
\]

\[
    x = [\tilde{x}(1), \tilde{x}(2), \ldots, \tilde{x}(N)]^T \in \mathbb{R}^{Nn_x}
\]
Iterative Learning Control

Lifted system representation

Map of the input time series $\tilde{u}(k)$ into the output time series $\tilde{y}(k)$. Deviations from the desired trajectory:

\[
\begin{align*}
    u &= [\tilde{u}(0), \tilde{u}(1), \ldots, \tilde{u}(N-1)]^T \in \mathbb{R}^{Nn_u} \\
    x &= [\tilde{x}(1), \tilde{x}(2), \ldots, \tilde{x}(N)]^T \in \mathbb{R}^{Nn_x} \\
    y &= [\tilde{y}(1), \tilde{y}(2), \ldots, \tilde{y}(N)]^T \in \mathbb{R}^{Nn_y}.
\end{align*}
\]
Iterative Learning Control

**Lifted system representation**

Map of the input time series \( \tilde{u}(k) \) into the output time series \( \tilde{y}(k) \).

Deviations from the desired trajectory:

\[
\begin{align*}
    u &= [\tilde{u}(0), \tilde{u}(1), \ldots, \tilde{u}(N - 1)]^T \in \mathbb{R}^{Nn_u} \\
    x &= [\tilde{x}(1), \tilde{x}(2), \ldots, \tilde{x}(N)]^T \in \mathbb{R}^{Nn_x} \\
    y &= [\tilde{y}(1), \tilde{y}(2), \ldots, \tilde{y}(N)]^T \in \mathbb{R}^{Nn_y}.
\end{align*}
\]

Lifted linear system:
Iterative Learning Control

Lifted system representation
Map of the input time series $\tilde{u}(k)$ into the output time series $\tilde{y}(k)$. Deviations from the desired trajectory:

$$u = [\tilde{u}(0), \tilde{u}(1), \ldots, \tilde{u}(N - 1)]^T \in \mathbb{R}^{Nn_u}$$

$$x = [\tilde{x}(1), \tilde{x}(2), \ldots, \tilde{x}(N)]^T \in \mathbb{R}^{Nn_x}$$

$$y = [\tilde{y}(1), \tilde{y}(2), \ldots, \tilde{y}(N)]^T \in \mathbb{R}^{Nn_y}.$$ 

Lifted linear system:

$$x = Fu + d^0$$
Iterative Learning Control

Lifted system representation

Map of the input time series $\tilde{u}(k)$ into the output time series $\tilde{y}(k)$. Deviations from the desired trajectory:

$$
\begin{align*}
    u &= [\tilde{u}(0), \tilde{u}(1), \ldots, \tilde{u}(N-1)]^T 
    &\in \mathbb{R}^{Nn_u} \\
    x &= [\tilde{x}(1), \tilde{x}(2), \ldots, \tilde{x}(N)]^T 
    &\in \mathbb{R}^{Nn_x} \\
    y &= [\tilde{y}(1), \tilde{y}(2), \ldots, \tilde{y}(N)]^T 
    &\in \mathbb{R}^{Nn_y}.
\end{align*}
$$

Lifted linear system:

$$
\begin{align*}
    x &= Fu + d^0 \\
    y &= Gx + Hu.
\end{align*}
$$
Iterative Learning Control

Noise
Iterative Learning Control

**Noise**

Process disturbance, initial condition and measurement noise:
Iterative Learning Control

Noise

Process disturbance, initial condition and measurement noise:

\[ x_j = Fu_j + d_j + N_\xi \xi_j \]
Iterative Learning Control

Noise
Process disturbance, initial condition and measurement noise:

\[ x_j = Fu_j + d_j + N_\xi \xi_j \]
\[ y_j = Gx_j + Hu_j + N_\eta \eta_j, \]
Iterative Learning Control

Noise

Process disturbance, initial condition and measurement noise:

\[ x_j = Fu_j + d_j + N_\xi \xi_j \]
\[ y_j = Gx_j + Hu_j + N_\eta \eta_j, \]

where \( d_j \) represents the repetitive disturbance along the reference trajectory.
Iterative Learning Control

**Noise**

Process disturbance, initial condition and measurement noise:

\[
    x_j = F u_j + d_j + N_\xi \xi_j \\
    y_j = G x_j + H u_j + N_\eta \eta_j,
\]

where \(d_j\) represents the repetitive disturbance along the reference trajectory.

**Optimal estimator**
Iterative Learning Control

Noise
Process disturbance, initial condition and measurement noise:

\[
x_j = F u_j + d_j + N \xi_j
\]
\[
y_j = G x_j + H u_j + N \eta j,
\]

where \( d_j \) represents the repetitive disturbance along the reference trajectory.

Optimal estimator
\( \hat{d}_j \) estimate using Kalman filter in the system:
Iterative Learning Control

Noise
Process disturbance, initial condition and measurement noise:

\[ x_j = Fu_j + d_j + N_\xi \xi_j \]
\[ y_j = Gx_j + Hu_j + N_\eta \eta_j, \]

where \( d_j \) represents the repetitive disturbance along the reference trajectory.

Optimal estimator
\( \hat{d}_j \) estimate using Kalman filter in the system:

\[ d_j = d_{j-1} + \omega_{j-1} \]
\[ y_j = Gd_j + (GF + H)u_j + \mu_j. \]
Iterative Learning Control

Input update
Iterative Learning Control

Input update

Optimization problem
Iterative Learning Control

Input update

Optimization problem to minimize the deviation from the desired trajectory:
Iterative Learning Control

**Input update**

Optimization problem to minimize the deviation from the desired trajectory:

\[
\min_{u_{j+1}} \quad \| Fu_{j+1} + \hat{d}_j \|_\ell + \alpha \| Du_{j+1} \|_\ell
\]

subject to

\[
Lu_{j+1} \leq q_{\text{max}},
\]
Iterative Learning Control

**Input update**

Optimization problem to minimize the deviation from the desired trajectory:

\[
\min_{u_{j+1}} \| Fu_{j+1} + \hat{d}_j \|_\ell + \alpha \| Du_{j+1} \|_\ell
\]

subject to

\[ Lu_{j+1} \leq q_{\max} , \]

**New reference trajectory**
Iterative Learning Control

Input update

Optimization problem to minimize the deviation from the desired trajectory:

$$\min_{u_{j+1}} \quad \| Fu_{j+1} + \hat{d}_j \|_\ell + \alpha \| Du_{j+1} \|_\ell$$

subject to

$$Lu_{j+1} \leq q_{max},$$

New reference trajectory

The updated input is fed into the model
Iterative Learning Control

**Input update**

Optimization problem to minimize the deviation from the desired trajectory:

$$\min_{u_{j+1}} \quad \| F u_{j+1} + d_j \|_\ell + \alpha \| D u_{j+1} \|_\ell$$

subject to

$$L u_{j+1} \leq q_{max},$$

**New reference trajectory**

The updated input is fed into the model to generate a new reference trajectory.
Iterative Learning Control

**Input update**

Optimization problem to minimize the deviation from the desired trajectory:

\[
\min_{u_{j+1}} \| Fu_{j+1} + \hat{d}_j \|_\ell + \alpha \| Du_{j+1} \|_\ell \\
\text{subject to} \quad Lu_{j+1} \leq q_{\text{max}},
\]

**New reference trajectory**

The updated input is fed into the model to generate a new reference trajectory → non intrusive with respect to the trajectory tracking controller.
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Trajectory planning

- Desired trajectory: Continuous Climb Operation.
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Trajectory planning

- Desired trajectory: Continuous Climb Operation.

Simulated environment
Experimental setup

Trajectory planning

- Desired trajectory: Continuous Climb Operation.

Simulated environment

- Realistic flight simulator,
Experimental setup

Trajectory planning

- Desired trajectory: Continuous Climb Operation.

Simulated environment

- Realistic flight simulator,
- estimator of the disturbances,
Experimental setup

Trajectory planning

- Desired trajectory: Continuous Climb Operation.

Simulated environment

- Realistic flight simulator,
- estimator of the disturbances,
- ILC controller.
Experimental setup

Continuous Climb Operations (CCO)
Experimental setup

Continuous Climb Operations (CCO)

Vertical flight profile
Experimental setup

Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:
Experimental setup

Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:
  - fuel efficient operations,
Experimental setup

Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:

- fuel efficient operations,
- less ATC intervention,
Experimental setup

Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:

- fuel efficient operations,
- less ATC intervention,
- noise mitigation.
Experimental setup

Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:

➢ fuel efficient operations,
➢ less ATC intervention,
➢ noise mitigation.

Precise trajectory tracking:
Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:

- fuel efficient operations,
- less ATC intervention,
- noise mitigation.

Precise trajectory tracking:

- avoid potential conflict between traffic flows,
Continuous Climb Operations (CCO)

Vertical flight profile optimized to the performance of the aircraft:

- fuel efficient operations,
- less ATC intervention,
- noise mitigation.

Precise trajectory tracking:

- avoid potential conflict between traffic flows,
- ensure that safety and capacity are not compromised.
Experimental setup

CCO associated with SID procedure
Experimental setup

CCO associated with SID procedure

Realistic flight
Experimental setup

CCO associated with SID procedure
Realistic flight from Adolfo Suárez Madrid-Barajas (LEMD) airport.
Experimental setup

**CCO associated with SID procedure**

Realistic flight from Adolfo Suárez Madrid-Barajas (LEMD) airport. SID procedure PINAR1U:

- Airspace constraints $\rightarrow$ waypoints,
Experimental setup

CCO associated with SID procedure
Realistic flight from Adolfo Suárez Madrid-Barajas (LEMD) airport.
SID procedure PINAR1U:

- Airspace constraints $\rightarrow$ waypoints,
- from 1000 m after takeoff to 10000 m (cruise level),
CCO associated with SID procedure

Realistic flight from Adolfo Suárez Madrid-Barajas (LEMD) airport. SID procedure PINAR1U:

- Airspace constraints → waypoints,
- from 1000 m after takeoff to 10000 m (cruise level),
- standard initial velocity and path angle values.
Experimental setup
Experimental setup

Trajectory generation
Experimental setup

Trajectory generation

DIDO has been used to generate a feasible trajectory:
Experimental setup

Trajectory generation

DIDO has been used to generate a feasible trajectory:

- MATLAB application developed by Elissar Global.
Experimental setup

Trajectory generation

DIDO has been used to generate a feasible trajectory:

- MATLAB application developed by Elissar Global.
- Optimal control pseudospectral method.
Experimental setup

Trajectory generation

DIDO has been used to generate a feasible trajectory:

- MATLAB application developed by Elissar Global.
- Optimal control pseudospectral method.
- Trajectory and control, Hamiltonian, costates, path covectors, and endpoint covectors.
Experimental setup

Trajectory generation

DIDO has been used to generate a feasible trajectory:

- MATLAB application developed by Elissar Global.
- Optimal control pseudospectral method.
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Inputs:
Experimental setup

Trajectory generation

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- MATLAB application developed by Elissar Global.
- Optimal control pseudospectral method.
- Trajectory and control, Hamiltonian, costates, path covectors, and endpoint covectors.

Inputs:

- system dynamics,
Experimental setup

**Trajectory generation**

DIDO has been used to generate a feasible trajectory:

- MATLAB application developed by Elissar Global.
- Optimal control pseudospectral method.
- Trajectory and control, Hamiltonian, costates, path covectors, and endpoint covectors.

**Inputs:**

- system dynamics,
- constraints,
Experimental setup

Trajectory generation

DIDO has been used to generate a feasible trajectory:

- MATLAB application developed by Elissar Global.
- Optimal control pseudospectral method.
- Trajectory and control, Hamiltonian, costates, path covectors, and endpoint covectors.

Inputs:

- system dynamics,
- constraints,
- cost function.
Experimental setup

Algorithm of the method
Experimental setup

Algorithm of the method

- Initialization:
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory,
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters,
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.
- \( j \)-th iteration:
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.
- $j$-th iteration: most recent input
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.
- $j$-th iteration: most recent input $\rightarrow$ flight simulator $\rightarrow$
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.

- $j$-th iteration: most recent input $\rightarrow$ flight simulator $\rightarrow$ tracking error estimation.
Experimental setup

Algorithm of the method

- **Initialization**: load desired trajectory, model and learning parameters, and compute Kalman gains.

- **$j$-th iteration**: most recent input $\rightarrow$ flight simulator $\rightarrow$ tracking error estimation.

- **$j + 1$-th iteration**:
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.

- \( j \)-th iteration: most recent input \( \rightarrow \) flight simulator \( \rightarrow \) tracking error estimation.

- \( j + 1 \)-th iteration: input update
Experimental setup

Algorithm of the method

- Initialization: load desired trajectory, model and learning parameters, and compute Kalman gains.
- \( j \)-th iteration: most recent input \( \rightarrow \) flight simulator \( \rightarrow \) tracking error estimation.
- \( j + 1 \)-th iteration: input update \( \rightarrow \) new reference trajectory.
Experimental setup

1. Linearization and lifted representation
2. Desired trajectory generation
3. System dynamics
4. Aircraft model
5. Weather forecast
6. Aircraft simulator
7. Disturbance estimation
8. Kalman gains calculation
9. Input update
10. Perturbations

Flowchart: A diagram illustrating the experimental setup process, linking each step with arrows to show the flow of information and processes.
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Evolution of the path $x_e - h_e$ over iterations
Evolution of the path $x_e - h_e$ over iterations
Results

Evolution of the path $x_e - h_e$ over iterations

![Graph showing the evolution of the path $x_e - h_e$ over iterations.](image-url)
Results

Evolution of the path $x_e - h_e$ over iterations

![Graph showing the evolution of $x_e - h_e$ over iterations.](image)
Results

Evolution of the path $x_e - h_e$ over iterations
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Evolution of the lift coefficient over iterations
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Evolution of the lift coefficient over iterations
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Evolution of the lift coefficient over iterations
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Results

Weighted state error

Trajectory and input vary
Results

Weighted state error

Trajectory and input vary due to non-repetitive disturbances.
Results

Weighted state error

Trajectory and input vary due to non-repetitive disturbances.

Weighted state error:
Results

Weighted state error

Trajectory and input vary due to non-repetitive disturbances.

Weighted state error:

\[ e_{w,j} = \| S y_j \|_2, \]
Results

Weighted state error

Trajectory and input vary due to non-repetitive disturbances. Weighted state error:

\[ e_{w,j} = \| S y_j \|_2, \]
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New reference trajectory
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New reference trajectory which compensates for repetitive disturbances
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New reference trajectory which compensates for repetitive disturbances

![Graph showing desired and reference trajectories]
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- Optimality in disturbance estimation and input update.
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Future work
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Future work

- Flights not restricted to vertical plane (4D).
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Future work

- Flights not restricted to vertical plane (4D).
- Other flight procedures (CDA, cruise, ...).
Conclusions

Conclusions

- High precision is achieved in few iterations.
- Optimality in disturbance estimation and input update.
- Non-intrusive with current aircraft controller.

Future work

- Flights not restricted to vertical plane (4D).
- Other flight procedures (CDA, cruise, ...).
- Knowledge transfer.
Thank you for your attention.