IDENTIFICATION IN CLOSED LOOP
A powerful design tool
(better models, simpler controllers)

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Outline

- Introduction
- An example (flexible transmission)
- Objectives of identification in closed loop
- Basic Schemes
- The CLOE Algorithms (closed loop output error)
- Properties of the algorithms
- Properties of the estimated models
- Validation of models identified in closed loop
- Iterative identification in c. l. and controller re-design
- Experimental results (flexible transmission)
- Filtered open loop identification algorithms
- Conclusions

I.D. Landau: Identification in closed loop/A powerful design tool
1) Identification of the dynamic model
2) Performance and robustness specifications
3) Compatible controller design method
4) Controller implementation
5) Real-time controller validation
   (and on site re-tuning)
6) Controller maintenance (same as 5)

(5) and (6) require identification in closed-loop
Comparison of « achieved » and « desired » performances

A useful interpretation:

Check to what extent the model used for design allows achievement of:
- desired nominal performances
- desired robustness specs. (sensitivity functions)
Real-Time Controller Validation

If the results are not satisfactory:

Plant model identification in *closed loop*  
+  
Controller redesign
There are systems where open loop operation is not suitable (instability, drift, ..)

A controller may already exist (ex. : PID)

Re-tuning of the controller

a) to improve achieved performances
b) controller maintenance

Iterative identification and controller redesign

*May provide better « design » models*

*Cannot be dissociated from the controller and robustness issues*
Identification in Closed Loop

The flexible transmission

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What is the *good* model?

- « open loop identified » model
- « closed loop identified » model

```
fs = 20Hz 0% load
```

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The pattern of *identified closed loop poles* is different from the pattern of *computed closed loop poles*.
Benefits of identification in closed loop (2)

The **computed** and the **identified** closed loop poles are very close
Identification in Closed Loop

Objective: development of algorithms which:
- take advantage of the “improved” input spectrum
- are insensitive to noise in closed loop operation
Objective of the Identification in Closed Loop

(identification for control)

Find the « plant model » which minimizes the discrepancy between the « real » closed loop system and the « simulated » closed loop system.
Identification in Closed Loop

- M.R.A.S. point of view:

- Identification point of view:
  A re-parametrized adjustable predictor of the closed loop
Closed Loop Output Error Identification Algorithms (CLOE)

Excitation added to reference signal

\[ u = -\frac{R}{S} y + \frac{T}{S} r \]
\[ \hat{u} = -\frac{R}{S} \hat{y} + \frac{T}{S} r \]

Excitation added to controller output

\[ u = -\frac{R}{S} y + r_u \]
\[ \hat{u} = -\frac{R}{S} \hat{y} + r_u \]
Notations

\[ G(q^{-1}) = \frac{q^{-d}B(q^{-1})}{A(q^{-1})} \]
\[ K(q^{-1}) = \frac{R(q^{-1})}{S(q^{-1})} \]

Sensitivity functions:
\[ S_{yp}(z^{-1}) = \frac{1}{1+KG} \; ; \; S_{up}(z^{-1}) = -\frac{K}{1+KG} \; ; \; S_{vy}(z^{-1}) = \frac{G}{1+KG} \; ; \; S_{yr}(z^{-1}) = \frac{KG}{1+KG} \]

Closed loop poles:
\[ P(z^{-1}) = A(z^{-1})S(z^{-1}) + z^{-d}B(z^{-1})R(z^{-1}) \]

True closed loop system: \((K,G), P, S_{xy}\)
Nominal simulated(estimated) closed loop: \((K, \hat{G}), \hat{P}, \hat{S}_{xy}\)
Closed Loop Output Error Identification Algorithms (CLOE)

Excitation added to reference signal

Excitation added to controller output

Same algorithm but different properties of the estimated model
Closed Loop Output Error Algorithms (CLOE)

The closed loop system:

\[
y(t + 1) = -A^*(q^{-1})y(t) + B^*(q^{-1})u(t - d) = \theta^T \psi(t)
\]

\[
\theta^T = [a_1, \ldots a_{n_A}, b_1, \ldots b_{n_B}]
\]

\[
\psi^T(t) = \left[ -y(t), \ldots -y(t - n_A + 1), u(t - d), \ldots u(t - d - n_B) \right]
\]

\[
u(t) = -\frac{R}{S} y(t) + r_u
\]
Adjustable predictor (closed loop)

\[ \hat{y}^o(t+1) = \hat{\theta}^T(t)\phi(t) \]
\[ \hat{y}(t+1) = \hat{\theta}^T(t+1)\phi(t) \]
\[ \hat{u}(t) = -\frac{R}{S} \hat{y}(t) + r_u \]
\[ \hat{\theta}^T(t) = [\hat{a}_1(t),...\hat{a}_{n_s}(t),\hat{b}_1(t),...\hat{b}_{n_s}(t)] \]
\[ \phi^T(t) = [-\hat{y}(t),..-\hat{y}(t-n_A+1),\hat{u}(t-d),..\hat{u}(t-d-n_B)] \]

The Parameter Adaptation Algorithm

\[ \epsilon_{CL}^0(t+1) = y(t+1) - \hat{\theta}^T(t)\phi(t) = y(t+1) - \hat{y}^0(t+1) \]
\[ \hat{\theta}(t+1) = \hat{\theta}(t) + F(t+1)\Phi(t)\epsilon_{CL}^0(t+1) \]
\[ F^{-1}(t+1) = \lambda_1(t)F^{-1}(t) + \lambda_2(t)\Phi(t)\Phi^T(t) ; 0 < \lambda_1(t) \leq 1 ; 0 \leq \lambda_2(t) < 2 \]
\[ \Phi(t) = \phi(t) \]
### CLOE Algorithms

- **CLOE** \( \Phi(t) = \phi(t) \)

- **F-CLOE** \( \Phi(t) = \frac{S(q^{-1})}{\hat{P}(q^{-1})} \phi(t); \hat{P} = \hat{A}(q^{-1})S(q^{-1}) + q^{-d}\hat{B}(q^{-1})R(q^{-1}) \)

- **AF-CLOE** \( \Phi(t) = \frac{S(q^{-1})}{\hat{P}(q^{-1}, t)} \phi(t); \hat{P}(q^{-1}, t) = \hat{A}(q^{-1}, t)S + q^{-d}\hat{B}(q^{-1}, t)R \)
CLOE Properties

Case 1: The plant model is in the model set
(i.e. the estimated model has the good order)

Asymptotic unbiased estimates in the presence of noise
subject to a (mild) sufficient passivity condition

\[
\begin{align*}
CLOE & : \frac{S}{P - \lambda/2} \quad \text{Strictly positive real tr. fct.} \\
F-CLOE & : \hat{P} / P - \lambda/2 \quad \max_i \lambda_2(t) \leq \lambda < 2 \\
AF-CLOE & : \text{none}
\end{align*}
\]

Case 2: The plant model is not in the model set
(ex.: the estimated model has a lower order)

See the next slides
Properties of the Estimated Model (1)

Excitation added to controller output

\[ \hat{\Theta}^* = \arg \min_{\theta} \int_{-\pi}^{\pi} \left[ |S_{yv} - \hat{S}_{yv}|^2 \phi_r(\omega) + |S_{yp}|^2 \phi_p(\omega) \right] d\omega \]

\[ = \arg \min_{\theta} \int_{-\pi}^{\pi} |S_{yp}|^2 \left[ |G - \hat{G}|^2 |\hat{S}_{yp}|^2 \phi_r(\omega) + \phi_p(\omega) \right] d\omega \]

- \( \hat{G} \) will minimize the 2 norm between the true sensitivity function and the sensitivity function of the closed loop estimator when \( r(t) \) is a white noise (PRBS)

- Plant-model error heavily weighted by the sensitivity functions

- The noise does not affect the asymptotic estimation
Properties of the Estimated Model (2)

Excitation added to reference signal

\[ \hat{\theta}^* = \arg \min_{\theta} \int_{-\pi}^{\pi} \left[ S_{yp} - \hat{S}_{yp} \right] \phi_r (\omega) + \left| S_{yp} \right|^2 \phi_p (\omega) d\omega \]

\[ = \arg \min_{\theta} \int_{-\pi}^{\pi} \left| S_{yp} \right|^2 \left[ G - \hat{G} \right] \left| \hat{S}_{up} \right|^2 \phi_r (\omega) + \phi_p (\omega) d\omega \]

- \( \hat{G} \) will minimize the 2 norm between the true sensitivity function and the sensitivity function of the closed loop estimator when \( r(t) \) is a white noise (PRBS)

- Plant -model error heavily weighted by the sensitivity functions

- The noise does not affect the asymptotic estimation
- The quality of the identified model is enhanced in the critical frequency regions for control (compare with open loop id.)

\[
\text{CLOE} \quad \hat{\theta}^* = \arg \min_{\theta} \int_{-\pi}^{\pi} \left| S_{yp} \right|^2 \left| G - \hat{G} \right|^2 \left| \hat{S}_{yp} \right|^2 \phi_r(\omega) + \phi_p(\omega) \right]d\omega
\]

\[
\text{OLOE} \quad \hat{\theta}^* = \arg \min_{\theta} \int_{-\pi}^{\pi} \left| G - \hat{G} \right|^2 \phi_r(\omega) + \phi_p(\omega) \right]d\omega
\]

- Identification in closed loop can be used for **model reduction**. The approximation will be good in the critical frequency regions for control.
Identification in Closed Loop of ARMAX Models

Extended Closed Loop Output Error
Validation of Models Identified in Closed Loop

Controller dependent validation!

1) Statistical Model Validation
2) Pole Closeness Validation
3) Time Domain Validation
Identification in Closed Loop

Statistical Model Validation

Controller dependent validation!

\[ |RN(i)| \leq \frac{2.17}{\sqrt{N}} ; i \geq 1 \]

Normalized crosscorrelation number of data

\[ N = 256 \rightarrow |RN(i)| \leq 0.136 \]

Practical value: \[ |RN(i)| \leq 0.15 \]
Identification in Closed Loop

Pole Closeness Validation

Closeness tests of achieved and desired (computed) poles and/or sensitivity functions by identification of the closed loop

Rem:
- use of open loop identification algorithms
- same signals as those used for the identification of the plant model in closed loop operation

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Identification in Closed Loop

Time Domain Validation

Comparison of « achieved » and « simulated » performance in the time domain

- not enough accuracy in many cases
- difficult interpretation of the results in some cases

Rem:
Methodology of Plant Model Identification in Closed Loop
Iterative Identification in Closed Loop and Controller Re-Design

Step 1: Identification in Closed Loop
- Keep controller constant
- Identify a new model such that $\varepsilon_{CL}$

Step 2: Controller Re-Design
- Compute a new controller such that $\varepsilon_{CL}$
  Repeat 1, 2, 1, 2, 1, 2,…
Experimental Results

Identification in closed loop and controller re-design for a flexible transmission
The flexible transmission

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Flexible Transmission
Frequency Characteristics of the Identified Models

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Model Validation in Closed Loop

Poles Closeness Validation

Model identified in open loop

Model identified in closed loop

The model identified in closed loop provides « computed » poles closer to the « real » poles than the model identified open loop
Model Validation in Closed Loop

Time Domain Validation

O.L.B.C.

Model identified in open loop

Model identified in closed loop

The simulation using the model identified in C.L. is closer to the real response than the simulation using the O.L. identified model

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Controller Re-design Based on the Model Identified in Closed Loop

(on-site controller re-tuning)

Re-designed controller (CLBC)  Initial controller (OLBC)

The CLBC controller provides performance which is closer to the designed performance than that provided by the OLBC controller
Identification in Closed Loop
Filtered Open Loop (FOL) Identification Algorithms

I/O Data Filters: $\hat{S}_{yp}$ or $S / \hat{P}$ or...

- Biased estimates
- Require (theoretically) time varying filters
- FOL alg. can be seen as approximations of CLOE alg.
- Are used in standard indirect adaptive control
Concluding Remarks

- Methods are available for efficient identification in closed loop
- CLOE algorithms provide unbiased parameter estimates
- CLOE provides “control oriented “reduced order” models
  (precision enhanced in the critical frequency regions for control)
- The knowledge of the controller is necessary
- In many cases the models identified in closed loop allow to improve the closed loop performance
- For controller re-tuning, opening the loop is no more necessary
- Identification in closed loop can be used for “model reduction”
- By duality arguments one can use the algorithms for controller reduction
- **Successful use in practice**
- A MATLAB Toolbox is available (CLID)
- A stand alone software is available (WinPIM/Adaptech)

