

Fully Probabilistic Design and Preference Elicitation

M. Kárný and many others

who try to understand it :(

Introduction

FPD uses ideal model for expressing user's aims.

In comparison to LQG control it has plus (+) and minus (-):

+

- ▶ more general
- ▶ demands on the whole closed loop can be expressed

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- ▶ setting of the ideal is not easy

Formulation

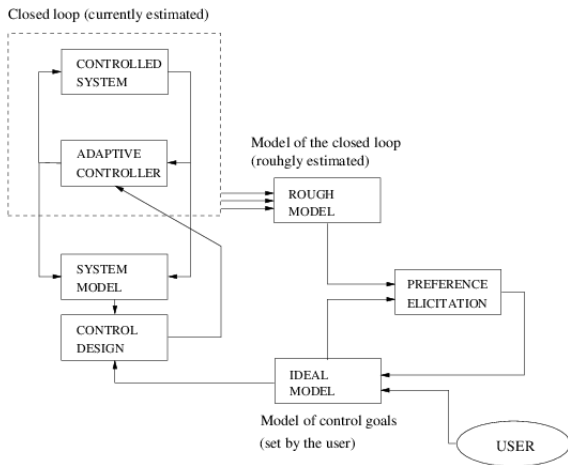
The task is to perform on-line setup of the ideal model, based on the currently evaluated behavior of the closed loop.

This behavior is described by a rough model. This model is roughly estimated from roughly measured data.

Rough = with larger period than basic period of sampling.

The block scheme of the situation follows: ↓

Scheme



Closed loop

At time t , the model of the closed loop is

$$f(d_t | \phi_{t-1})$$

where

$d_t = \{y_t, u_t\}$ is the current data item (y_t output, u_t input)

ϕ_{t-1} is a vector of old data items on which y_t depends

It can be factorized

$$f(d_t | \phi_{t-1}) = \underbrace{f(y_t | u_t, \phi_{t-1})}_{\text{system model}} \underbrace{f(u_t | \phi_{t-1})}_{\text{controller}}$$

Uninteresting outputs

Example: When modeling car consumption, we have

- ▶ inputs: gas, break, gear
- ▶ outputs: consumption, speed, moment, revs

There is no reason for penalizing moment and revs = uninteresting outputs

Model of the closed loop

$$\begin{aligned} f(d_t | \phi_{t-1}) &= f(y_t^n | y_t^i, u_t, \phi_{t-1}) f(y_t^i | u_t, \phi_{t-1}) f(u_t | \phi_{t-1}) = \\ &= f(y_t^n | y_t^i, u_t, \phi_{t-1}) \underbrace{f(u_t | u_t, \phi_{t-1}) f(y_t^i | \phi_{t-1})}_{f(y_t^i, u_t | \phi_{t-1})} \end{aligned}$$

Models

- ▶ Model of the **controlled system** $\dots f(\cdot|\cdot)$
 - *used for adaptive controller*
- ▶ Rough model of the **closed loop** $\dots f^R(\cdot|\cdot)$
 - *behavior of the closed loop*
- ▶ Ideal model of the **closed loop** $\dots f^I(\cdot|\cdot)$
 - *desired behavior of the closed loop*

FPD + uninteresting outputs

Rough model

$$f^R(d_t|\phi_{t-1}) = f^R(y_t^n|y_t^i, u_t, \phi_{t-1}) f^R(y_t^i|u_t, \phi_{t-1}) f^R(u_t|\phi_{t-1})$$

Ideal model

$$f^I(d_t|\phi_{t-1}) = f^I(y_t^n|y_t^i, u_t, \phi_{t-1}) f^I(y_t^i|u_t, \phi_{t-1}) f^I(u_t|\phi_{t-1})$$

Minimization of

$$KL\left(\prod f^R \mid \prod f^I\right)$$

→

FTP result

$$f(u_t | \phi_{t-1}) = \frac{f^l(u_t | \phi_{t-1}) \exp\{-\varsigma(u_t, \phi_{t-1})\}}{\gamma(\phi_{t-1})}$$

where

$$\varsigma(u_t, \phi_{t-1}) = E \left[\ln \frac{f(y_t^i | y_t^n, u_t, \phi_{t-1})}{f^l(y_t^i | y_t^n, u_t, \phi_{t-1}) \gamma(\phi_{t-1})} \middle| u_t, \phi_{t-1} \right] \leftarrow$$

$$\gamma(\phi_{t-1}) = \int_{u^*} f^l(u_t | \phi_{t-1}) \exp\{-\varsigma(u_t, \phi_{t-1})\} du_t$$

ς only from y^i (y^n is canceled)

Elicitation task formulation

Control problem to be solved:

- ▶ setpoint following for interesting outputs

$$\int y_t^i f^I(y_t^i | \phi_{t-1}) dy_t^i = \int y_t^s f^R(y_t^s | \phi_{t-1}) dy_t^s = \bar{y}_t^s$$

- ▶ conservative controller - not to move the behavior of the closed loop too far from the existing one

Setpoint following

- ▶ the request for setpoint following concerns only y^i - the expectation is

$$E [y_t^i | \phi_{t-1}] = \int y_t^i f^l (y_t^i | \phi_{t-1}) dy_t^i$$

i.e. it concerns the marginal $f^l (y_t^i | \phi_{t-1})$

- ▶ the corresponding factorization is

$$f^l (y_t^i, u_t | \phi_{t-1}) = \underbrace{f^l (u_t | y_t^i, \phi_{t-1})}_{\text{non causal controller}} \underbrace{f^l (y_t^i | \phi_{t-1})}_{\text{marginal in } y_t^i}$$

- ▶ $f^l (y_t^i | \phi_{t-1})$ is chosen from f^R and with expectation \bar{y}_t^s we denote it by

$$f^{OI} (y_t^i | \phi_{t-1}) \text{ Optimistic Ideal}$$

($f^l (u_t | y_t^i, \phi_{t-1})$ is still free)

Conservative controller

- ▶ the last term of the ideal model that is to be determined is $f^I(u_t|y_t^i, \phi_{t-1})$
- ▶ under condition of minimum KL distance between ideal and rough models, the result is

$$f^I(u_t|y_t^i, \phi_{t-1}) = f^R(u_t|y_t^i, \phi_{t-1})$$

which is obtained from the reverse factorization of the rough model

Example

Simulation

- ▶ 2 dimensional dynamic 2nd order regression model with constant

Filtration

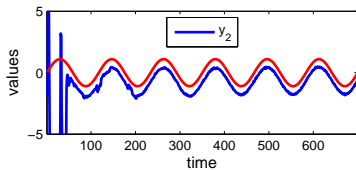
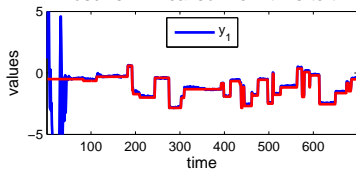
- ▶ data normalization
- ▶ no structure estimation

Rough model

- ▶ the same structure as system model + static controller
- ▶ period for estimation = 10
- ▶ practically no limitation for inputs

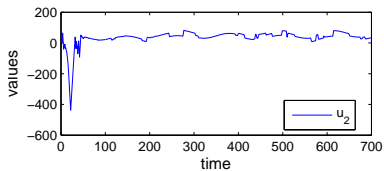
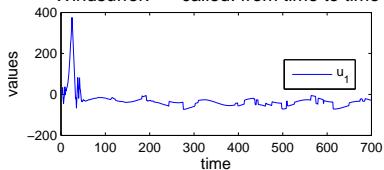
System outputs

Windsurfer: – called: from time to time

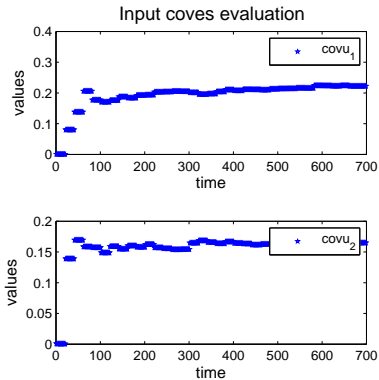


System inputs

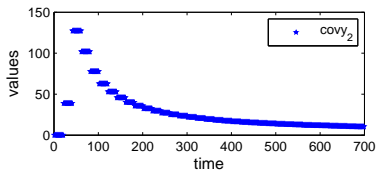
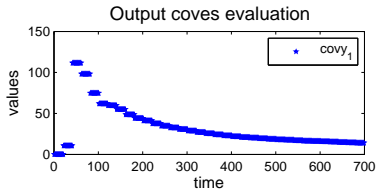
Windsurfer: – called: from time to time



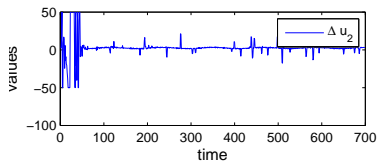
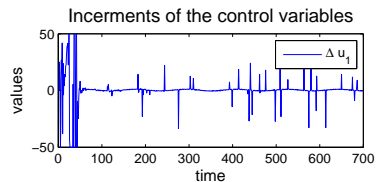
Input variances



Output variances



Increments of control variables



Conclusions

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