Simulation Based Evaluation of Condition Change Methods – Applications to Wear Monitoring in Industrial Robots

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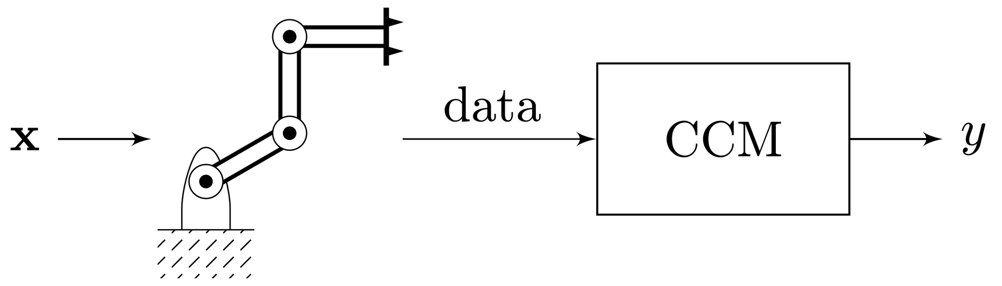
Motivation

A Condition Change Method (CCM) is an algorithm (e.g. fault detection filter) designed to process data collected from a system to generate a quantity y used to infer about a state of interest, x_1 (e.g. a fault).



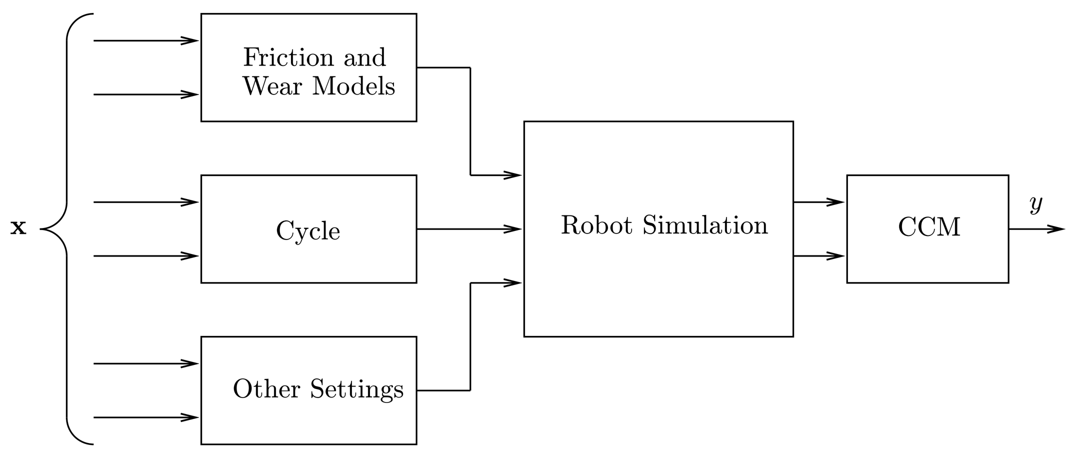
x_1, of interest (fault)
$x_{i\neq 1}$, nuisance (dist)
y, relate to x_1 (res)

In practice, the data and therefore y is affected not only by x_1 but by $\mathbf{x} = [x_1, \cdots, x_i, \cdots, x_K]^T$ where $x_{i\neq 1}$ are nuisance factors (e.g. disturbances) and the ability to infer about x_1 from y might deteriorate.

Some practical issues

Which factors x_i affect a CCM the most?
How can different CCM's be *compared*?
How can the *performance* of a CCM be quantified?
What is the *practical scope* of a CCM?

Ideally, these questions should be answered using *field data* but *simulation* studies are a ***cheaper and faster*** solution.



The factors

x_1 wear at current joint
$x_{2,3}$ wear in other joints
x_4 joint temperature
x_5 Path accuracy
x_6 Load disturbance

Regression Models

In either case, a *regression model* can be used to ***bypass the need for data***. It is a map from $\mathbf{x}$ to y.

E.g.: $y = \varphi(\mathbf{x})^T\boldsymbol{\beta} + \epsilon$
$\varphi(\mathbf{x}) = [x_1,\ x_i,\ x_i x_j,\ x_i^2]$
is a regressor function.

Several regression models might be needed depending on ***design parameters***. In the robotics application, a different model is needed for each combination of CCM, robot, axis and cycle.

$$(2 \text{ robots } \times 3 \text{ axes } \times 6 \text{ cycles}) = 36 \text{ design parameters / CCM}$$

Experiment design is to choose $X = [\varphi(\mathbf{x}_1), \cdots, \varphi(\mathbf{x}_j), \cdots, \varphi(\mathbf{x}_N)]^T$ to find β efficiently (accurate estimate with small N).

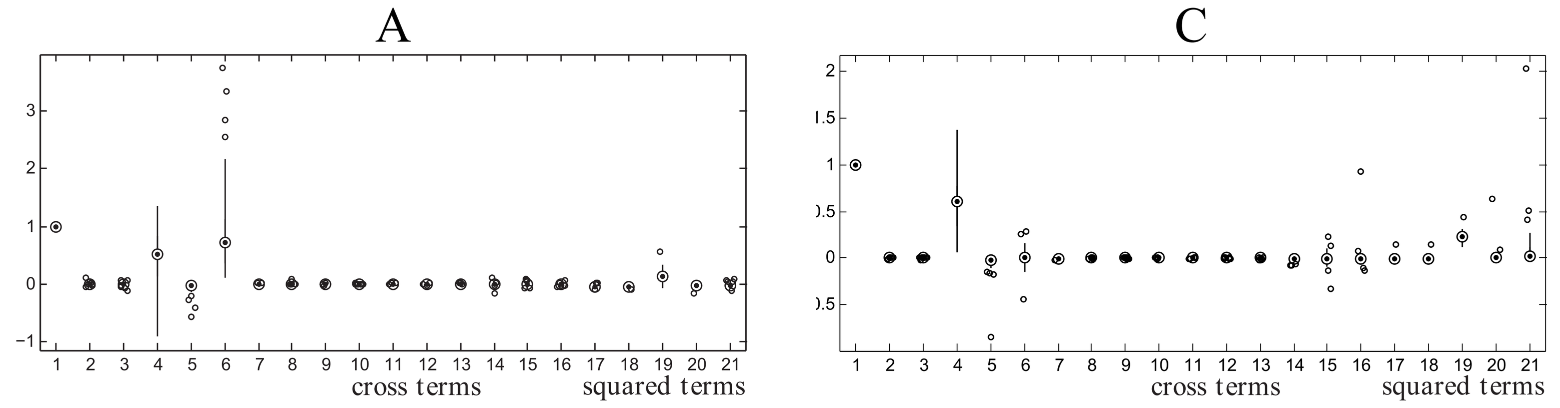
$$\mathbf{y} = X\boldsymbol{\beta} + \boldsymbol{\epsilon}$$
$$\hat{\boldsymbol{\beta}} = \left(X^T X\right)^{-1} X^T \mathbf{y}$$

E.g. X chosen using full factorial / composite design and $\boldsymbol{\beta}$ found through LS.

Important! x_i are **normalized**, e.g. between $[-2, 2]$. The resulting model *must* be **validated**.

Sensitivity Analysis

Investigate normalized regression coefficients $\boldsymbol{\beta}/\beta_1$ for each CCM to conclude which factors x_i are relevant relative to the factor of interest x_1.



In this example, CCM A shows sensitivity to both temperature and load while CCM C shows sensitivity to temperature. The boxplots are for the coefficients over all design parameters.

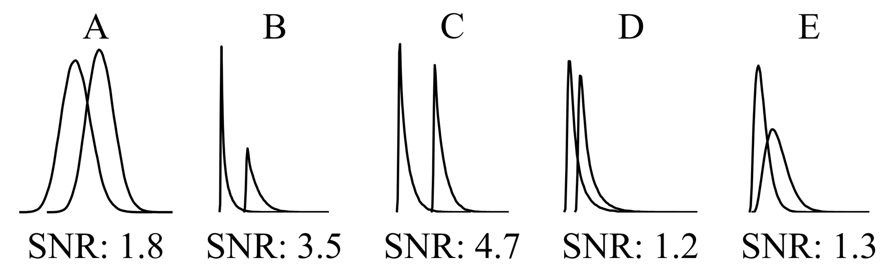
Signal to Noise ratio

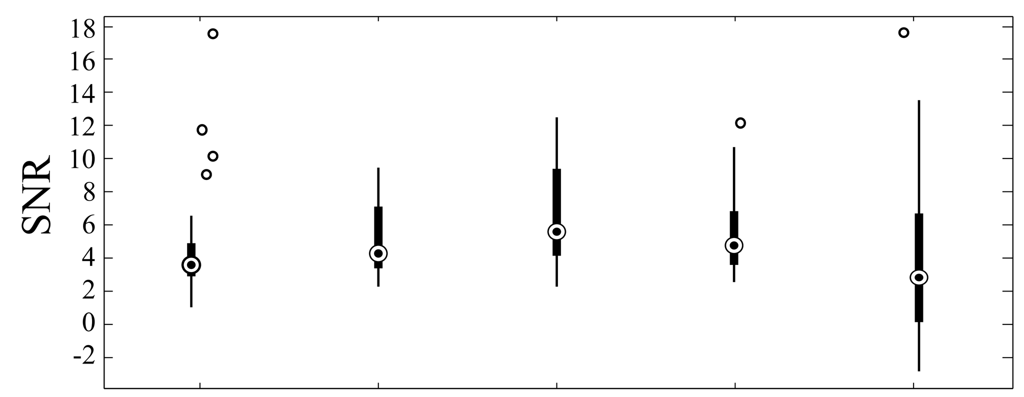
Investigate the average effect in y caused by a change δ in x_1 relative to variations in x_i, e.g. using a regression model

$$y^{(-)} = \varphi(\mathbf{x})^T\boldsymbol{\beta} - \beta_1\delta$$
$$y^{(+)} = \varphi(\mathbf{x})^T\boldsymbol{\beta} + \beta_1\delta$$

Using MC simulations, estimate $p(y^{(-)})$ and $p(y^{(+)})$ when $x_i \sim \mathcal{N}(\mu, \sigma^2)$.

The resulting SNR$=\mu^{(+)}/\sigma^{(+)} - \mu^{(-)}/\sigma^{(-)}$ for each CCM and cases can be used for a ***performance comparison***.





MC simulations are run *efficiently* with regression models.

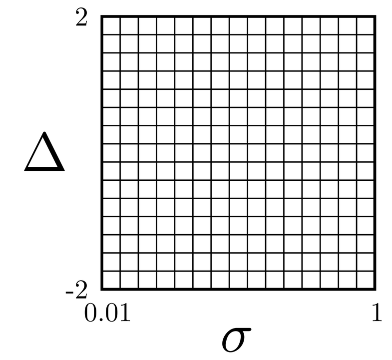
Boxplots are for all design parameters.

Outliers should be investigated carefully.

Determining the scope based on ROC

Build binary hypothesis tests where a change is introduced in x_1 for a random disturbance in another variable x_i

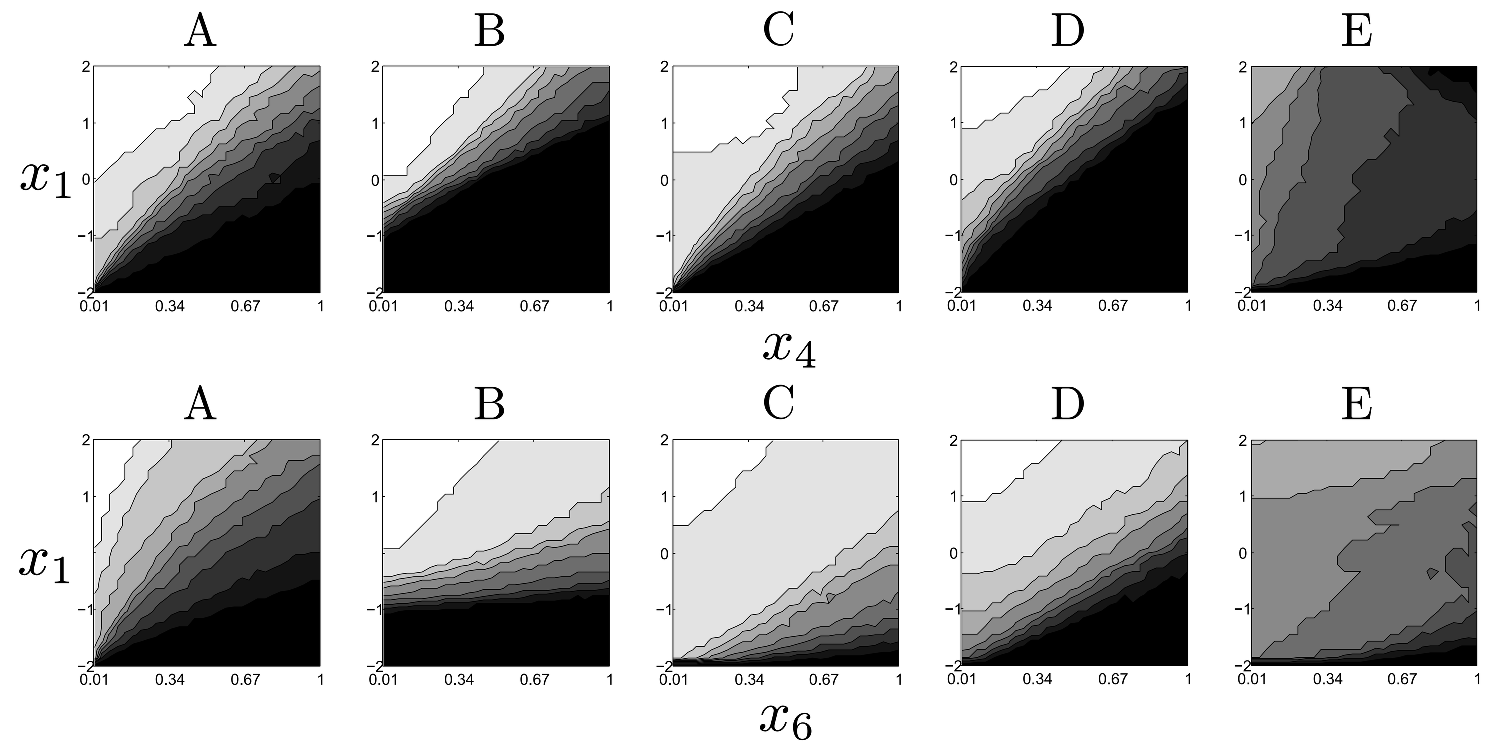
$$\mathcal{H}_0 : x_1 = -2,\ x_i \sim \mathcal{N}(0, \sigma^2)$$
$$\mathcal{H}_1 : x_1 = \Delta,\ \ x_i \sim \mathcal{N}(0, \sigma^2)$$



A threshold check $y \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \hbar$ gives

$$P_f = \int_{\hbar}^{\infty} p(y|\mathcal{H}_0),\ P_d = \int_{\hbar}^{\infty} p(y|\mathcal{H}_1)$$

Evaluate P_d for a fixed $P_f = 0.01$ over different combinations of Δ and σ (in a grid), add 1 to the grid if the related $P_d \geq 0.99$. Repeat this for all design parameters and store in a ***scope matrix***.



The colormap relates to how often the criterion was achieved over all design parameters (B to W, $[0, 100]$%.) The clearer the plot, the better! In a glance, it is possible to see what combination of change in x_1 and variability in x_i restricts the usefulness of a method.

Summary

A framework for evaluation and comparison of CCMs.

- Need for data can be bypassed with *regression models*
- Important to *validate* the regression models
- *Sensitivity analyses* reveal the factors that drive the CCM
- *Outlier analyses* useful for CCM development/comparison
- The *scope matrix* shows the CCM effective regions in the factor space
- Conclusions should be taken with care (*model dependent*)