A Data-driven Method for Monitoring of Repetitive Systems – Robust Wear Monitoring in an Industrial Robot Joint

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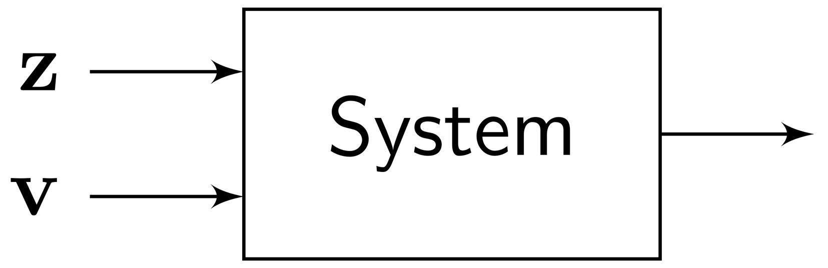
Systems that Operate Repetitively

Consider a general system:



$\mathbf{v}$ is *random* unknown

$$\mathbf{z}: \begin{cases} \mathbf{u}, \text{ known} \\ \mathbf{d}, \text{ unknown} \\ \mathbf{f}, \text{ unknown of interest} \end{cases}$$

A task $\mho$ is executed M times and data is collected from each execution

$$\mathbf{y}^j = [y_1^j, \cdots, y_i^j, \cdots, y_N^j]^T, \quad \mathbf{Y}^M = [\mathbf{y}^0, \cdots, \mathbf{y}^j, \cdots, \mathbf{y}^{M-1}]$$

With the purpose of monitoring $\mathbf{y}^j$ to detect changes in $\mathbf{f}^j$, the following **assumptions** are made

Faults are observable: changes in $\mathbf{f}^j$ affect $\mathbf{y}^j$.
Regularity of $\mathbf{y}^j$ if no fault: $\mathbf{y}^j$ is similar along j unless $\mathbf{f} \neq 0$.
Regularity of $\mathbf{d}^j$: $\mathbf{d}^j$ is similar along j.
Nominal data are available: At $j=0$, $\mathbf{f}^0=0$ and $\mathbf{y}^0$ is available.

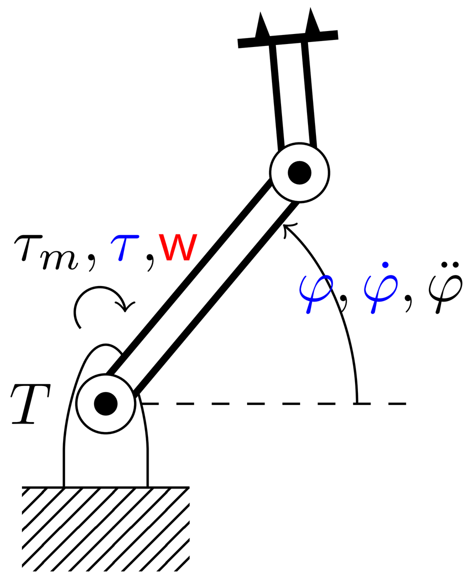
The basic idea is then to compare $\mathbf{y}^0$ with $\mathbf{y}^j$.

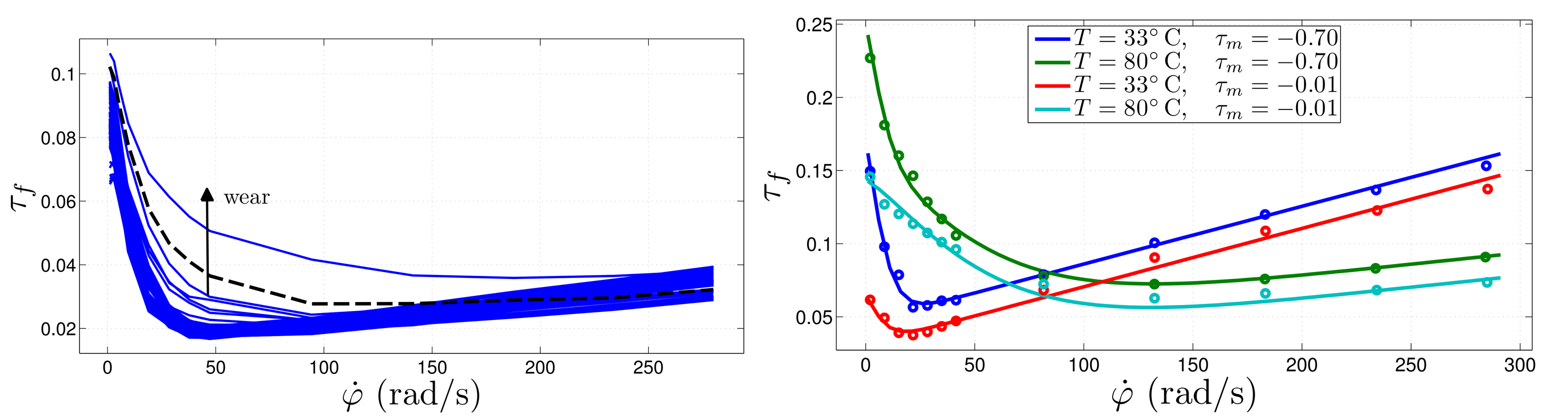
An industrial robot subject to wear and temperature changes

$$\tau = M(\varphi)\ddot{\varphi} + C(\varphi,\dot{\varphi}) + D\dot{\varphi} + \tau_g(\varphi) + \tau_s(\varphi) + \tau_f(\dot{\varphi}, \tau_m, T, \mathsf{w})$$

A task $\mho$ is executed regularly

$$\mathbf{y} = \tau, \; \mathbf{f} = \mathsf{w}, \; \mathbf{d} = \underbrace{\varphi, \dot{\varphi}, \ddot{\varphi}, \tau_m}_{\mho}, T$$





For more. This work is available as a technical report at
`http://www.control.isy.liu.se/~andrecb/publications/`

Characterizing and Comparing Data

There are several possible options to characterize $\mathbf{y}^j$. Here, the **data distribution** is considered.

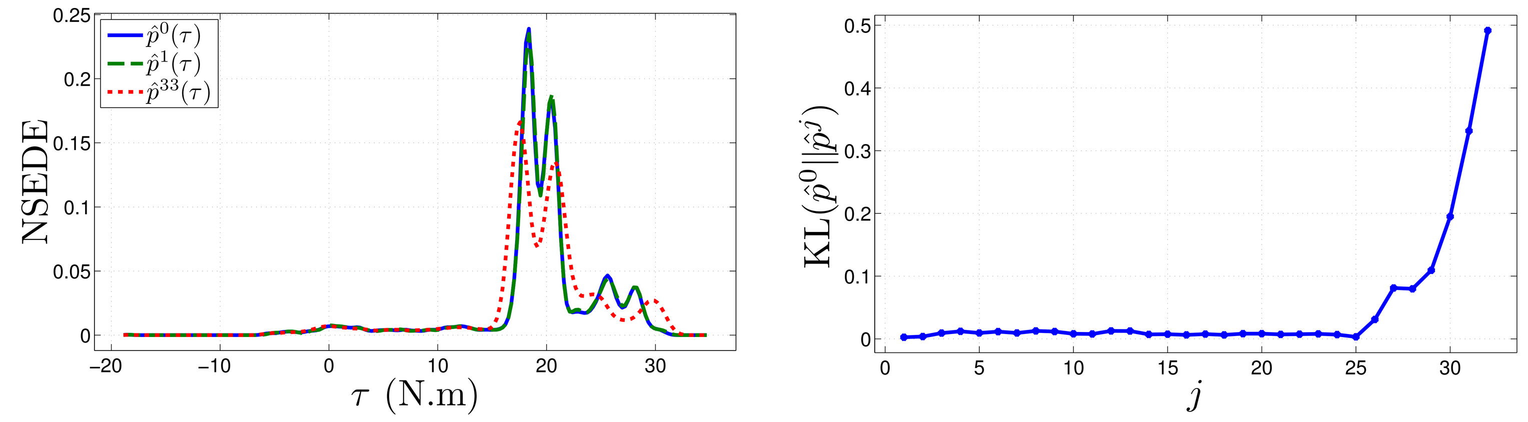
Characterizing the data / Comparing the data
Smooth Density Estimate / Kullback-Liebler distance

$$\hat{p}^j(y) \triangleq \frac{1}{N}\sum_{i=1}^{N} k_h(y - y_i^j)$$

$$\mathrm{KL}\left(\hat{p}^0 \| \hat{p}^j\right) \triangleq D_{\mathrm{KL}}\left(\hat{p}^0 \| \hat{p}^j\right) + D_{\mathrm{KL}}\left(\hat{p}^j \| \hat{p}^0\right)$$

$$D_{\mathrm{KL}}\left(\hat{p}^0 \| \hat{p}^j\right) \triangleq -\int_{-\infty}^{\infty} \hat{p}^0(y) \log \frac{\hat{p}^j(y)}{\hat{p}^0(y)} \mathrm{d}y$$

Real robot wear fault. Left: densities. Right: fault indicator.



+ no synch., no ordering, little tuning, no model.
– requires $\mathbf{y}^0$, same $\mho$, regular $\mathbf{d}^j$.

Monitoring the Accumulated Changes

The objective is to relax the assumptions of known $\mathbf{y}^0$ and regularity of $\mathbf{y}^j$ (same $\mho$).

No assignment of $\mathbf{y}^0$
the KL $(\cdot\|\cdot)$ is a metric

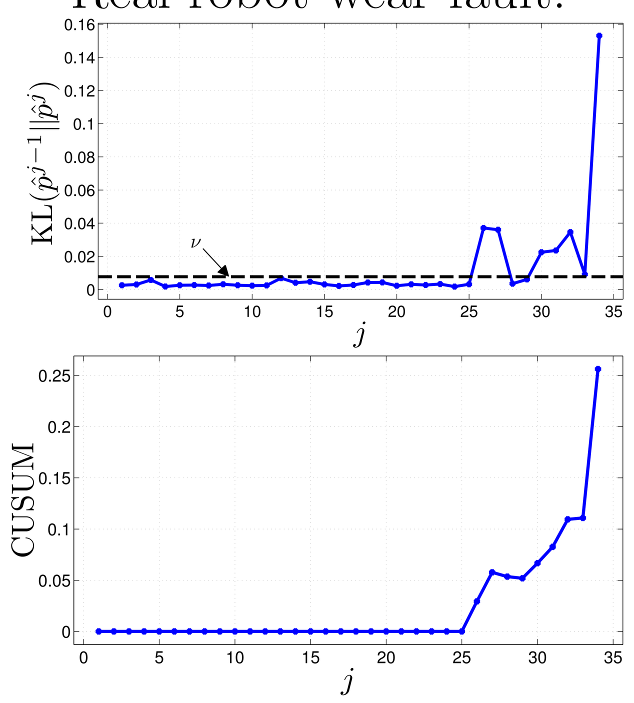
$$\mathrm{KL}\left(\hat{p}^0 \| \hat{p}^j\right) \leq \sum_{k=1}^{j} \mathrm{KL}\left(\hat{p}^{k-1} \| \hat{p}^k\right)$$

Monitor increments with a CUSUM

$$\begin{cases} g^j = g^{j-1} + \mathrm{KL}\left(\hat{p}^{j-1} \| \hat{p}^j\right) - \nu \\ g^j = 0 \text{ if } g^j < 0 \end{cases}$$

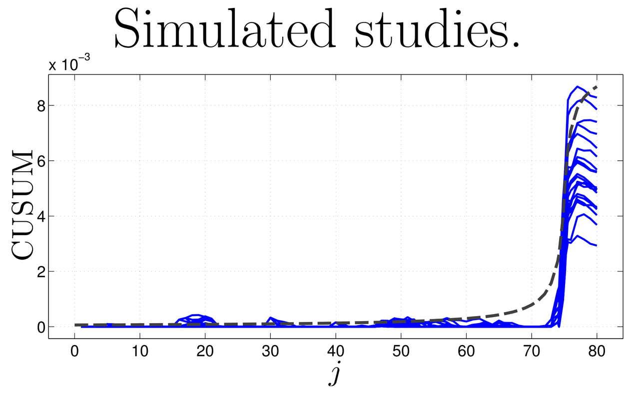
with $\nu = \kappa\sigma + \mu$.

Real robot wear fault.



Handling several $\mho$s
same! but $\mho^{j-1} = \mho^j$
with $\nu^j = \kappa\sigma(\mho^j) + \mu(\mho^j)$

Simulated studies.



+ does not require $\mathbf{y}^0$, handles several $\mho$s.
– regular $\mathbf{d}^j$, more tuning, sensitive to sampling rate.

Reducing Sensitivity to Disturbances

In practice, it is important to cope with irregular $\mathbf{d}$ to achieve robustness.

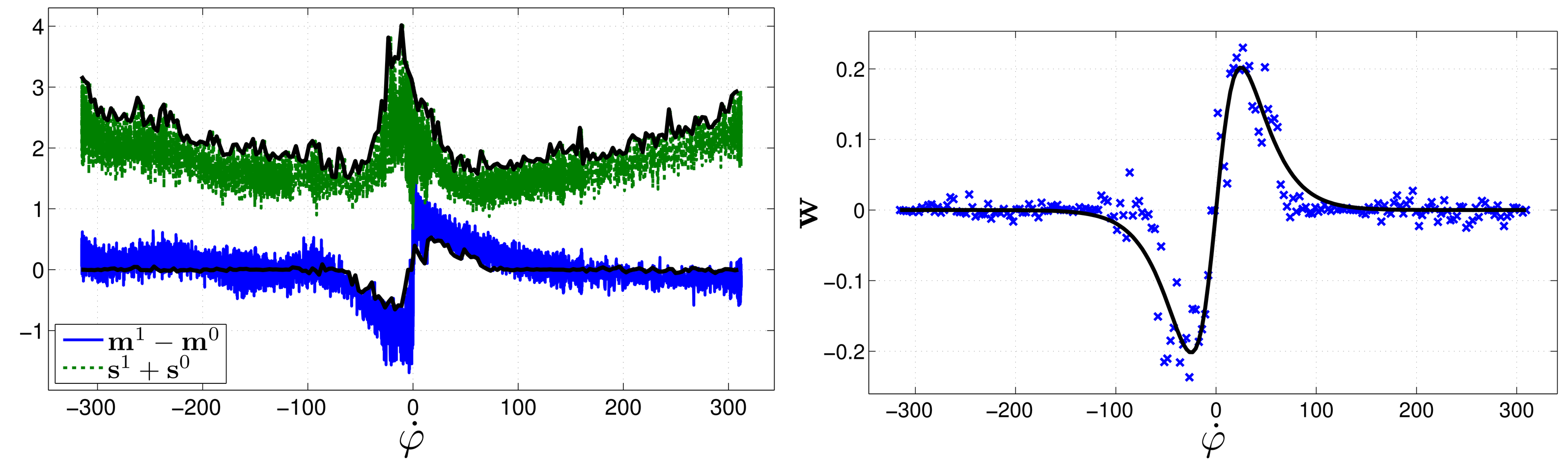
Handling disturbances d
apply weights to the data

$$\bar{\mathbf{y}} \triangleq \mathbf{w} \circ \mathbf{y}$$

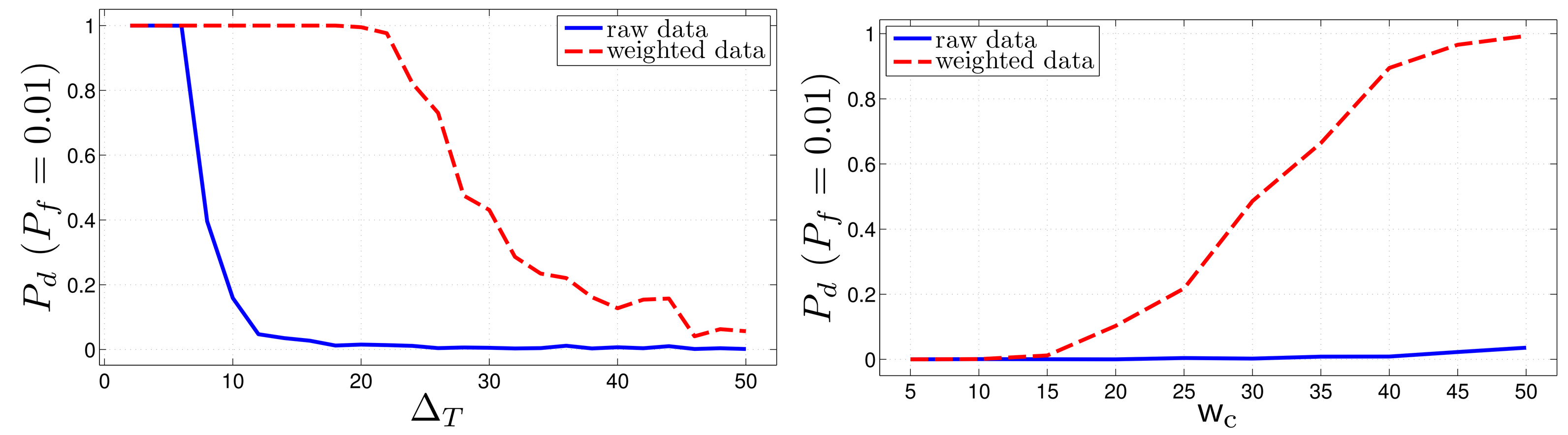
The idea is to weight data according to knowledge about disturbances and faults. Criteria similar to LDA can be used. Let $\bar{m}^k$ and $\bar{s}^k$ be the average mean and variance for the weighted faulty data, $k=1$, and weighted nominal data, $k=0$. The criterion

$$\max_{\mathbf{w}} \frac{\left[\bar{m}^1(\mathbf{w}) - \bar{m}^0(\mathbf{w})\right]^2}{\bar{s}_1(\mathbf{w}) + \bar{s}_0(\mathbf{w})} \quad \text{gives,} \quad \mathbf{w} \propto (\mathbf{S}^1 + \mathbf{S}^0)^{-1}(\mathbf{m}^1 - \mathbf{m}^0)$$

For an industrial robot, optimal weights correlate with speed!



The use of weights considerable improves the detection performance.



Left: Abrupt fault of fixed size $\mathsf{w}_c = 35$ and varying T disturbances, Δ_T.
Right: Abrupt fault for fixed $\Delta_T = 25\mathrm{C}^\circ$ and varying fault size, w_c.

Summary

A data-driven method for monitoring of systems that operate in a repetitive manner is proposed which

- can be used online, in a batch manner
- requires no synchronization or ordering of data sequences
- can handle disturbances
- requires nearly no knowledge of the system
- is simple and easy to implement, with little tuning