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Reference-free Detection of Spike Faults in Wireless Sensor Networks

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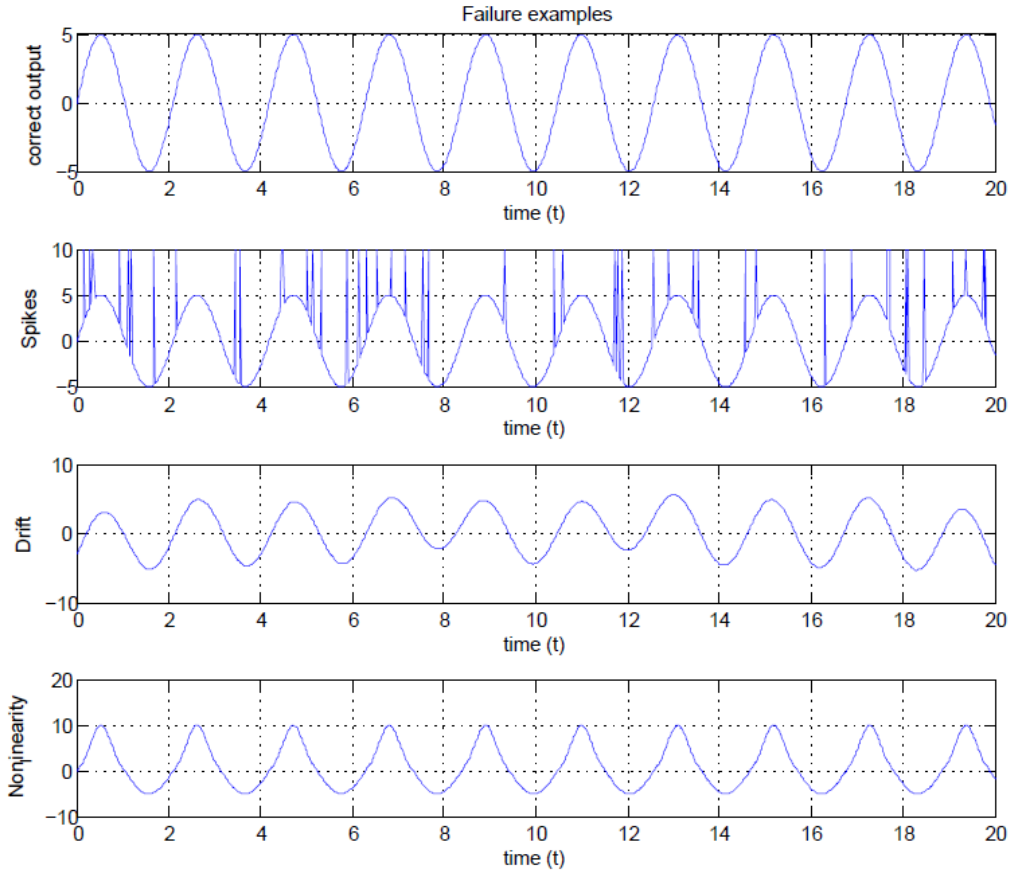
Motivation:

- Wireless sensor networks (WSNs) have been proposed for many applications:
  - Monitoring and control of machinery, structural health monitoring, environmental monitoring.
- Sensor nodes are lower-cost and thus potentially more vulnerable to faults and failure
- Deployed in large quantities and often in locations with low accessibility
- Automatic fault detection and identification is needed

Taxonomy of Sensor Fault:

- Not completely inoperable, but measurement output is partially corrupted



Normal Signal

Spike: shaking of wire connector

Drift: fluctuation of temperature

Non-linearity: loose attachment of sensor

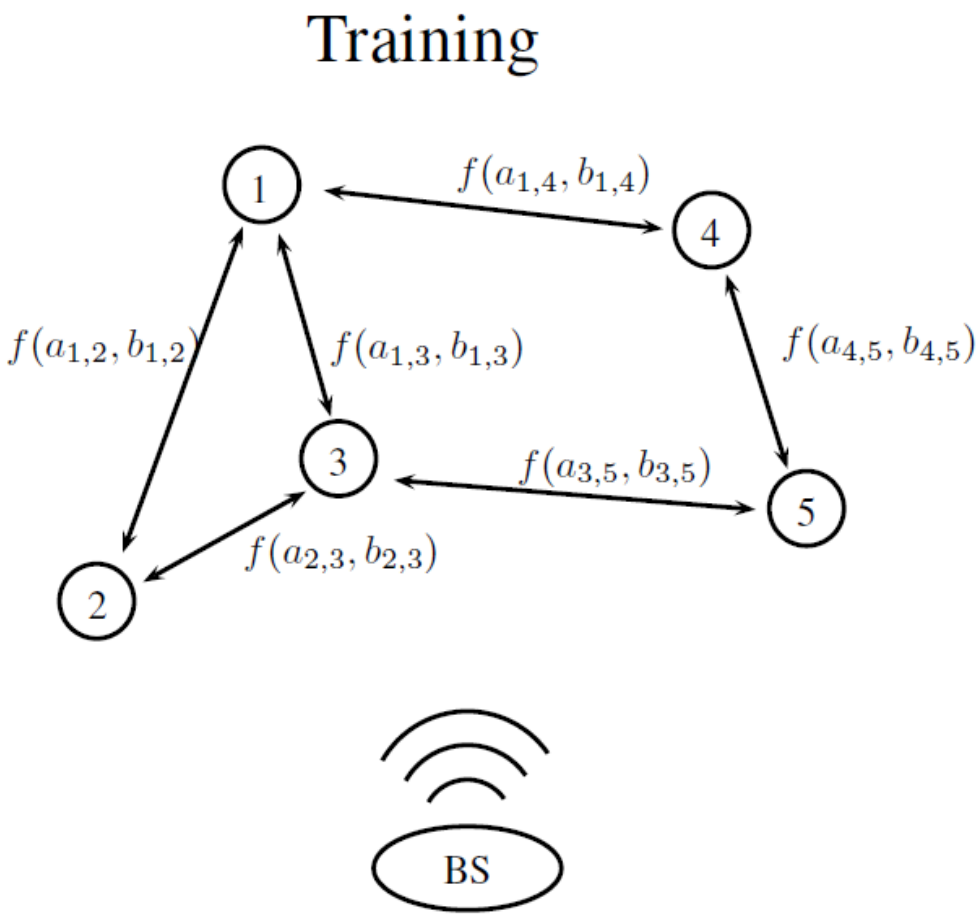
Outline:

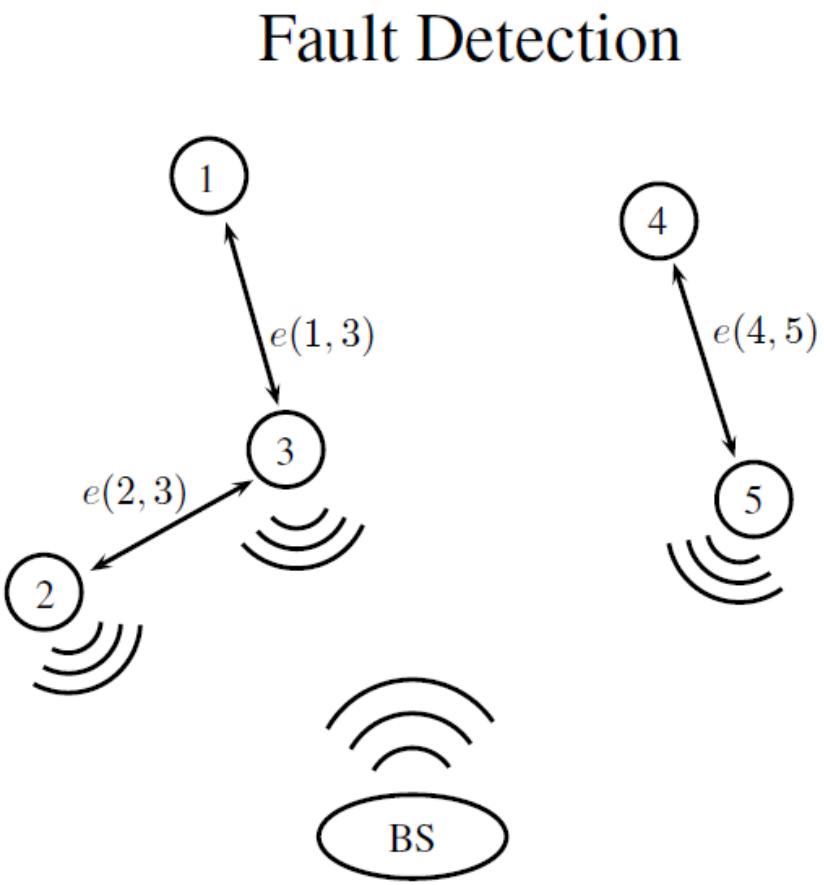
- Reference-free and decentralized fault detection algorithm for WSNs
- Linear relationship between sensor pairs
- Spike detection using autoregressive modeling
- Simulation and results
- Conclusion and future work

Analytical Redundancy:

- Nodes are not independent:
  - There exist a relationship between sensors monitoring a physical system
- Different methods have been developed based on redundancy:
  - Discrepancies detection by Kalman filter [Da & Lin 1995]
  - Output estimation by reference sensors [Li et al. 2007]
- Technical challenges:
  - However, system model and reference sensors are sometimes “expensive” to obtain
  - Centralized algorithms require heavy communications

The Big Picture:





Pair-wise Linear Relationship:

- Consider all the sensors are attached to a physical system. Sensor outputs can be modeled by a LTI state-space model:

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k)$$
$$\boldsymbol{y}(k) = \boldsymbol{C}\boldsymbol{x}(k) + \boldsymbol{D}\boldsymbol{u}(k)$$

- $\boldsymbol{Y}(z) = (\boldsymbol{C}(z\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{B} + \boldsymbol{D})\boldsymbol{U}(z)$
- Assume the excitations of the system can be viewed as a single source, we have
- $\frac{\boldsymbol{Y}_1(z)}{\boldsymbol{Y}_2(z)} = \frac{\boldsymbol{C}_1(z\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{B}+\boldsymbol{D}_1}{\boldsymbol{C}_2(z\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{B}+\boldsymbol{D}_2} = \frac{a_0+a_1z+\cdots+a_nz^n}{b_0+b_1z+\cdots+b_nz^n}$

Pair-wise Linear Relationship:

- Each sensor pair has a direct linear relationship which can be captured by a linear model
- ARX model

$$\frac{\boldsymbol{Y}_1(z)}{\boldsymbol{Y}_2(z)} = \frac{a_0 + a_1 z + \cdots + a_n z^n}{b_0 + b_1 z + \cdots + b_n z^n} \Rightarrow \sum_{i=0}^{m} a_i y_1(t-i) = \sum_{i=0}^{n} b_i y_2(t-i)$$

- Train model parameter a_i and b_i by linear regression methods
  - $m, n \geq$ dimension of state $\boldsymbol{x}$
  - Coefficients are stored for future failure detection

Spike Error Detection:

- ARX model

$$\sum_{i=0}^{n} a_i y_1(t-i) = \sum_{i=0}^{n} b_i y_2(t-i)$$

- Express y_1 in terms of its past outputs and the outputs of its "partner" sensor
  - $y_1(t) = \sum_{i=1}^{n} -a_i\, y_1(t-i) + \sum_{i=0}^{n} b_i\, y_2(t-i)$

- Error function $e_{12}(t) = \tilde{y}_1(t) - \hat{y}_1(t)$

$$\begin{aligned} e_{12}(t) &= \overbrace{(y_1(t) + e_1(t))}^{\text{measurement } \tilde{y}_1(t)} - \overbrace{(\sum_{i=1} -a_i(y_1(t-i) + e_1(t-i)) + \sum_{i=0} b_i(y_2(t-i) + e_2(t-i))}^{\text{estimation } \hat{y}_1(t)} \\ &= \boldsymbol{a}^T \boldsymbol{e}_1 - \boldsymbol{b}^T \boldsymbol{e}_2 \ . \end{aligned}$$

where $\boldsymbol{a} = [1, a_1, \ldots, a_n], \boldsymbol{b} = [b_0, b_1, \ldots, b_n]$

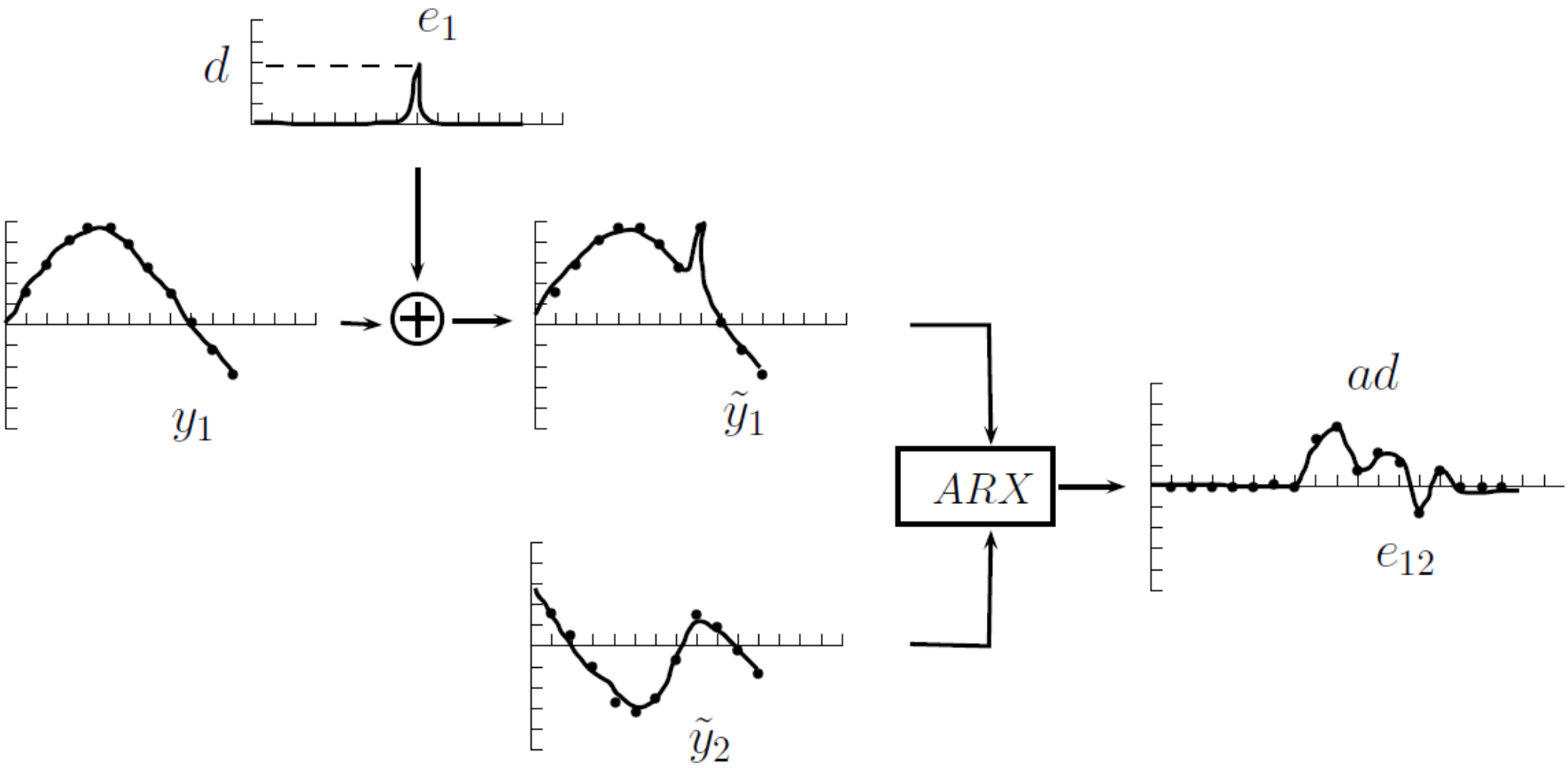
The Error Function:

- $e_{12}(t) = \boldsymbol{a}^T \boldsymbol{e}_1 - \boldsymbol{b}^T \boldsymbol{e}_2$
- Four possible cases
  1. Both sensors are normal
  2. Sensor 1 is normal and sensor 2 is faulty
  3. Sensor 1 is faulty and sensor 2 is normal
  4. Both sensors are faulty
- No reference sensors in the system, error could due to either sensor or both.
  - Difficult to classify cases 2,3 and 4

Individual Spike Fault as a Signal:

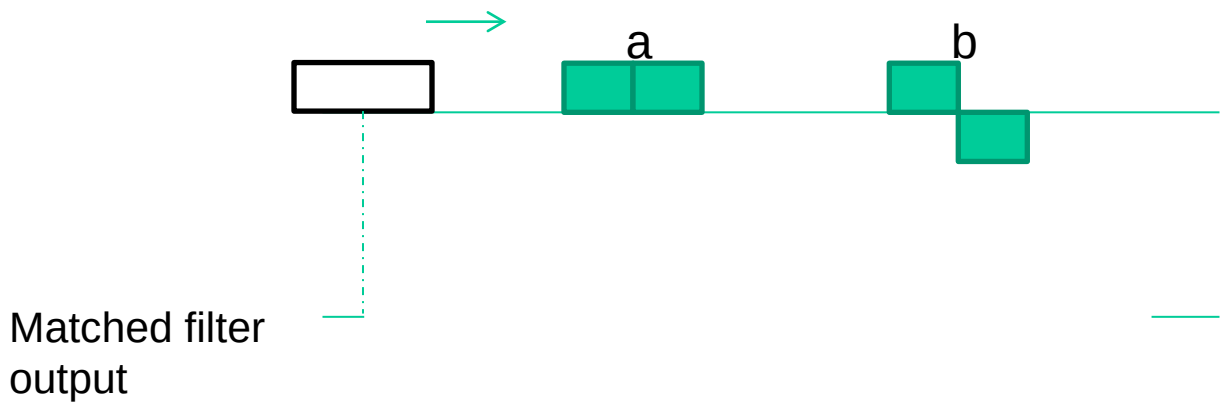
- If the error is a spike, e_1 or e_2 will be a delta function
- $e_{12}(t) = \boldsymbol{a}^T \boldsymbol{e}_1 = a_i d$ if a spike occurred in sensor 1 at time $t - i$ with amplitude d and no spike occurred in sensor 2
- Spike error shows up as ARX coefficient waveforms in error function
  - Spike in sensor 1 has waveform a
  - Spike in sensor 2 has waveform b
- Spike detection becomes a signal detection problem

Spike as a signal:



Spike Detection:

- Case 1: $a \neq kb$ where $k \in \mathbb{R}$
  - As arrival time of the spike signals is unknown, matched filter is used for signal detection
  - Use target signal as a filter and convolve it with the error function
  - When the target signal shows up, it will match with the filter and gives a high signal

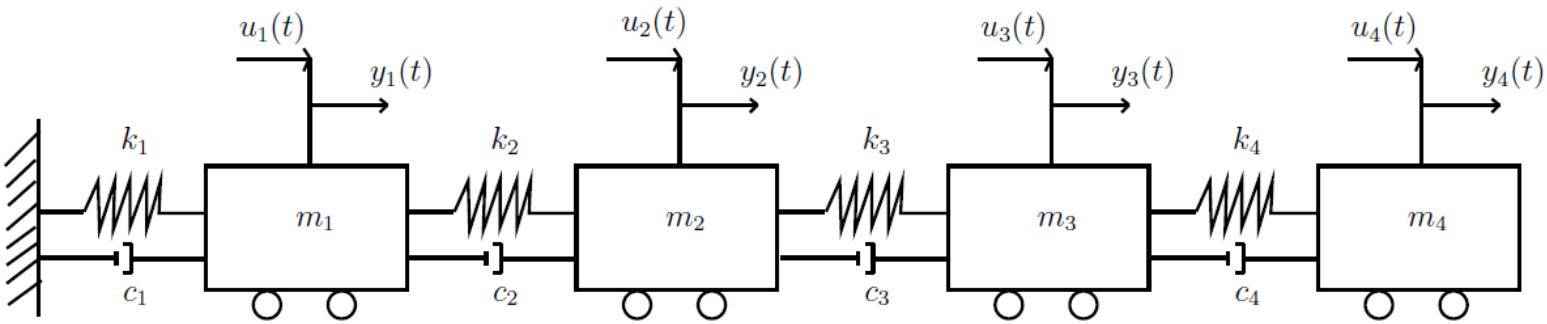


Spike Detection:

- Case 2: $\mathrm{a} \approx kb$ for some $k \in \mathbb{R}$
  - The outputs of the two sensors are highly correlated
  - Unable to suppress the other signal
  - Assume the magnitude and sign of the spike is unknown
  - Still able to detected there exist an error in the sensor pair but cannot determine which sensor has problem, unless the spikes magnitude match each other and the $e_{12} = 0$

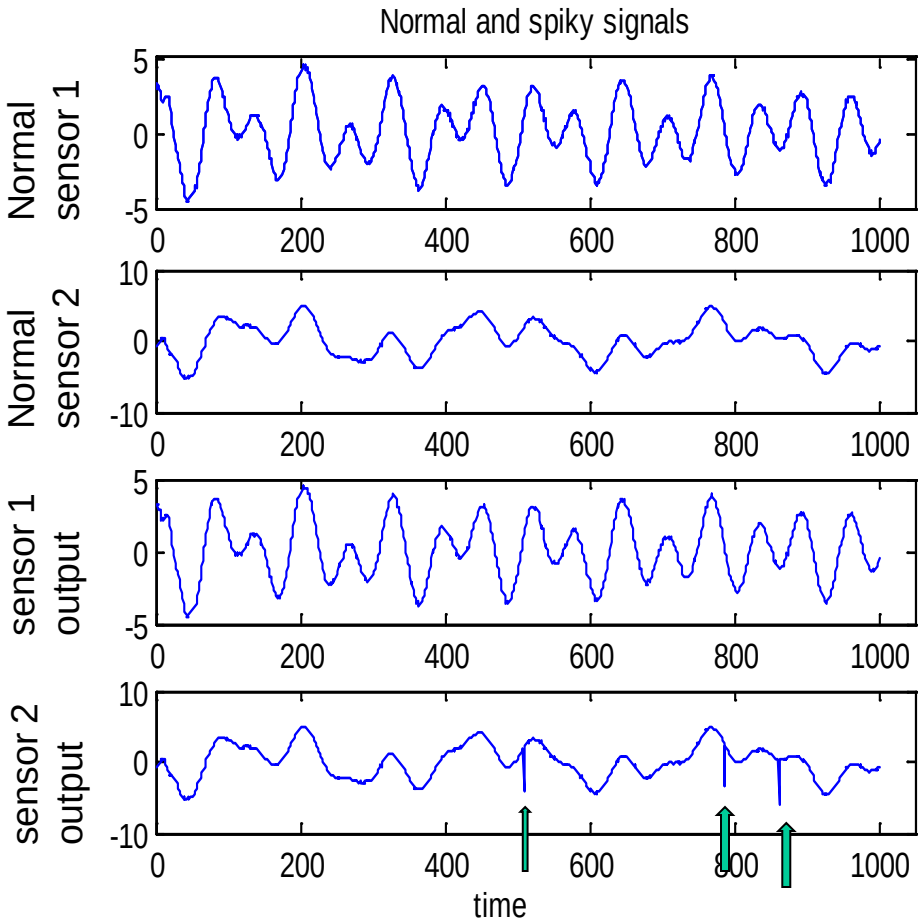
Simulation:

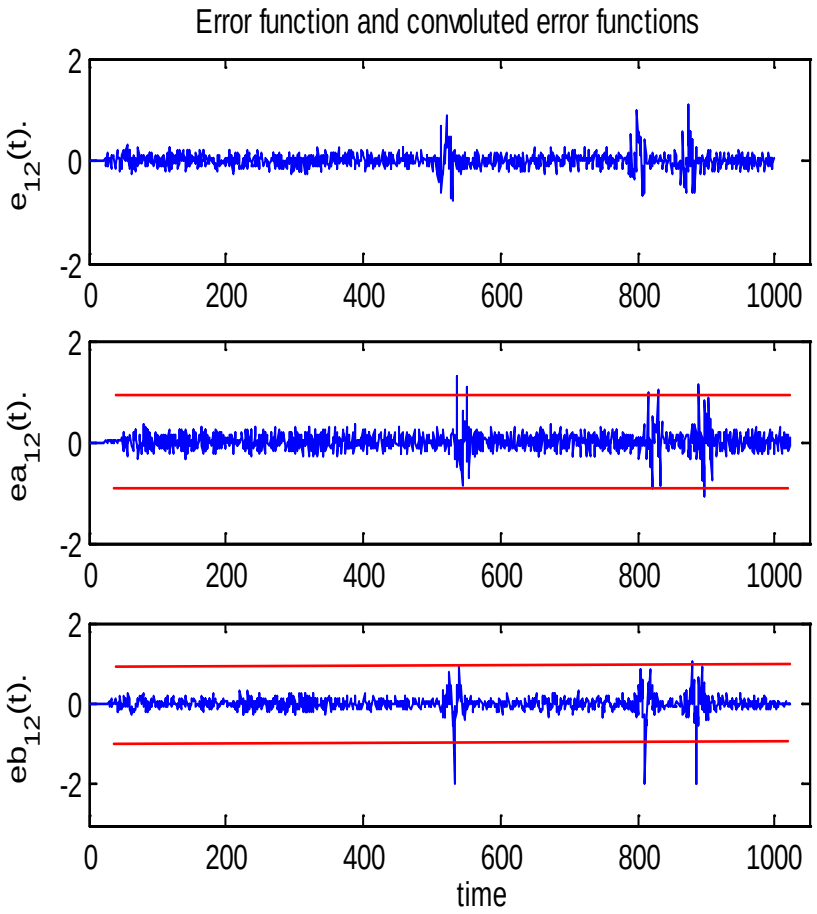
- Four-degree-of-freedom spring-mass-damper system



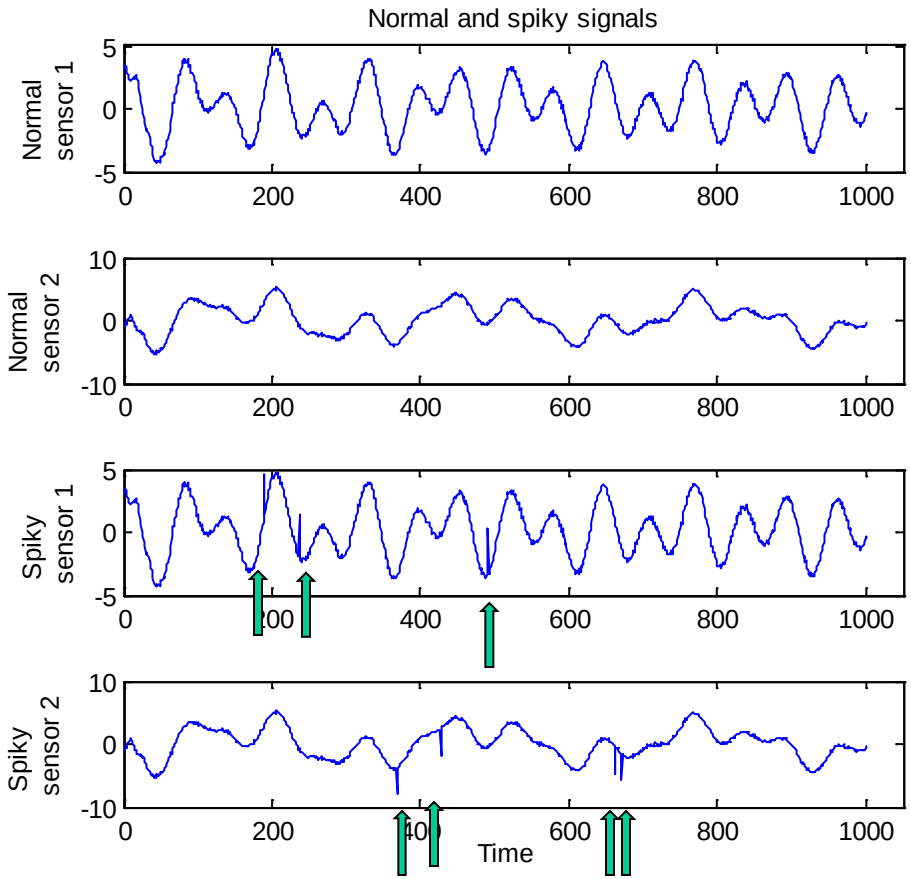
  - Mathematically is a general problem whose model corresponds to electrical circuits and vibrating structures

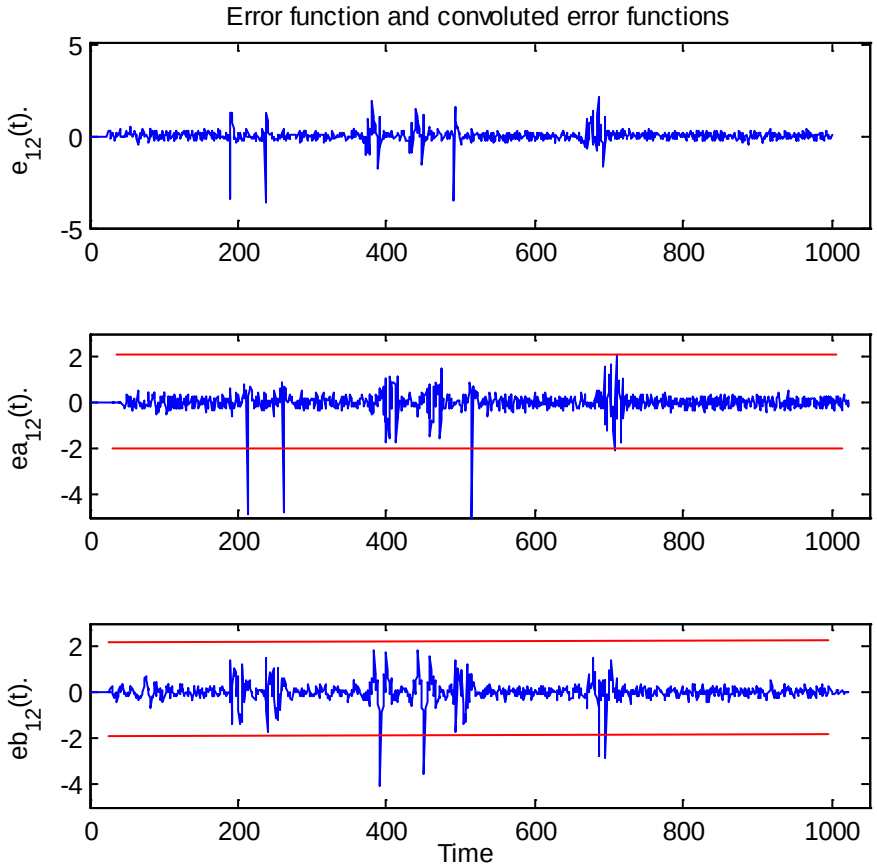
Results:


Normal and spiky signals
Normal sensor 1
Normal sensor 2
sensor 1 output
sensor 2 output
5
0
-5
10
0
-10
0
200
400
600
800
1000
time

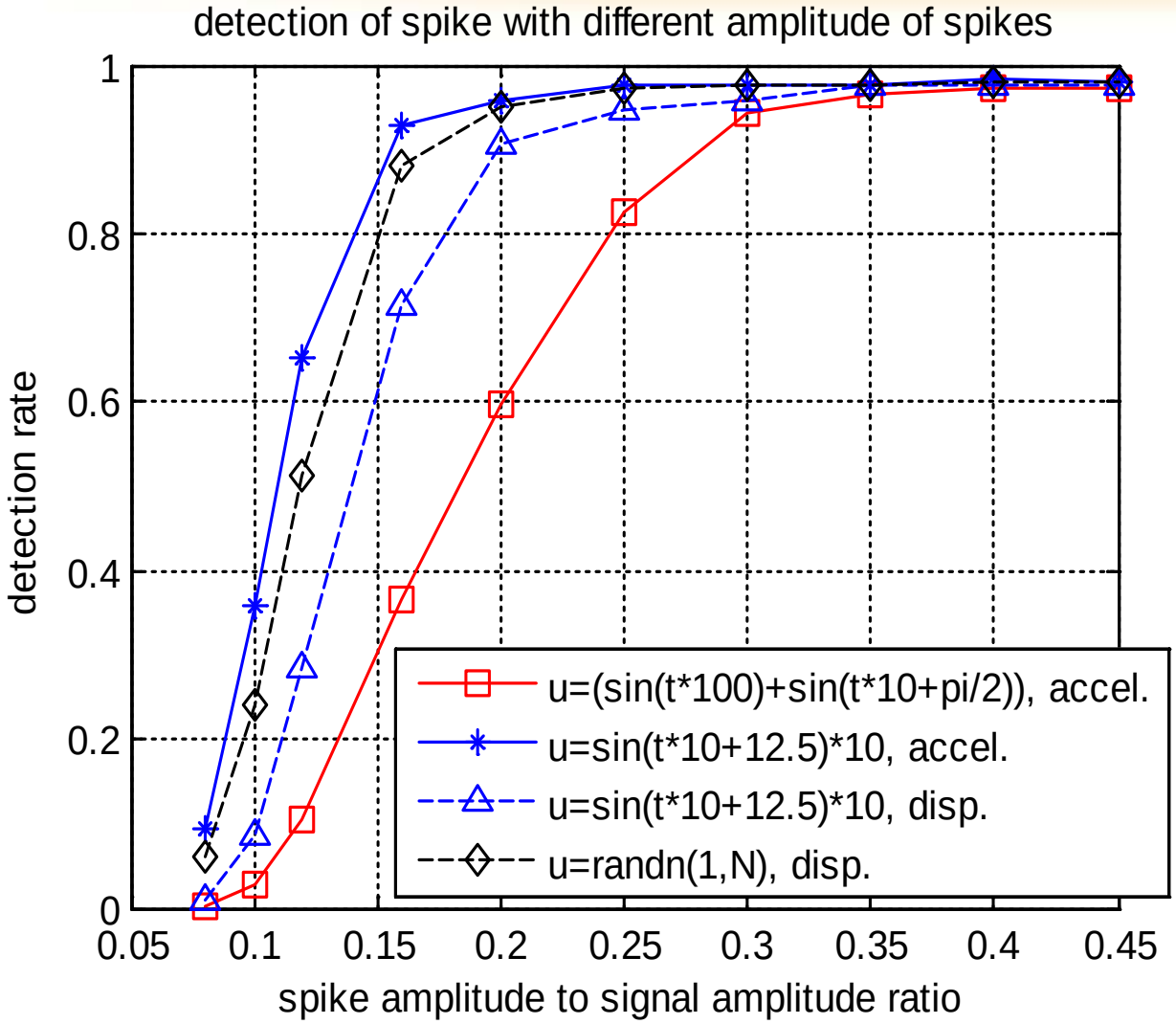

Error function and convoluted error functions
$e_{1,2}(t)$.
$ea_{1,2}(t)$.
$eb_{1,2}(t)$.
2
0
-2
0
200
400
600
800
1000
time

Results:

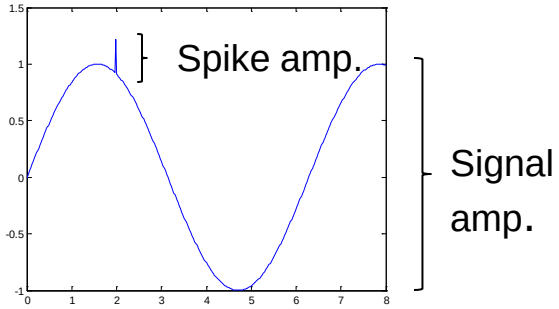

Normal and spiky signals
Normal sensor 1
Normal sensor 2
Spiky sensor 1
Spiky sensor 2
Time


Error function and convoluted error functions
$e_{12}(t)$.
$ea_{12}(t)$.
$eb_{12}(t)$.
Time

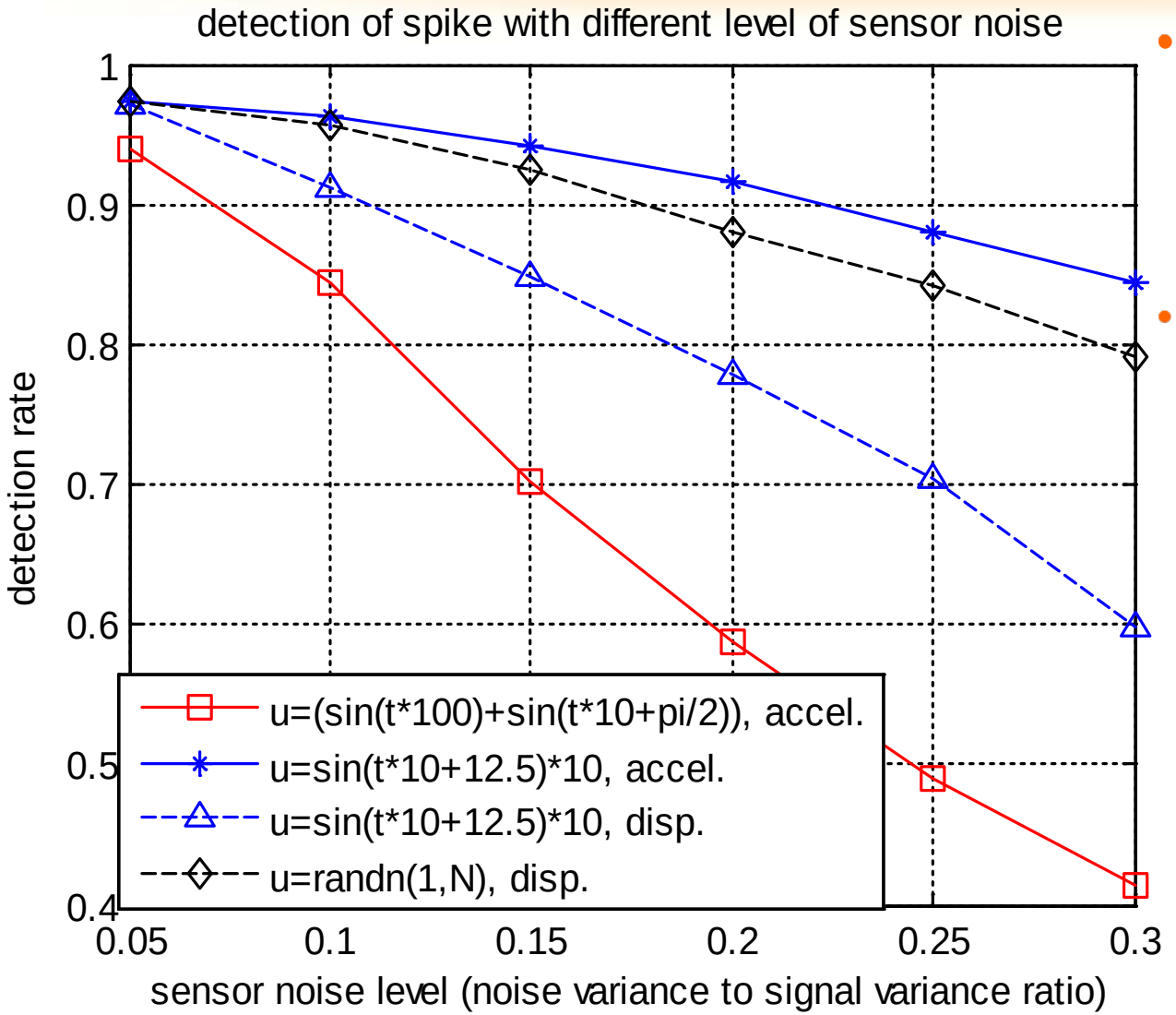
Results:



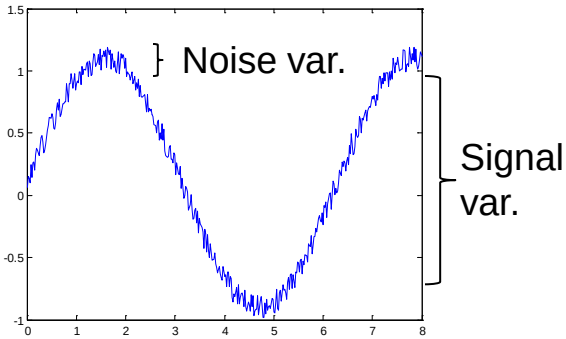
- The sensor noise was set to 10% of the sensor output magnitude
- When the amplitude of spike reaches 20% of the sensor output magnitude, the algorithm in most cases achieved over 90% of accuracy.



Results:



- The magnitude of the spike errors are fixed at 20% of the peak-to-peak magnitude of the sensor outputs.
- The accuracy is above 80% for 18% of noise for most of the cases.



Conclusion:

- Proposed an ARX-based spike failure detection method
- Reference-free, decentralized and does not require the system input
- Requires all excitations can be regarded as a single source and there are good signals to train ARX model
- The performance depends on the shape of ARX coefficients, detection threshold, spike amplitude and observation noise of the sensors.

Future Work:

- Control the shape of the ARX coefficients through regularized training
- Evaluate more than two sensors at a time
- Detect other fault type using ARX models:
  - Drifts
  - Nonlinearities

Thank you!

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