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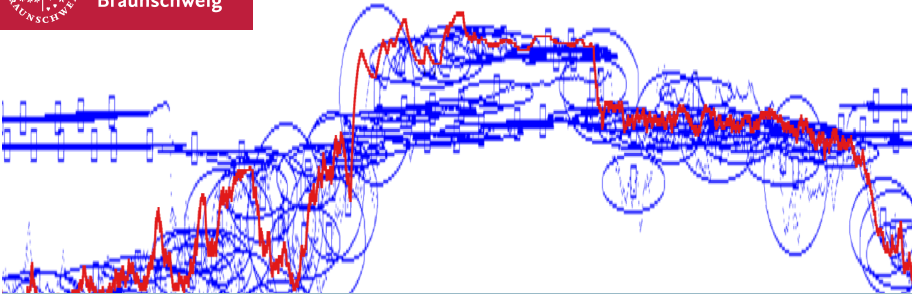


A Clustering-Based Characteristic Model for Unreliable Sensor Network Data

WF-IoT 2015

Ulf Kulau, Tobias Breuer and Lars Wolf, December 14, 2015

Technische Universität Braunschweig, IBR

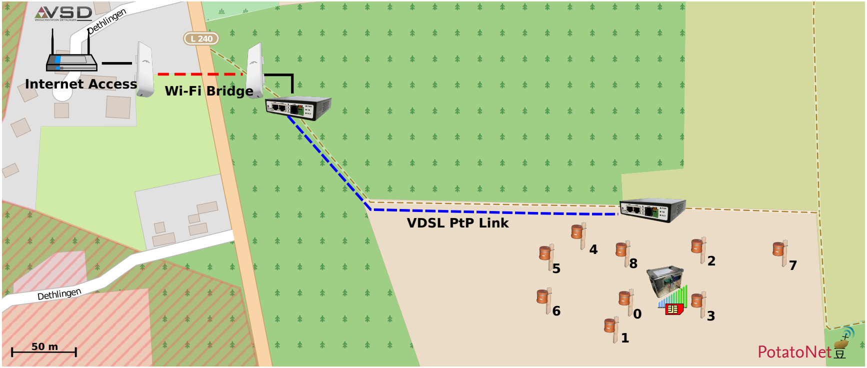
Introduction – Background

Many WSN/IoT applications deployed in challenging areas

- Harsh environmental conditions
  $\rightarrow$ Reliability of nodes decreases
  $\rightarrow$ Correctness of data-collection might be affected

Introduction – PotatoNet

Outdoor WSN testbed – Central box and field-nodes



https://www.ibr.cs.tu-bs.de/projects/potatonet/

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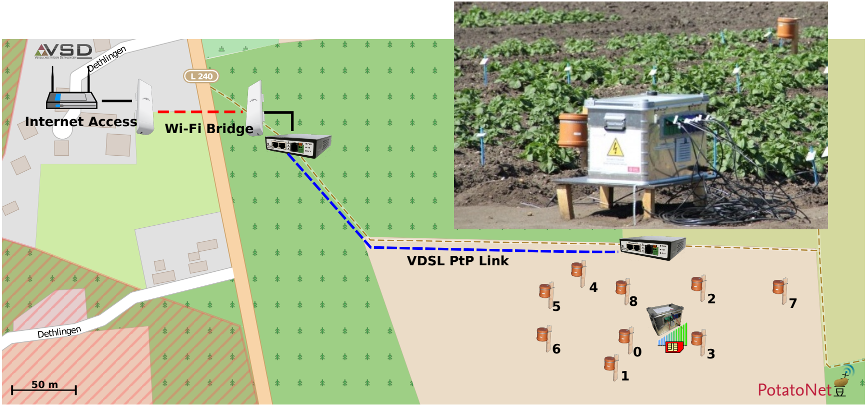

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Introduction – Proposed Approach

Convenient data handling – System overview

- Collection of *many* (potentially faulty) data elements at the sink

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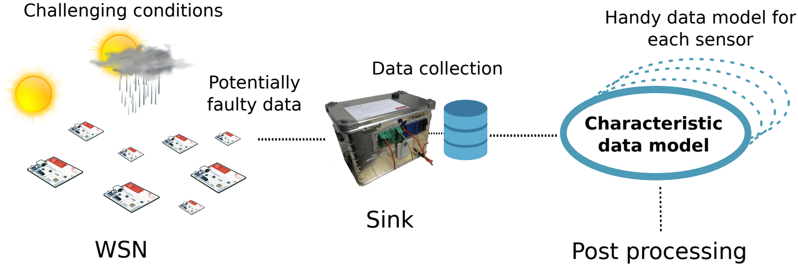
  $\rightarrow$ Generate a more handy data model for processing and storage

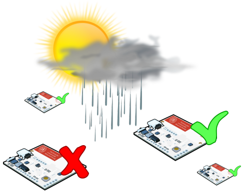


Data model – Motivation

Characteristics of data can be used to...

- detect errors

  → Unreliable sensing (challenging environment, undervolting, ...)



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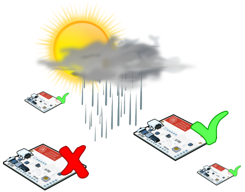

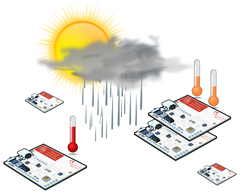

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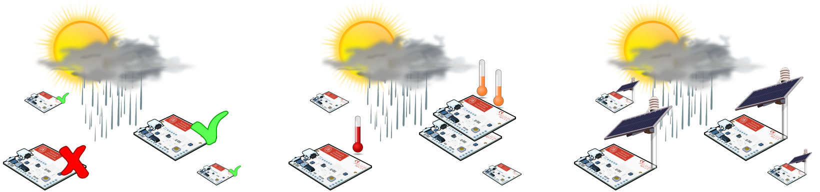
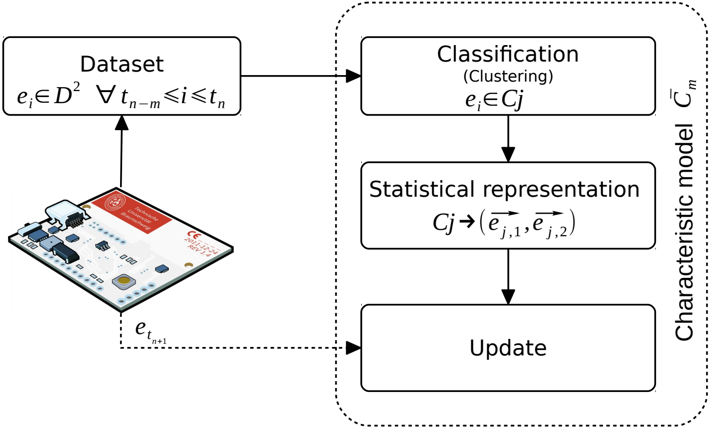
- predict further system states

  → Energy efficiency/budget can be predicted to schedule tasks



Course of action

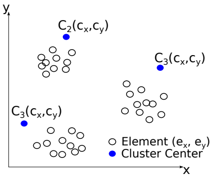
Generation of the characteristic data model



Data model – Classification of data

Classification using k-means algorithm

1. Generate potential clusters C_j with a random center $C_j(c_x, c_y)$.



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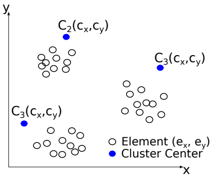

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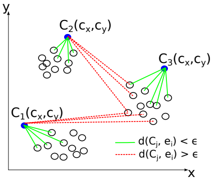

Step 2

Data model – Classification of data

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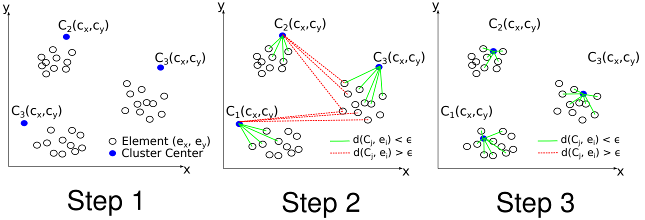
3. Assign elements to a cluster C_j and recalculate centroid of C_j



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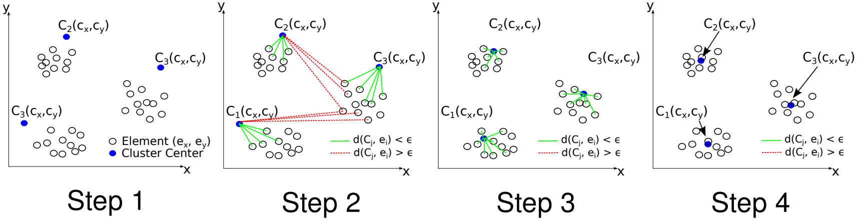
4. Repeat step 2 and 3 – add more C_j if necessary



Data model – Statistical representation

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1. Covariance matrix of the clusters elements

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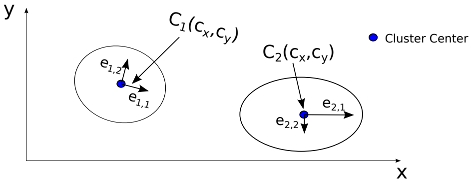
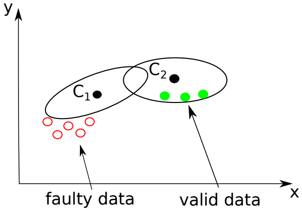
2. Solve $Cov_{C_j} - \lambda E = 0$ to get the eigenvectors $\vec{e_1}$, $\vec{e_2}$
   $\rightarrow$ Normalized eigenvectors represent the cluster C_j statistically



Characteristic model – Continuous update

Online update – Adding new sampled data

- Incoming data elements are added to pre-clustered dataset



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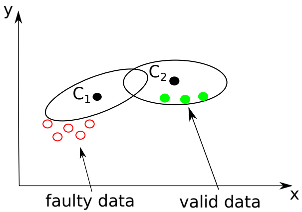

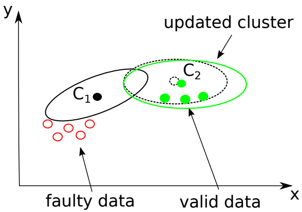

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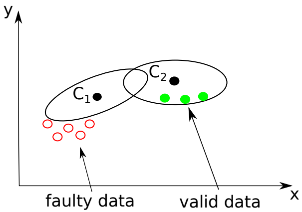

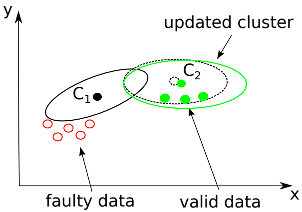

- Data model gets too tolerant after enduring update
  $\rightarrow$ Recalculate the characteristic model periodically

Characteristic model – Detection of invalid data

Check if an element is part of the characteristic model

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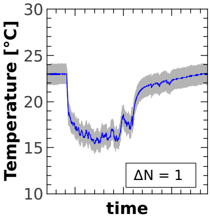
- Mahalanobis distance (considers covariance)

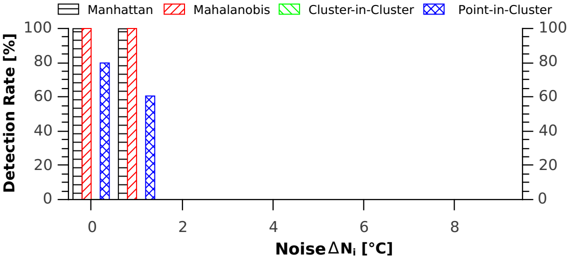
$$d_{Maha}(C_j, e_i) = \sqrt{\begin{pmatrix} c_x - e_x \\ c_y - e_y \end{pmatrix}^T Cov_{C_j}^{-1} \begin{pmatrix} c_x - e_x \\ c_y - e_y \end{pmatrix}}$$

Interim evaluation

Robustness of the characteristic model

- Calculate the characteristic model $\overline{C_m}$ of sample data
  1. Add noise $[0, N_i]$ to the sample data
  2. Feed $\overline{C_m}$ with noised data iteratively
  3. Update model





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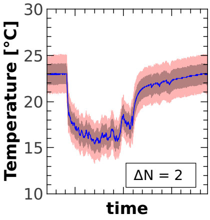

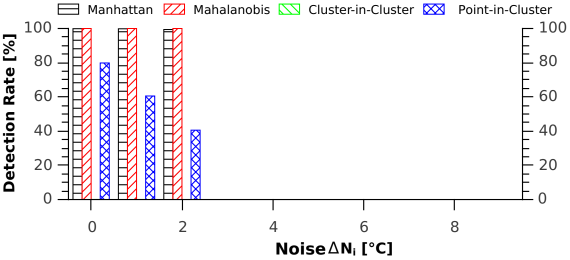

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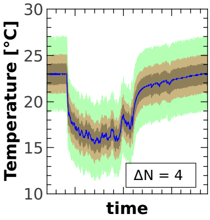

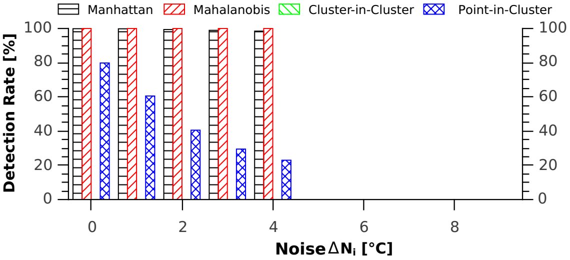

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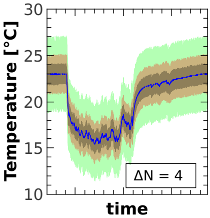

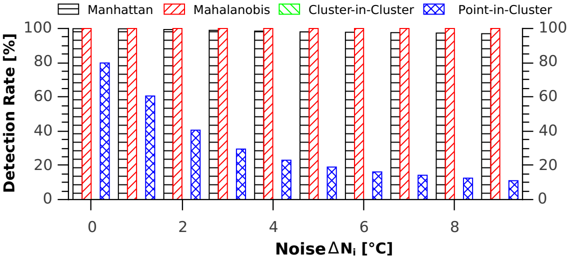

Functionality and evaluation

Real world experiment

- Temperature sensing with 4 nodes with 1Hz sampling rate (5 days)

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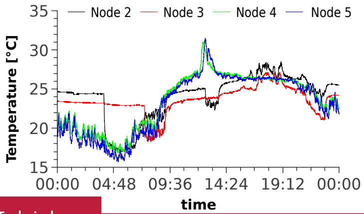
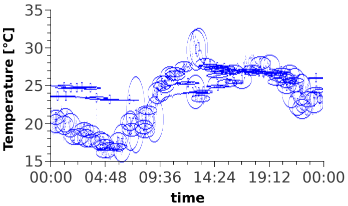
  $\rightarrow$ Exemplary results of 24h measurement

Node ID	Samples	Runtime	Iterations	Cluster
2	83162	429ms	17	22
3	83635	521ms	19	22
4	83592	581ms	22	28
5	83635	457ms	23	24





Sample application – Redundancy analysis

Detect redundancy between data

Overlapping areas of characteristic models imply redundant sensing

- Experimental setup: *node 4* and *node 5* located side by side
- Calculate intersection $S_{i,j} = \overline{C_i} \cap \overline{C_j}$

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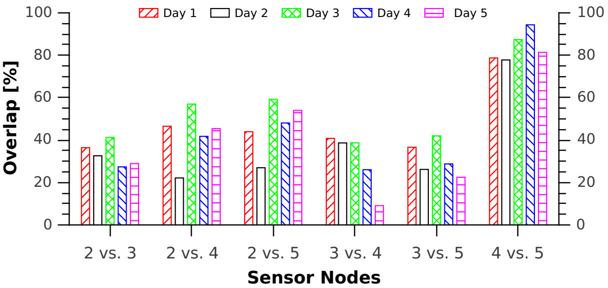

Summary and outlook

Goal: Convenient data handling of (potentially faulty) WSN data

- Unreliable sensing: environmental conditions, undervolting, ...

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- Next steps

  → Integrate the modelling of data to our PotatoNet testbed

Thank you for your attention! Questions?

Ulf Kulau

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