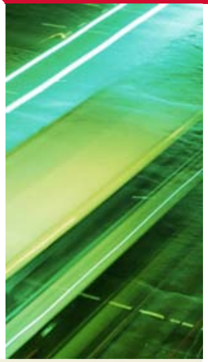
SFB 637
Autonomous Logistics



The minimum number of sensors
Interpolation of spatial temperature profiles in chilled transports

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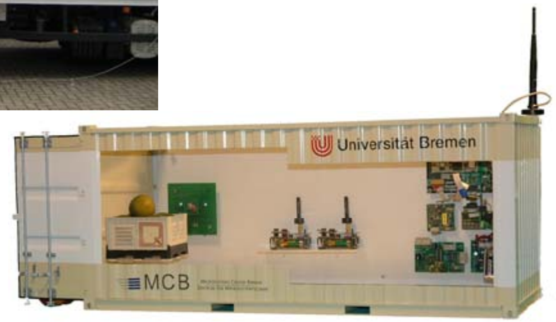
The intelligent container



The Question

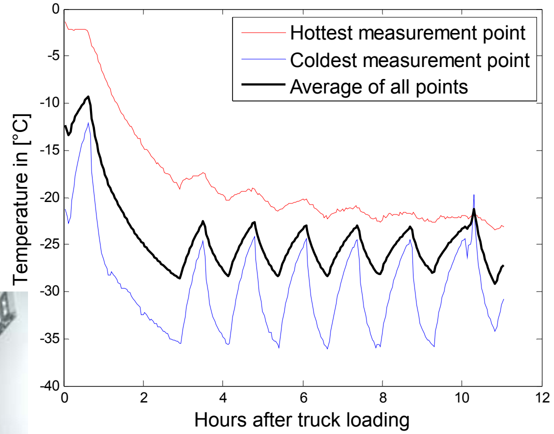
Supervision in food logistics

- **Problem:** Spatial temperature deviations of 5 Kelvin or more
- **Goal:** Predict temperature and resulting quality deviations for each box / pallet
- **Questions:**
  - Do we really need a sensor in each box / pallet?
  - Can we replace sensors by interpolation?
  - What is the minimum number of sensors?

Outline

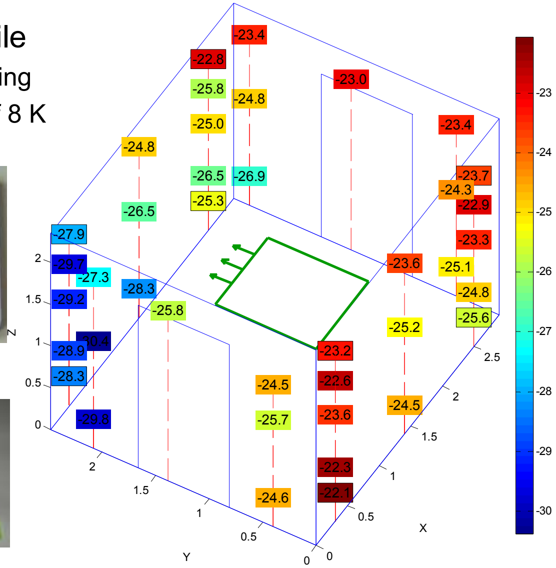
- Experimental test data set
  - Temperature profile of delivery truck
- Introduction into spatial interpolation / Kriging
- Prediction error
  - Compare methods
  - Dependency from number of sensors
- Additional applications of Kriging
  - Where to place to sensors?
  - Indicator for sensor faults

Experimental Data 1



Experimental Data 2

- Temperature profile
  - 8 hours after loading
  - Still differences of 8 K



Approach

How many sensors can be replaced by interpolation?

- → Split first data set:
  - Sensors only at a limited number of **Source Points (s)**
  - Predict value in **Destination Points (z)** points by interpolation
- Test case for future measurements
  - 8 source points → 32 destination points
  - 30 source points → 10 destination points
- Evaluate mean square error between prediction and measurement in destination points

Linear weighting of neighbor measurements

- How to predict temperature in destination points?

→ Linear combination of measurements at source points

- Repeated for each Sampling instance **(k)**, 265 in total

$$\hat{z}_i(k) = \sum s_j(k) \cdot w_{ij}$$

- Set up weighting factors w_{ij} by different methods
- Inverse Distance Weighting: $w_{ij} \sim \frac{1}{h_{ij}^2}$

Improved Method: Kriging

- Invented by German geologic engineer in 1950s
- Based on statics
- Best possible estimator
- **Assumptions:** Expected values are independent of position!
  - Expected value $\{s_i\}$ = const over space
  - Expected value $\{0.5\cdot(s_i\text{-}s_J)^2\}$ = Function of distance (h)
  - Isotropic **Variogram**

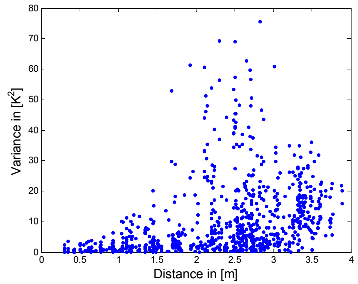
(General form: Distance **Vector**)

Experimental Variogram

- The critical part in Kriging:
  - Estimate Variogram by experimental data set

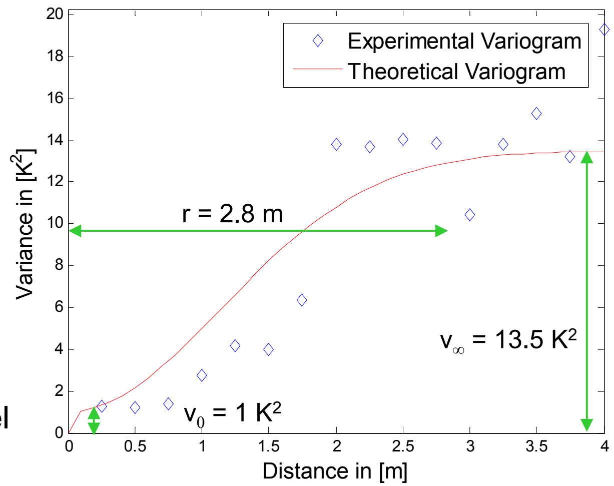
$$v = \frac{1}{2 \cdot N_k} \cdot \sum \left(s_i(k) - s_j(k)\right)^2$$

- Testing all possible combinations between our 40 measurement points
- Group data by distance



Theoretical Variogram

Gaussian Model $v(h) = v_o + (v_\infty - v_0)\cdot\left(1 - e^{-(3h/r)^2}\right)$



Other Models:

- Exponential Model
- Spherical Model

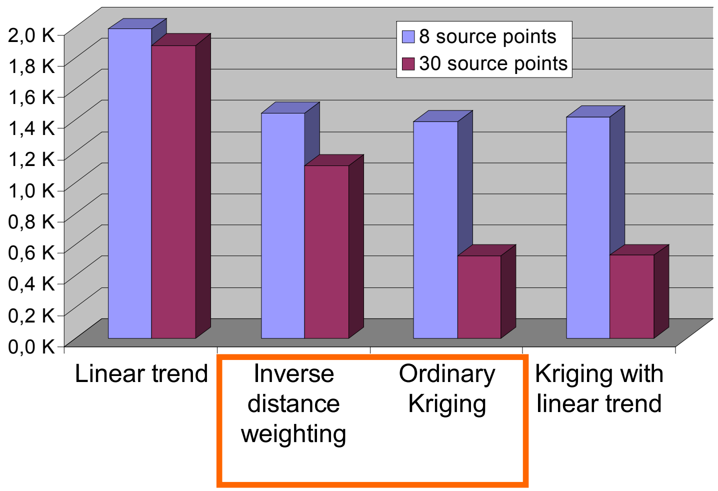
Calculation of weighting coefficients

- Solve set of linear equations
- Coefficients given by Variogram values for distances between source and destination points

$$\begin{bmatrix} v_{1,1} & & v_{1,N_S} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ v_{N_S,1} & \dots & v_{N_S,N_S} & 1 \\ 1 & \dots & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} w_{1,q} \\ \vdots \\ w_{N_S,q} \\ \mu \end{bmatrix} = \begin{bmatrix} v_{1,q} \\ \vdots \\ v_{N_S,q} \\ 1 \end{bmatrix}$$

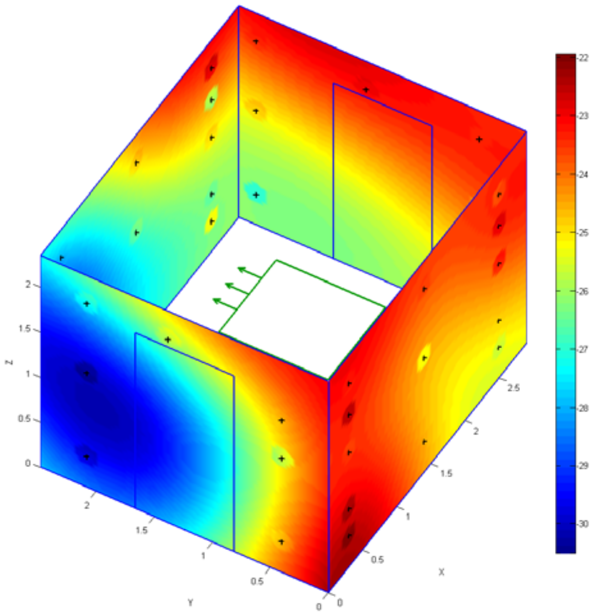
Variogram values | Weighting factors | Variogram values

Comparison of methods



Surface Diagram

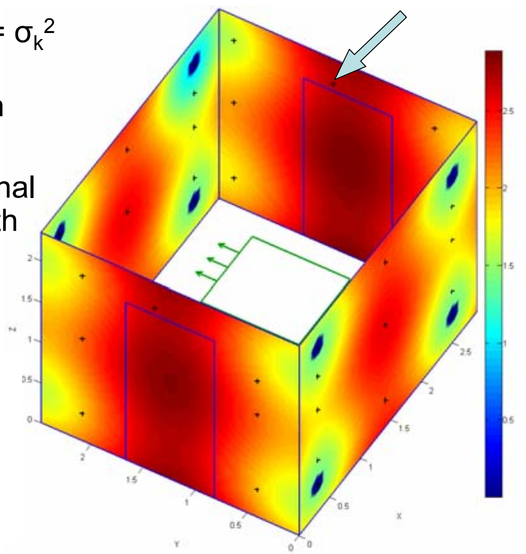
- Take surface grid as destination points
- Color spots indicate sensor tolerances



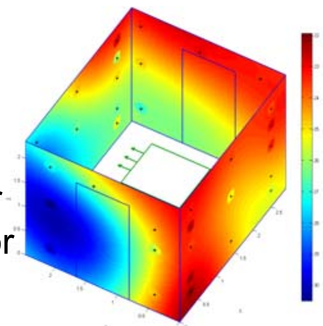
Kriging Variance

- Kriging Variance = σ_k^2
- σ_k gives expected error for prediction
- 8 source points
- Place new additional sensor at point with highest KV

$$KV = \sigma_K^2 = \begin{bmatrix} w_{1,q} \\ \vdots \\ w_{N_S,q} \\ \mu \end{bmatrix}^T \cdot \begin{bmatrix} v_{1,q} \\ \vdots \\ v_{N_S,q} \\ 1 \end{bmatrix}$$

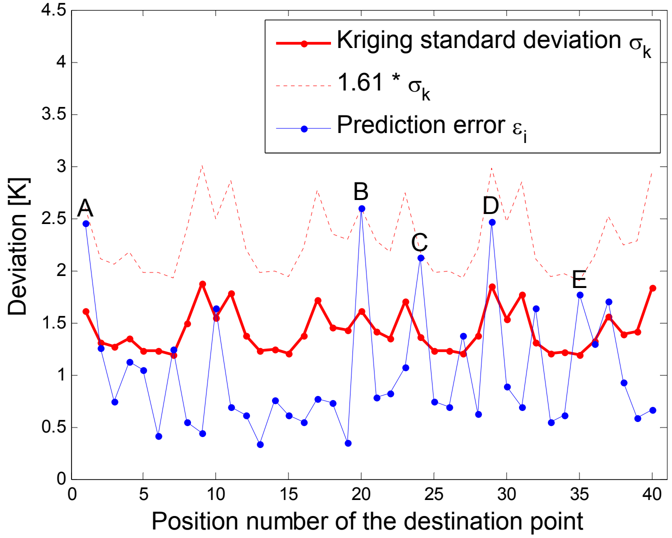


Test for sensor faults

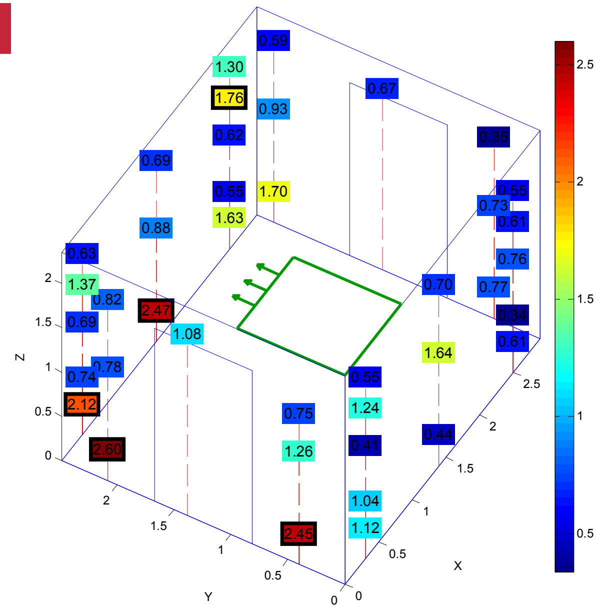


- Color spots indicate high tolerance or faulty sensors
  How can we judge on a sensor by comparison with its neighbor measurements?
  1. Calculate prediction: Take all sensors as source points except for the sensor under test
  2. Deviation ε_i between prediction and real measurement
  3. Set limit for ε_i by Kriging standard deviation σ_k
  4. 81 % of all ε_i should be $\leq 1.3 \cdot \sigma_k$

Compare prediction error

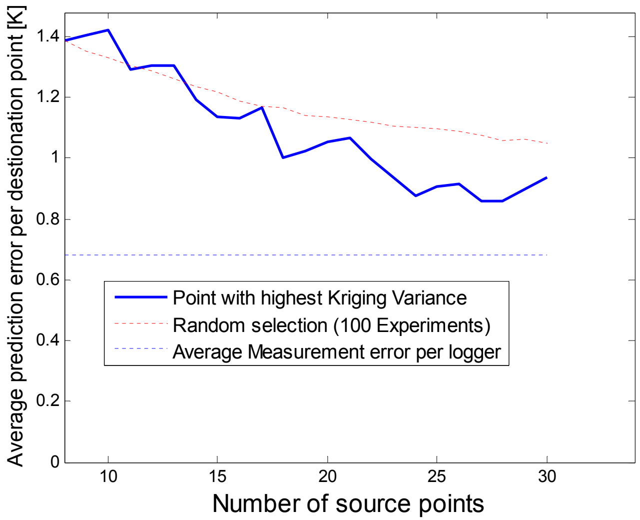


Prediction error 2



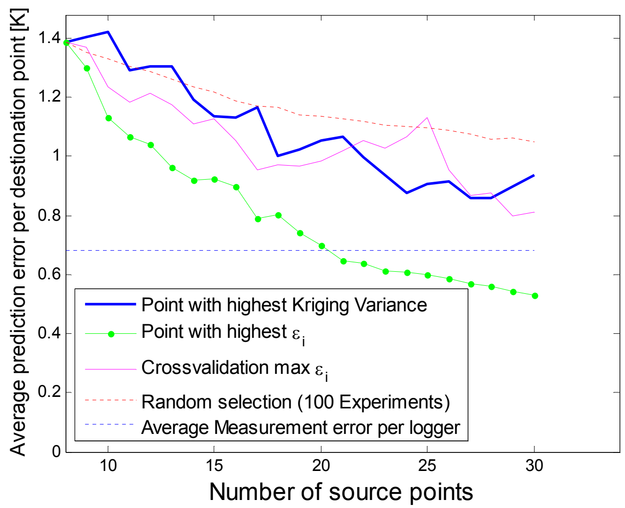
Adding points by Kriging Variance

- How many sensors required?
- Adding sensors one by one
- Calculate average ε_i



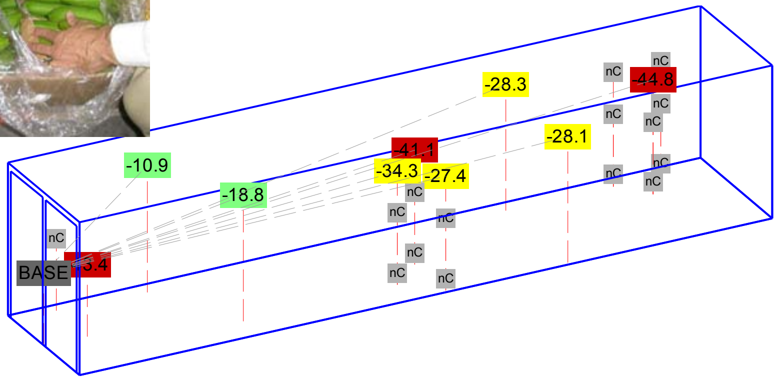
Other strategies for adding points

- Place new sensors in cold / hot spots
- Select new point to minimize average ε_i
- Works only if location of cold / hot spots does not change!



Reading range of wireless sensors

- Container with Bananas was equipped with wireless sensors
- Base station could read only 1/3 of all sensors
- RSSI Received signal strength indicator
- Multi hop protocol required to access all sensor nodes



Conclusion

- Avoid oversampling by to many sensors
- Kriging is a useful tool
  - Interpolation between measurement points
  - More accurate that Inverse Distance Weighting
  - Estimate prediction error by Kriging Variance
  - Fault detection
- Problem: At least one data set with a high number of measurement point required
  - Estimate Variogramm
  - Verify prediction
  - Works with 40 points, but will be problematic with less points

The End

Thanks for your attention
www.intelligentcontainer.com

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