SCAN: Multi-Hop Calibration for Mobile Sensor Arrays

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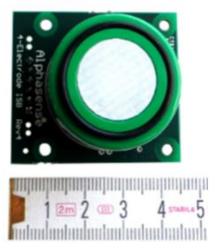
Mobile Air Pollution Monitoring

- Mobile air quality sensors collect vast amounts of measurements with high resolution

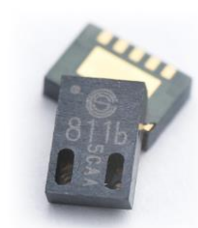
Air pollution measurements collected by Google Streetview cars in Oakland, CA

- Low cost air pollution sensors

SGX Sensortech MiCS-OZ-47 O_3



AlphaSense CO-B4



ams CCS811

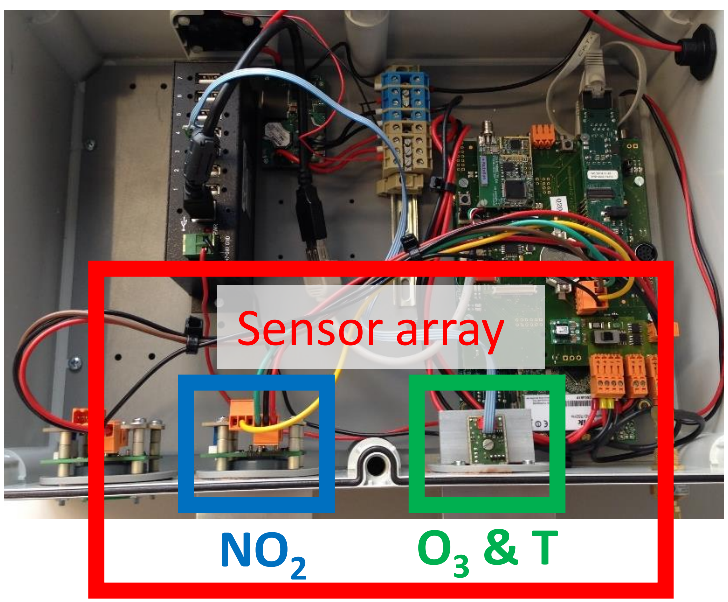
Honeywell Particle Sensor

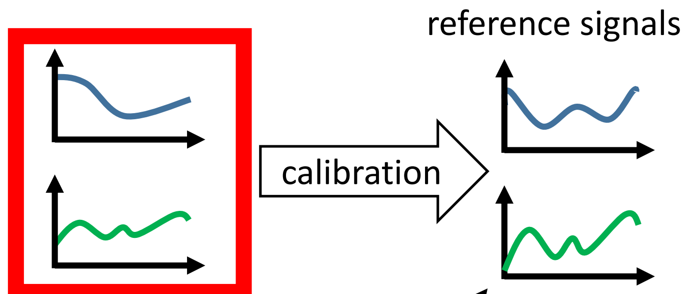
Figaro TGS8100

Reliable long-term monitoring with mobile low-cost sensors is challenging!

Sensor Array Calibration

- **Problem 1**: Low-cost sensors suffer from **low selectivity** and dependencies on meteorological conditions
- **Solution**: Sensor array calibration
  - Compensate for cross-sensitivities by augmenting multiple low-cost sensor and collectively calibrate the signals to references
- State-of-the-art: Multiple Least Squares (MLS) based regression





calibration matrix → $$B \cdot X = Y + N$$ ← calibration error

Real-world example: A sensor array reduces the NO_2 measurement error by a factor of 2 compared to a single NO_2 sensor

Multi-Hop Calibration

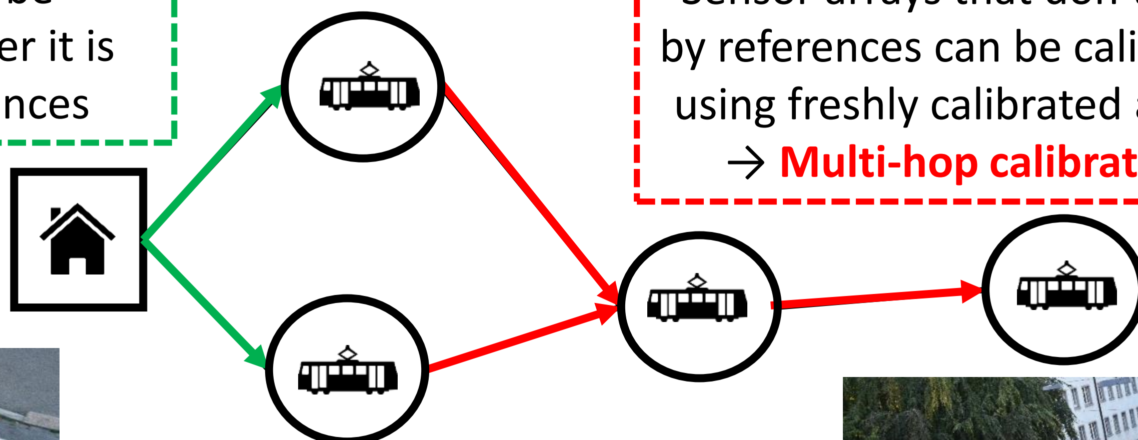
- **Problem 2**: Due to ageing effects and changing environmental conditions sensor arrays need **frequent recalibration**
- **Solution:** Opportunistic calibration during sensor rendez-vous

A sensor array can be calibrated whenever it is in vicinity of references

Sensor array

Sensor arrays that don't pass by references can be calibrated using freshly calibrated arrays
→ **Multi-hop calibration**

High quality references

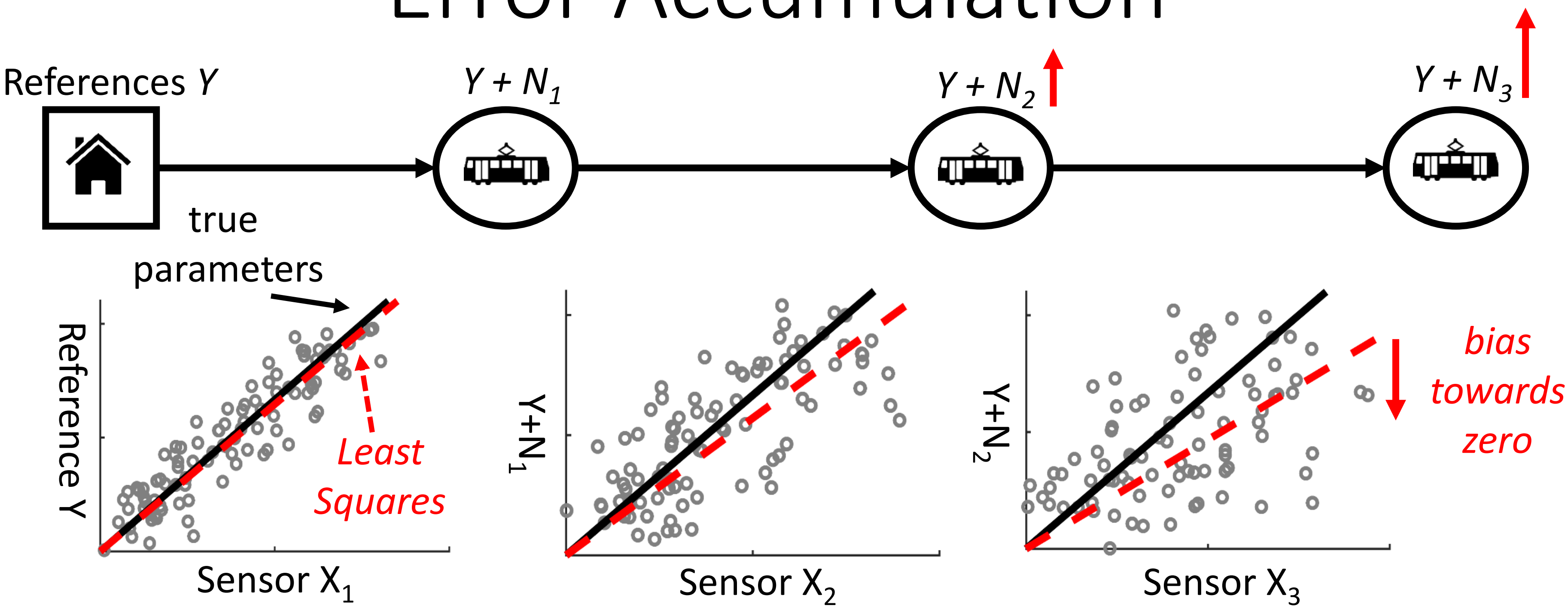


Sensor array on top of streetcar

Rendez-vous between array and references

Rendez-vous between two arrays

Error Accumulation



- Least Squares based regression suffers from error accumulation over multiple hops
  - Due to *regression dilution*, also known as *bias towards zero*
- Saukh et al. [IPSN15]: Geometric Mean Regression (GMR) minimizes error accumulation
- **Problem**: GMR is a single-variable model
  - Not applicable for sensor arrays
  - Poor performance when used to calibrate a cross-sensitive sensor

Our Solution

	One-hop calibration	Multi-hop calibration
Sensor array calibration	Multiple Least Squares	SCAN
Single sensor calibration	Ordinary Least Squares	Geometric Mean Regression

- SCAN: Sensor Array Network Calibration
  - Multi-variable regression model applicable to typical **sensor arrays**
  - Minimizes error accumulation when applied to **multi-hop calibration**

SCAN: Sensor Array Network Calibration

$$\min_{B} tr\left((Y - B \cdot X)(Y - B \cdot X)^T\right)$$
$$\text{subject to} \quad BXX^TB^T = YY^T$$

- SCAN minimizes the **least squares error** with a novel **constraint** on the parameters B
- A **unique and closed-form** expression of the calibration matrix B always exists
- For single sensor calibration, i.e. a single variable regression problem, SCAN and GMR yield the same solution

Calibration Matrix B

- Applicable to calibration matrizes *B* with **general form**
  - For instance, there are not always the same set of references signals available as low-cost sensor signals:

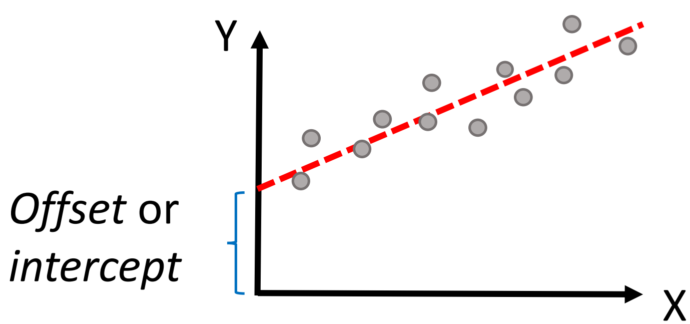
$\in \mathbb{R}^{2 \times 3}$

$$B \cdot X = Y + N$$

NO_2, O_3 and T

NO_2 and O_3

- SCAN can calculate an offset regression term similar to MLS



No Bias Towards Zero

- Contraint is able to completely remove error accumulation if the error components *N* of both arrays exhibit the same covariance matrix

$$B\overbrace{(XX^T+\underbrace{\boxed{NN^T}})}^{\text{Uncalibrated array}}B^T = \overbrace{YY^T+\underbrace{\boxed{NN^T}}}^{\text{Calibrated array}}$$

compensated

  Although in reality the two covariance matrices are usually similar but not perfectly identical, SCAN is still minimizing error accumulation

- More details and proofs are in the paper

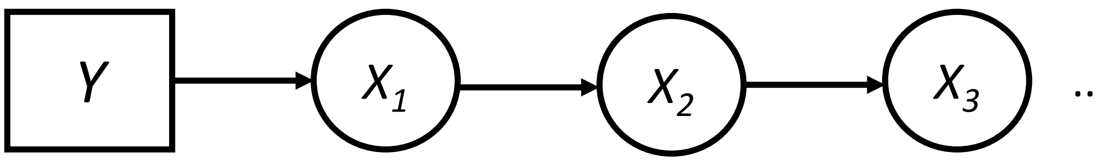
Evaluation: Simulation

- We artificially generate sensor arrays X_i with

$$X_i = B^{-1}(Y_i + N_i)$$

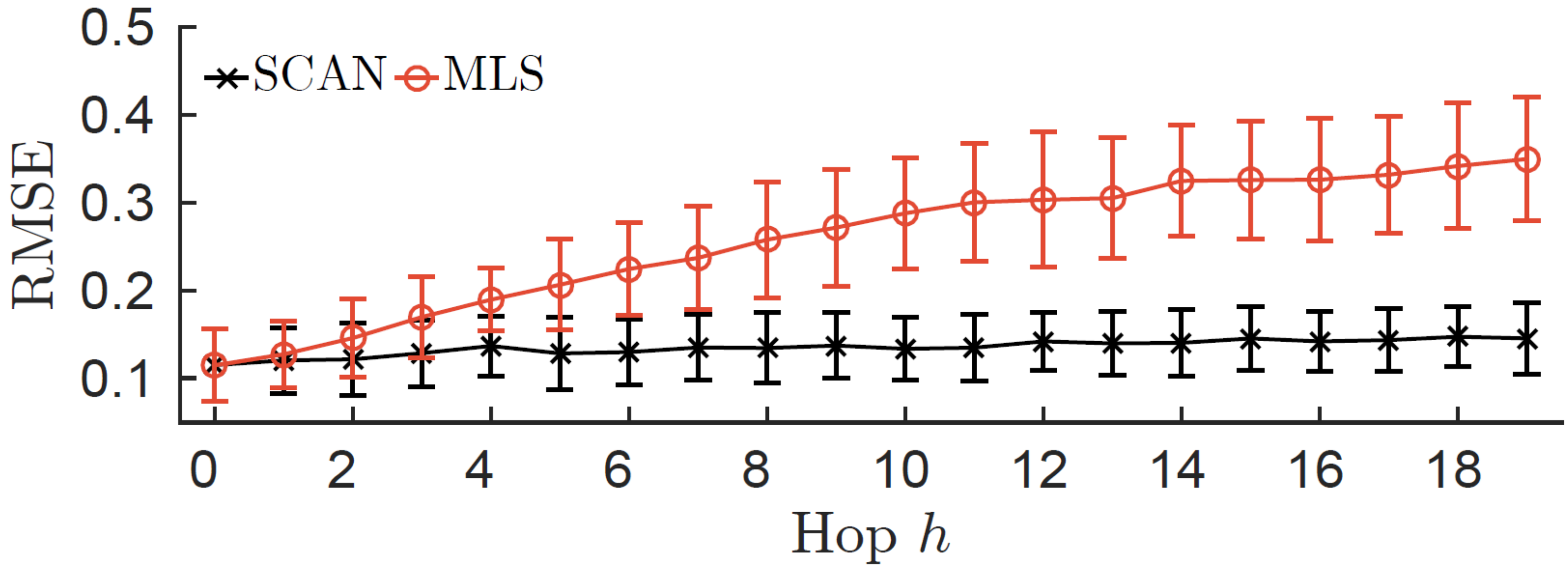
typical calibration matrizes *4 reference signals* *typical error components*

- Sensor arrays X_i form a calibration path



  - X_1 is calibrated to reference Y
  - X_2 to virtual reference provided by calibrated array X_1
- 500 samples for training, 500 samples for testing

Results: Simulation



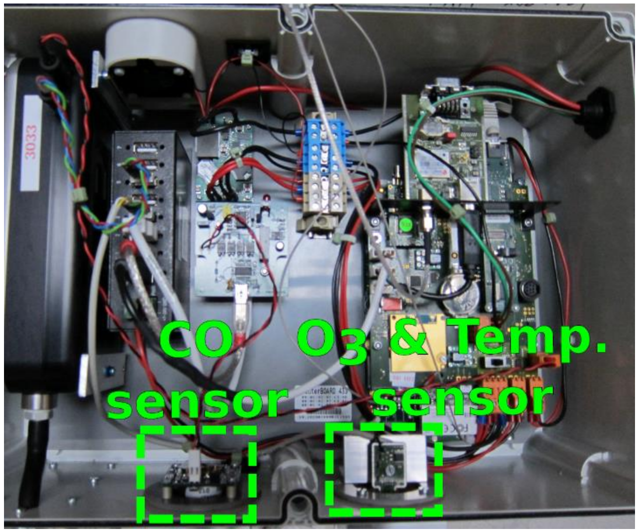
- Over a 20 hop calibration path SCAN clearly outperforms multiple least-squares
- MLS only performs better in the first hop

Comparison with Other Methods

Method	Hop = 0	Hop = 5	Hop = 19
SCAN	0.12	**0.12**	**0.14**
Multiple least squares (MLS)	**0.11**	0.21	0.34
Geometric mean regression (GMR)	0.4	0.54	0.54
Total least squares (TLS)	0.14	0.62	4.2
Neural Networks	0.19	>100	>100
GMR Generalization by Draper	0.13	0.24	0.34
GMR Generalization by Tofallis	0.14	0.25	0.35

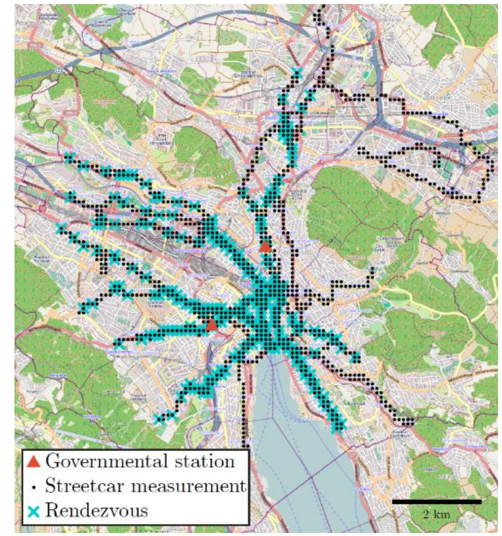
- As expected GMR performs poorly when applied to cross-sensitive sensors
- Over multiple hops SCAN outperforms all other methods

Evaluation: Streetcar Deployment



Sensors

Box on streetcar



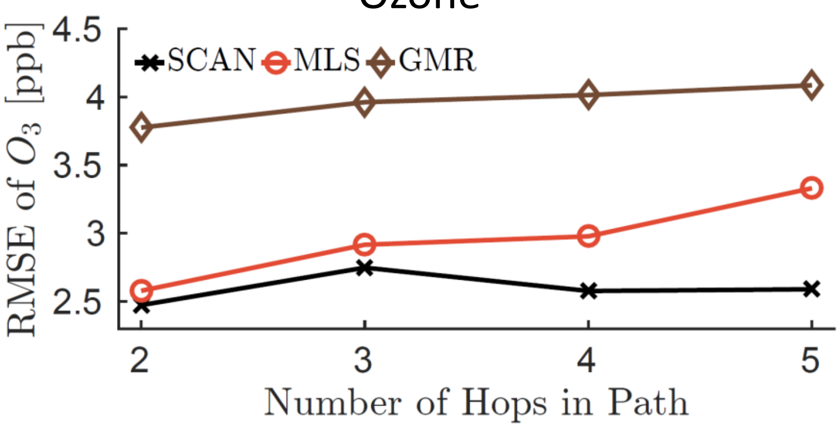
Measurement coverage

- 7 sensor arrays deployed on streetcars in the city of Zürich, Switzerland
  - Ozone (O3), carbon monoxide (CO) and temperature sensor
  - Gas sensors suffer from substantial meteorological dependencies
- Reference measurements provided by two governmental stations
- 56 Mio. measurements recorded between 03/2014 and 03/2016
  - Trained on at least 200 within 4 weeks
  - Tested on data from consecutive 4 weeks

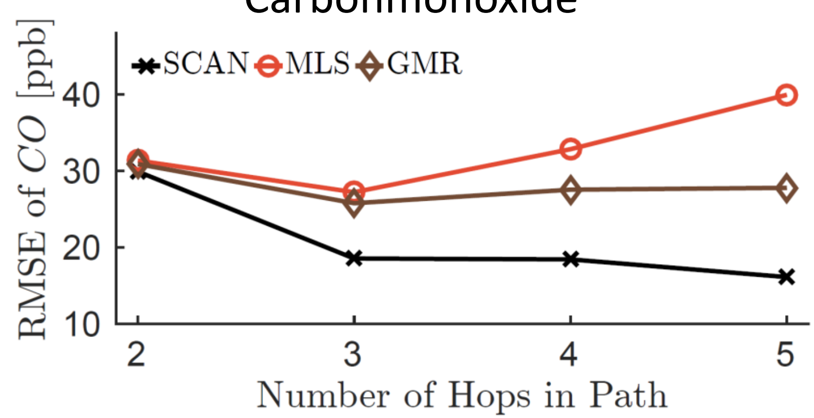
Results: Streetcar Deployment

- Network-wide calibration
  - At most three streetcars pass by reference stations
  - Multi-hop calibration allows to calibrate all seven streetcars in 94% of all months
- SCAN outperforms GMR by up to 42% and MLS by up to 60% over 5 hops

Ozone



Carbonmonoxide



Conclusion

- Multi-hop sensor array calibration is a powerful tool to provide reliable data over long time periods in mobile low-cost sensor deployments
- We propose SCAN, novel constrained multi-variable linear regression technique that
  - calibrates sensor arrays and
  - reduces error accumulation over multiple hops
- Evaluation based on two different datasets show that SCAN is able to outperform different calibration techniques

Thank you!
Questions?

Streetcar data is publicly available:

www.opensense.ethz.ch

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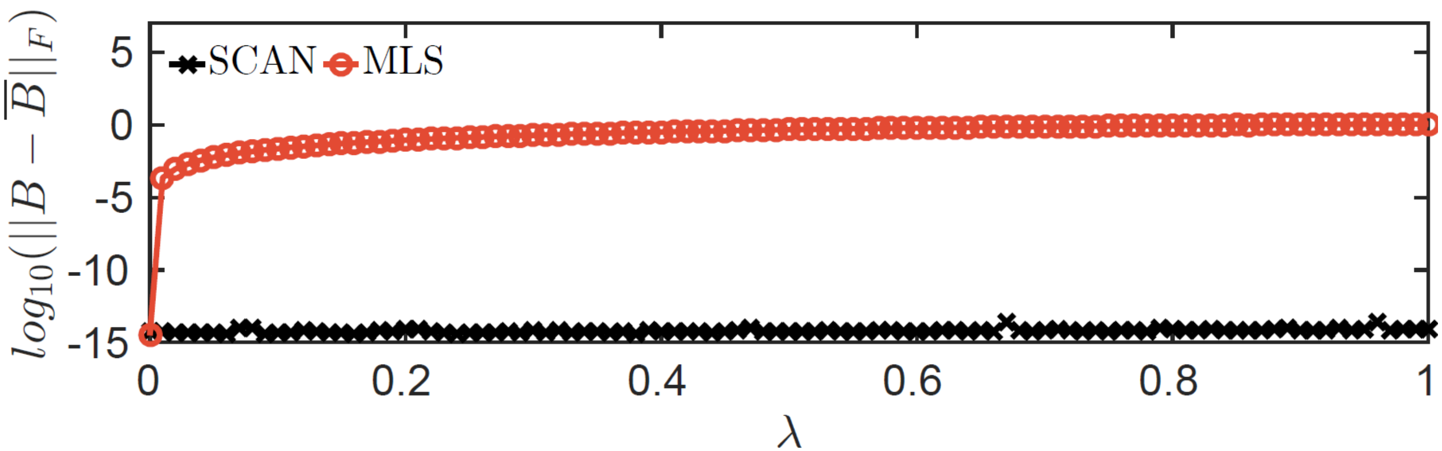
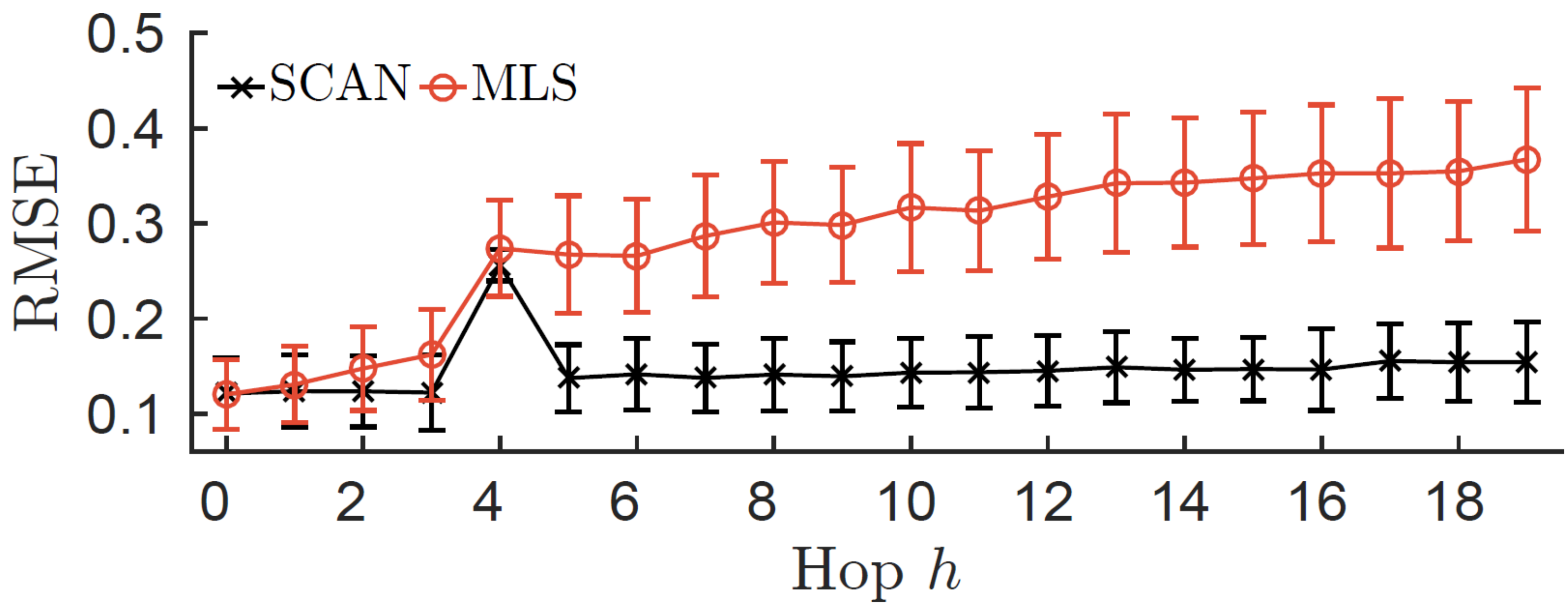
Backup: No Bias Towards Zero

- If calibration error is uncorrelated, i.e. $NN^T = \sigma I$ SCAN is able to recover the true underlying calibration matrix B
- Simulation:

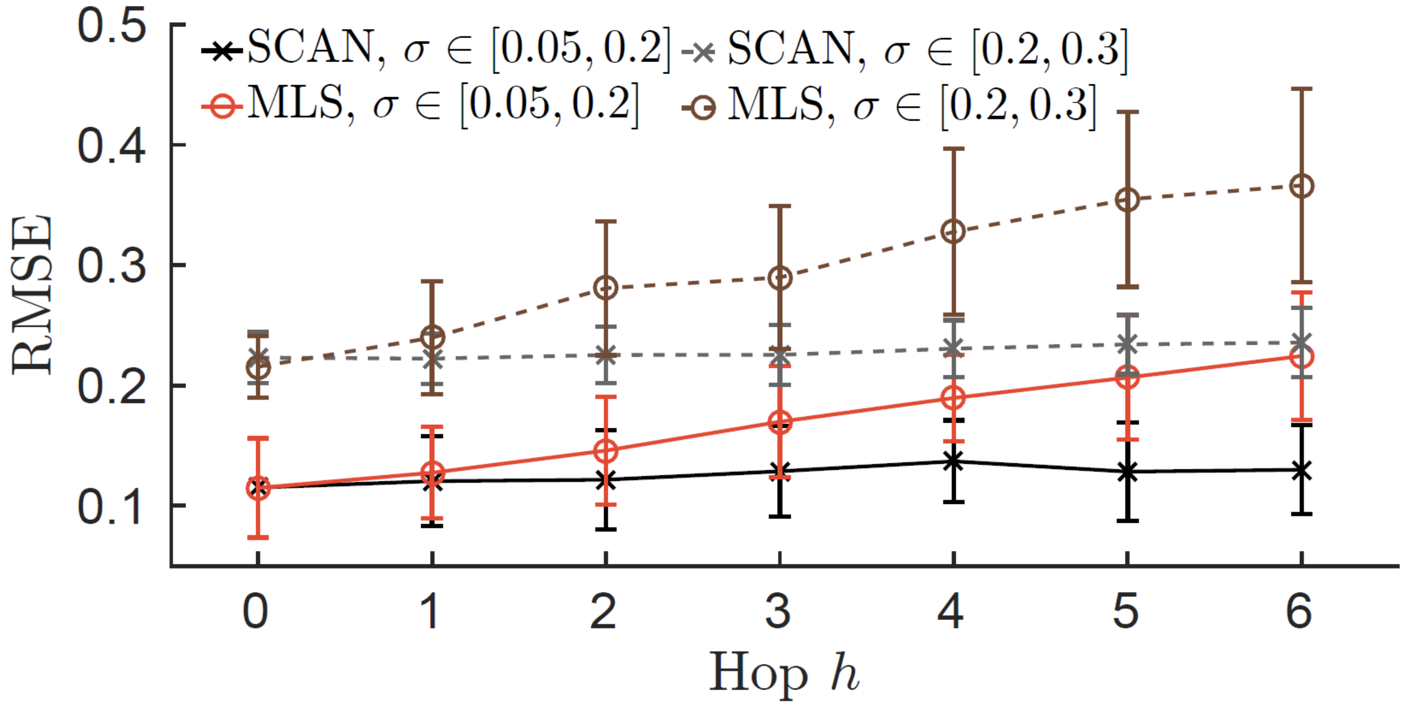


Backup: Increased noise variance



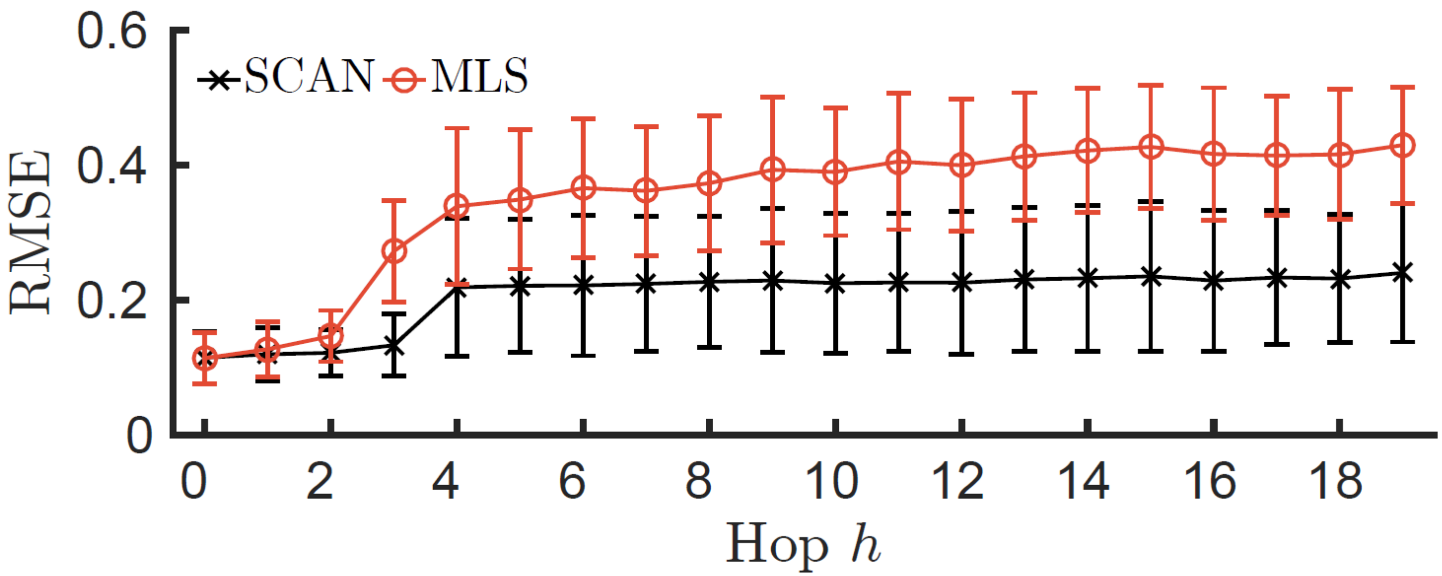
Increased noise in measurements (2x standard deviation) of node 4 has no effect on nodes after hop 5

Backup: Noise Independence



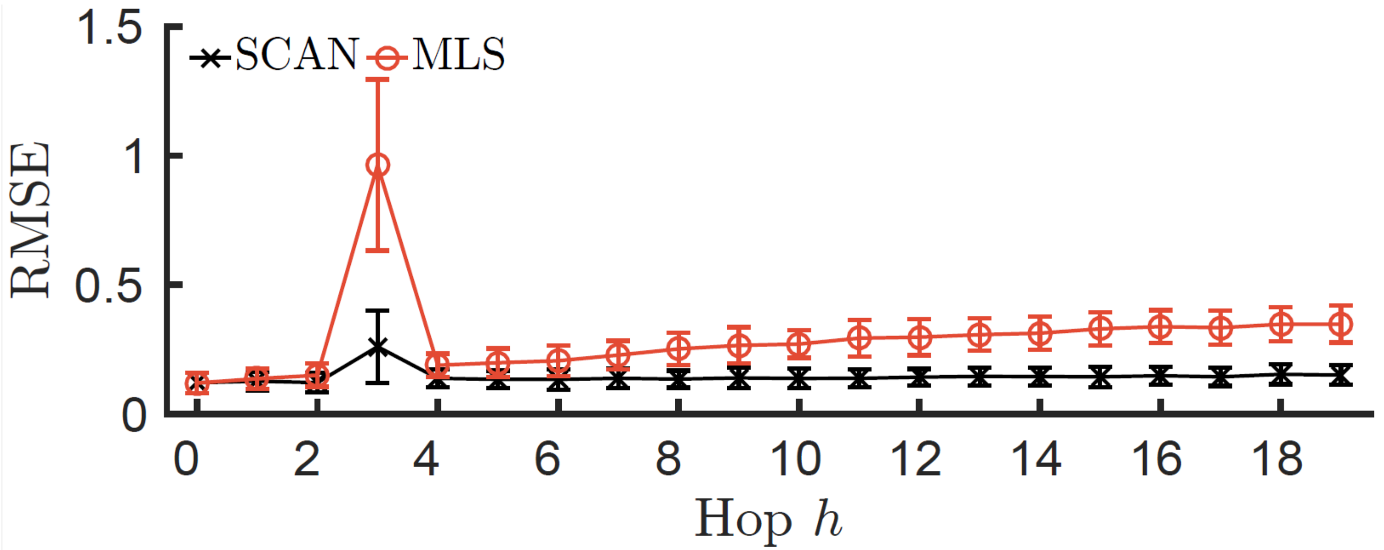
Increased noise in measurements has only an effect on the average calibration error but not on the error accumulation

Backup: Measurement range 1/2



- 3x smaller measurement range of rendezvous between array 3 and 4
- Measurement range = interval defined by the smallest and highest absolute value of the phenomena measurements
- General problem for any method due to missing training data

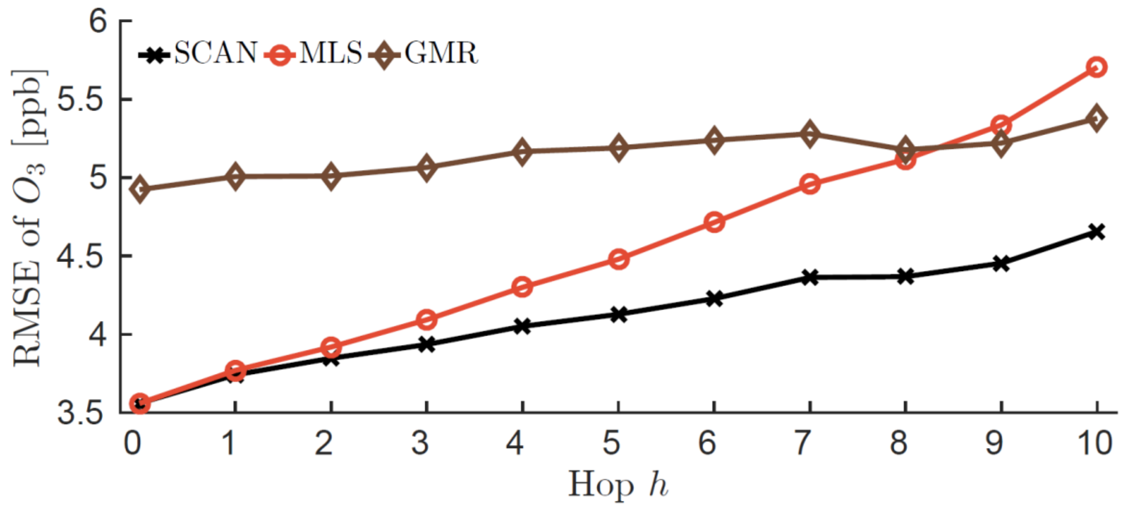
Backup: Measurement Range 2/2



- 3x higher measurement range of rendezvous between array 3 and 4
- Only affects array 4, because calibration paramters are only vaild for the measurement range of all other arrays

Backup: Metaloxide Sensors

- Calibration path with 11 sensor arrays consisting of
  - 2 different metaloxide low-cost gas sensors
  - 1 temperature sensor
- Deployed next to high quality reference station in Switzerland
- Calibrated to ozone (O3) provided by reference station
- 10 Mio. samples recorded between 07/2015 and 07/2016
  - 200 samples for training within two weeks
  - 200 samples for testing within consecutive two weeks



Over all hops SCAN achieves a 16% to 38% smaller error than GMR and an up to 23% smaller error than MLS

Backup: Typical Calibration Error

- Based on metal-oxide sensors
- Variance of calibration error shows strong similarity to diagonal matrix