Position Estimation of BLDC Motors Using Gaussian Processes

Bachelor Student: Fabian Sordon
Supervisors: Ajit Basarur, Jana Mayer
Referee: Uwe D. Hanebeck

Intelligent Sensor-Actuator-Systems Laboratory (ISAS),
Institute for Anthropomatics and Robotics,
Karlsruhe Institute of Technology (KIT),
Karlsruhe, Germany

Karlsruhe Institute of Technology

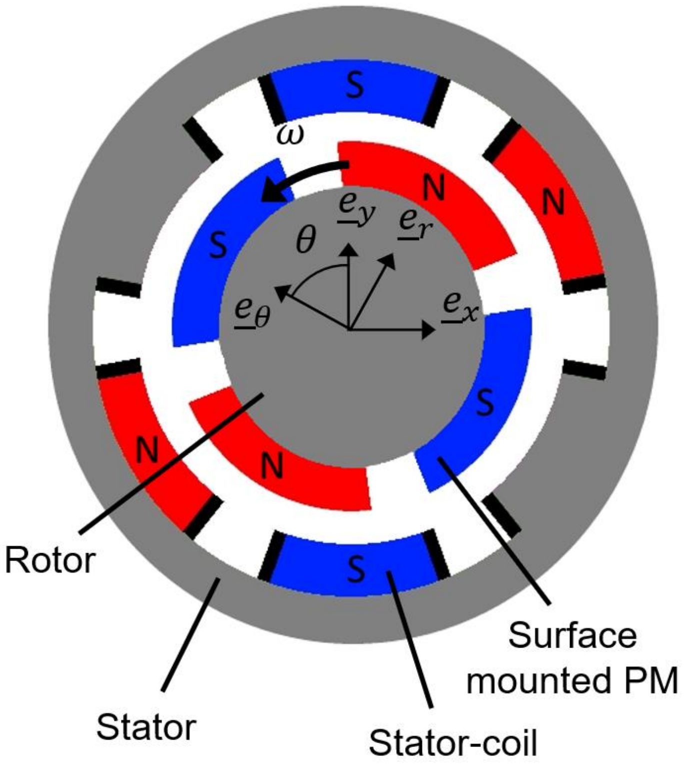
http://isas.uka.de

Intelligent Sensor-Actuator-Systems

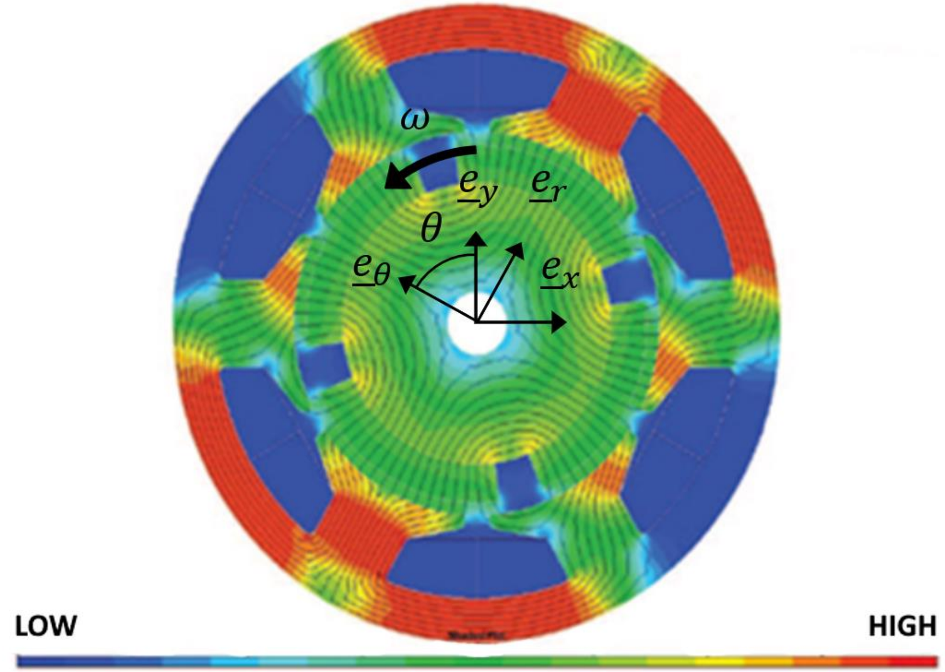
Motivation

Target: We want to estimate the position and speed of BLDC motors by measuring the magnetic field of the rotor

Typical BLDC Motor:



FEM Simulation of B-field in X-/Y-Direction [1]



→ B-field within the area of the rotor is weakly affected by the stator current

Sources: [1] https://www.researchgate.net/publication/236667263_Electrically_Actuated_Thrusters_for_Autonomous_Underwater_Vehicle

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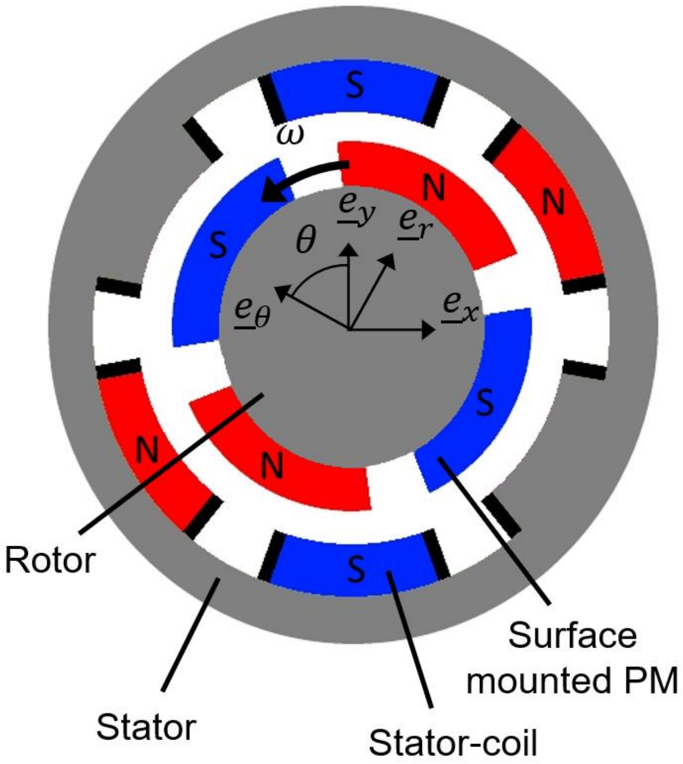
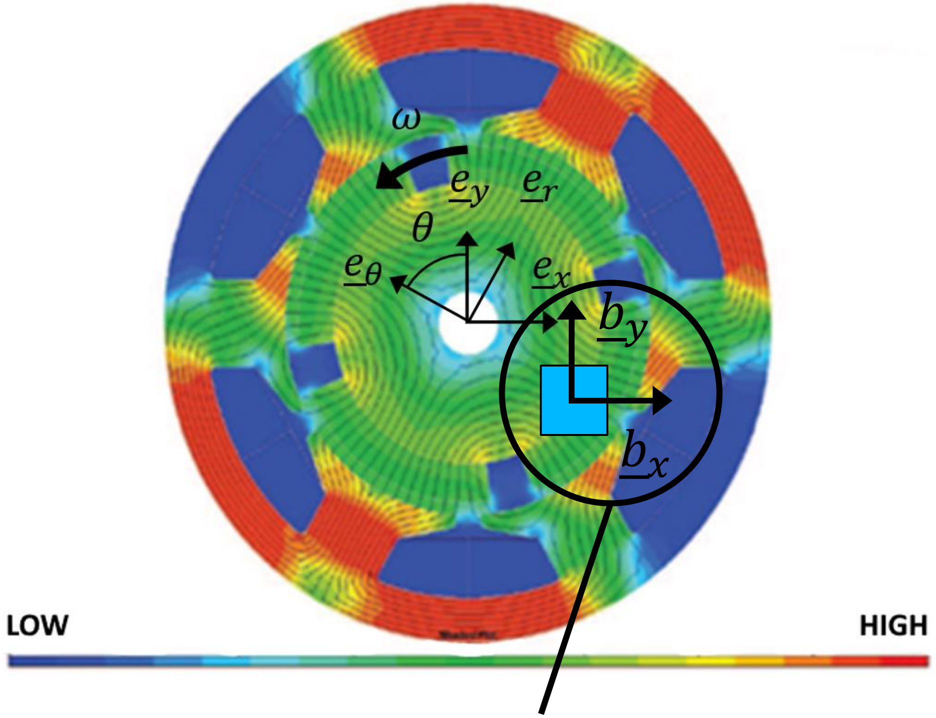


FEM Simulation of B-field in X-/Y-Direction [1]



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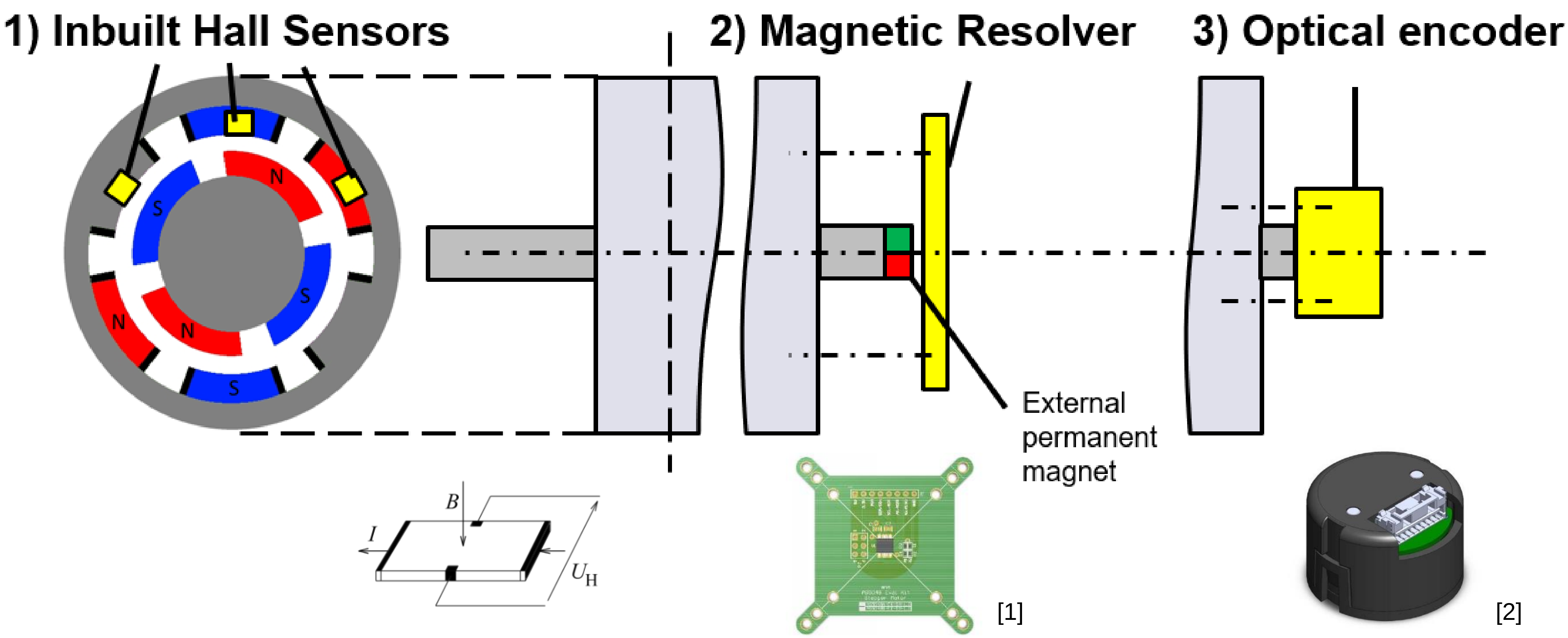
Agenda

1. **State of the Art**
2. **The Position Estimation Approach**
   - Experimental Setup
   - Regression of Training Data
   - The Kalman Filter
3. **Evaluation**
4. **Conclusion**
5. **Outlook**

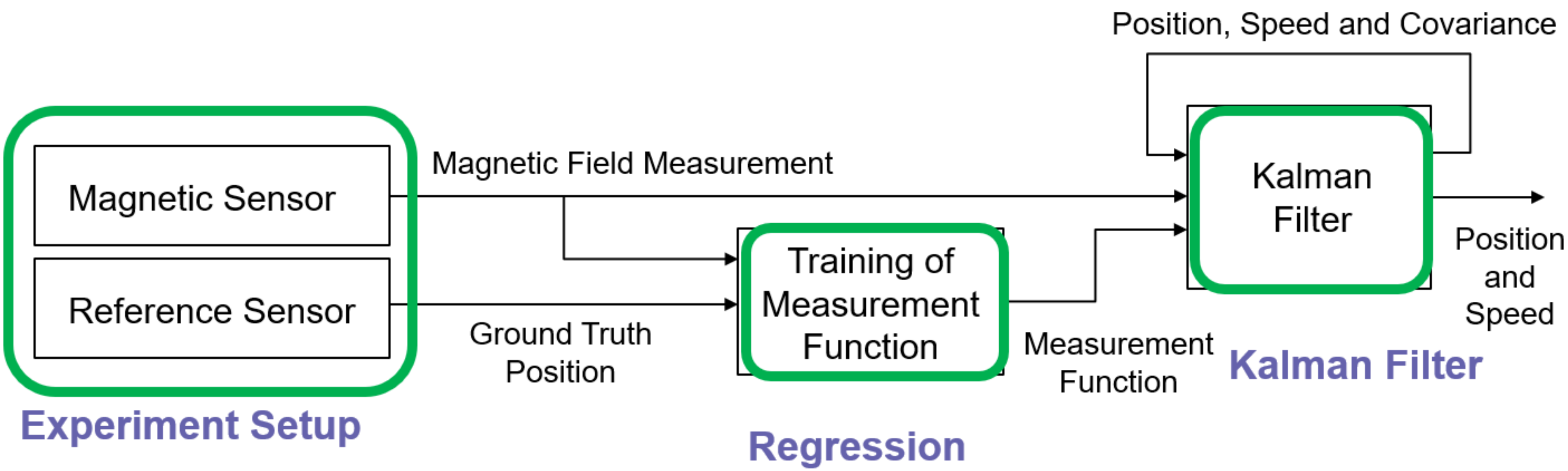
1. State of the Art - Angular Position Sensors



	Inbuilt Hall Sensors	Magnetic Resolver	Optical Encoder
Sensing Principle	Hall-effect	Hall-effect	Optical sensing through code disc
Accuracy	Middle	High	Very high
Speed Sensing?	No	No	No

Sources: [1] https://www.mouser.de/datasheet/2/588/ams_AS5048-EK-AB-STM1-1214674.pdf
[2] https://www.trinamic.com/fileadmin/assets/Products/Encoder_Documents/TMCS-28_datasheet_Rev1.00.pdf

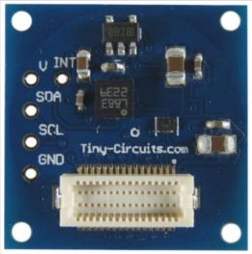
2. The Position Estimation Approach - Overview



2. Experimental Setup: Sensor Selection

TinyShield Compass HMC5883L

[1]



- 3-axis measurement of the magnetic field
- +/- 8 gauss range
- Digital output, 200 Hz sample rate

No high speed applications

HMC1052L Analog Sensor

- 2-axis measurement of the magnetic field
- +/- 6 gauss range
- Analog output, 3 MHz bandwidth

High speed application

Reference Sensor: Optical Encoder 10000PPR

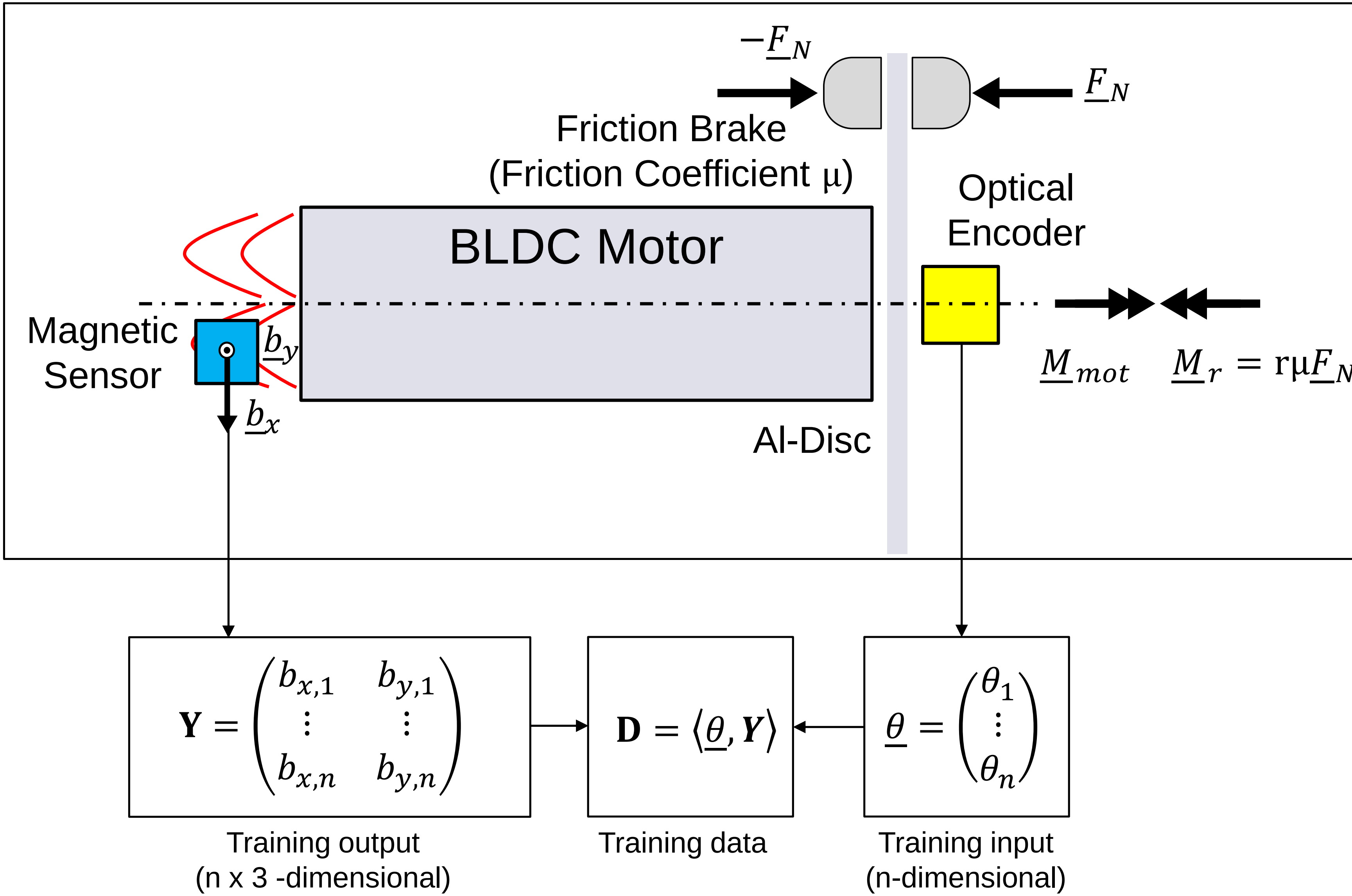
[2]

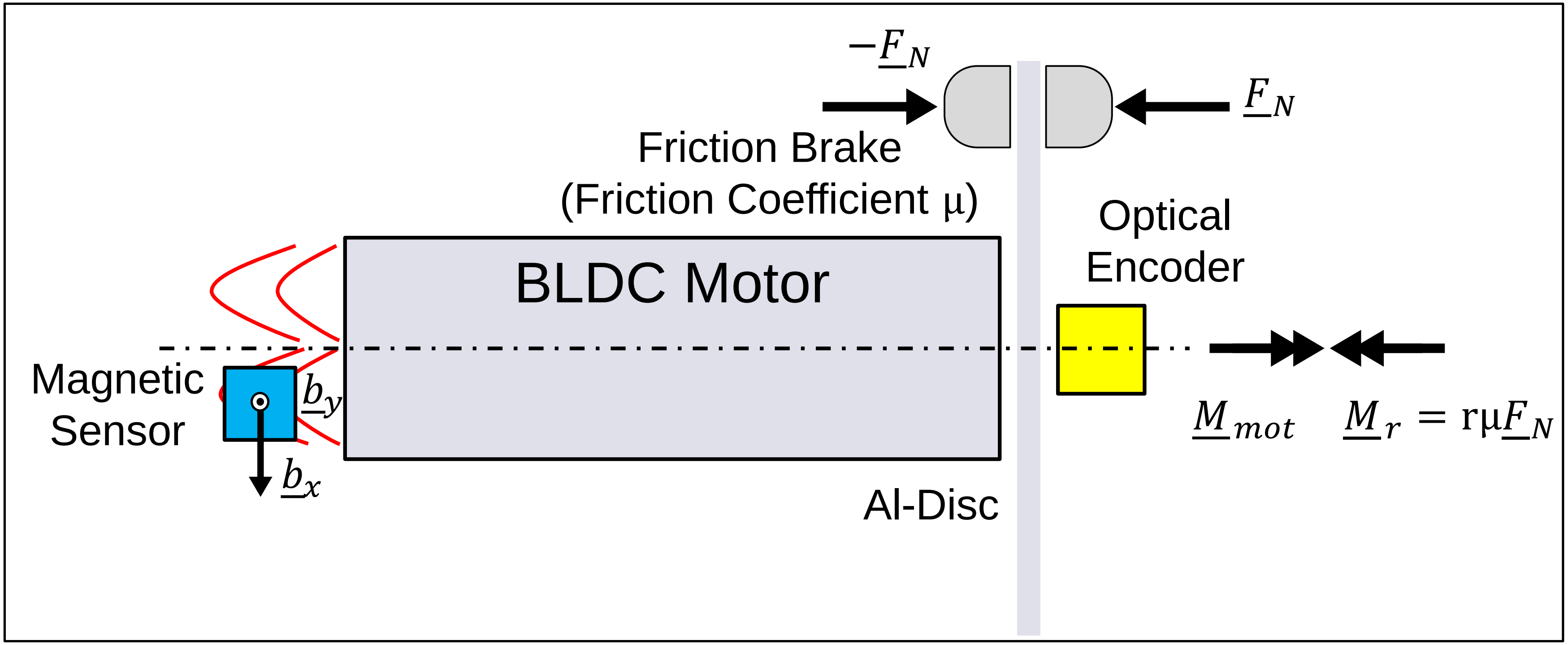
- ABZ-Interface
- Resolution: 40,000 steps per rotation

→ Assumption: Ground truth

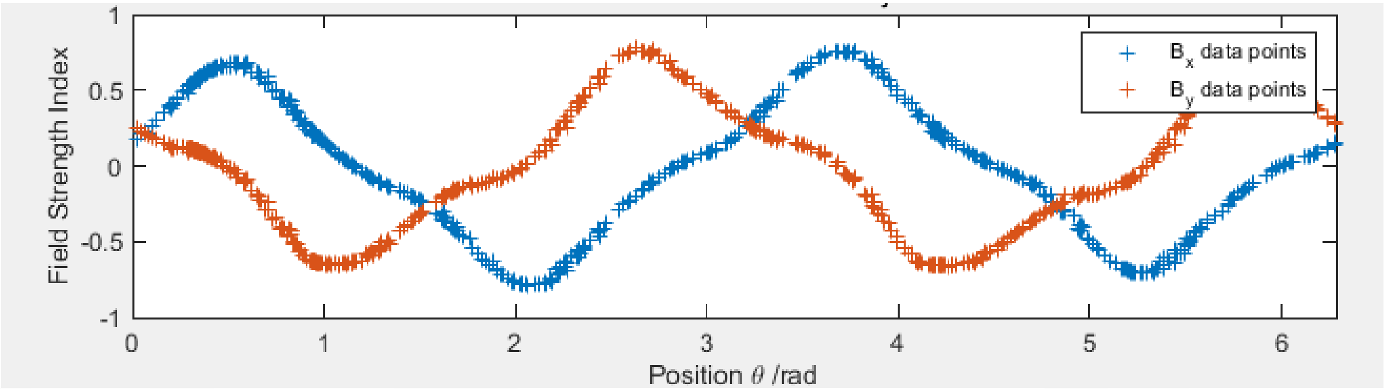
Sources: [1] https://www.mouser.de/datasheet/2/588/ams_AS5048-EK-AB-STM1-1214674.pdf
[2] https://www.trinamic.com/fileadmin/assets/Products/Encoder_Documents/TMCS-28_datasheet_Rev1.00.pdf

2. Experimental Setup: Overview





Visualization of a Training Set D



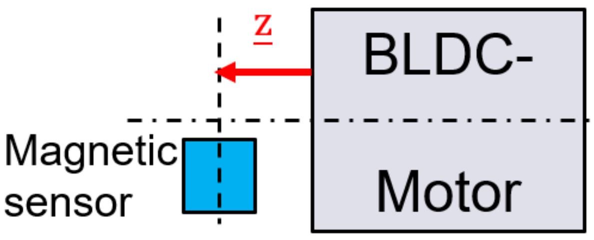
2. Experimental Setup: Sensor Positioning (1)

Target: Optimize signal-to-noise ratio (SNR) for Measurements

In axial direction (z-axis)

2 tendencies:
- ↑ distance → ↑ measurement noise
- ↓ distance → ↑ high signal amplitude

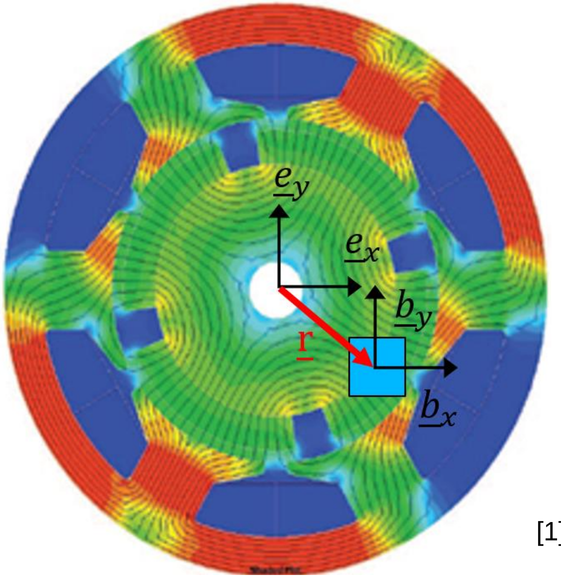
→ **Compromise:** $\|\underline{z}\| = 13mm$



In radial direction (x-/y-axis)

2 tendencies:
- ↑ distance → ↓ amplitude, ↑ noise
- ↓ distance → ↓ amplitude

→ **Compromise:** $\|\underline{r}\| = \sqrt{x^2 + y^2} = 10.6mm$

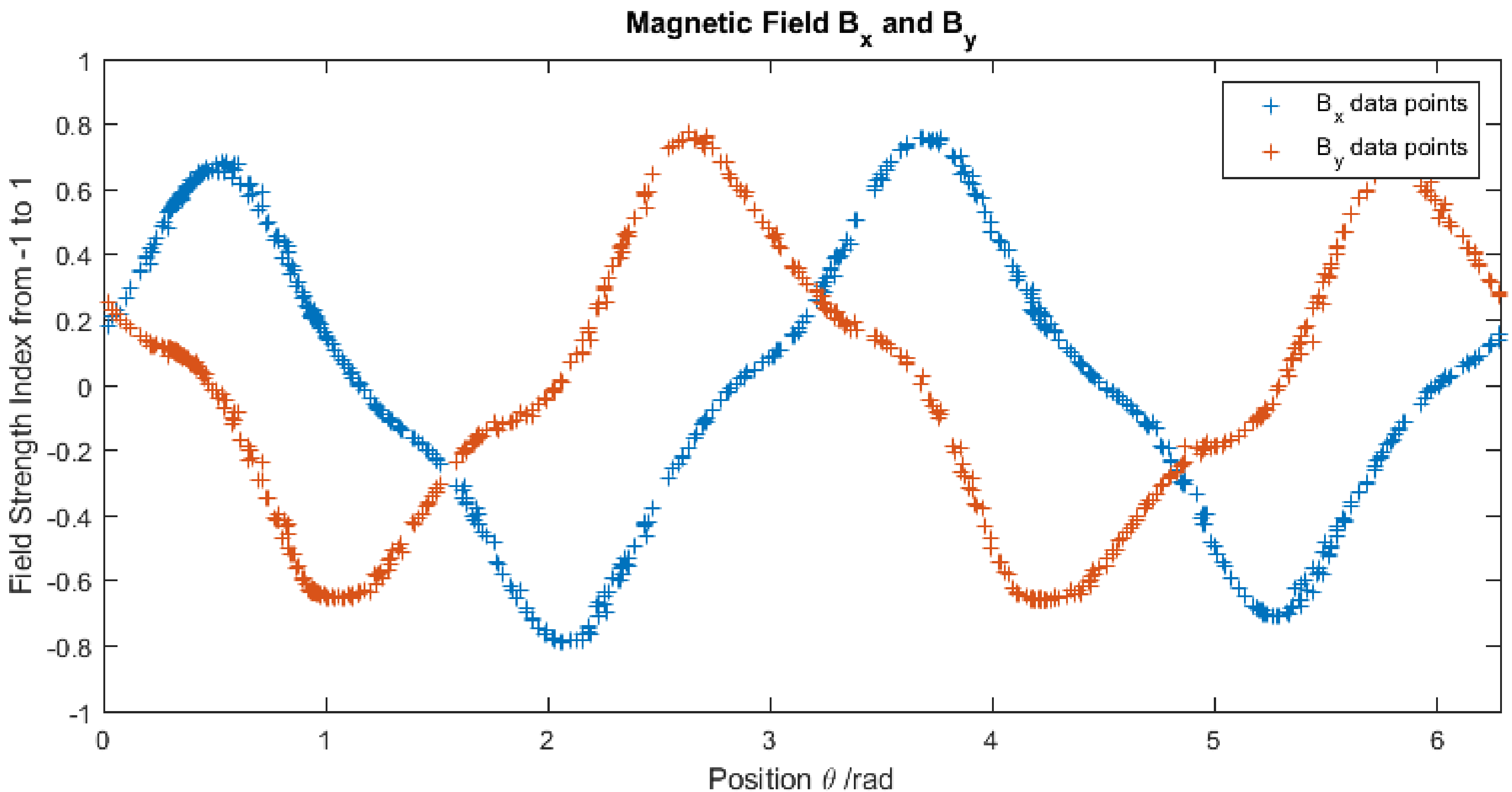


[1]

Sources: [1] https://www.researchgate.net/publication/236667263_Electrically_Actuated_Thrusters_for_Autonomous_Underwater_Vehicle

2. Experimental Setup: Sensor Positioning (2)

Optimal Position



Choice: Position at Z=13mm, r=10.6

2. Regression and Kalman Filter

Regression Approaches

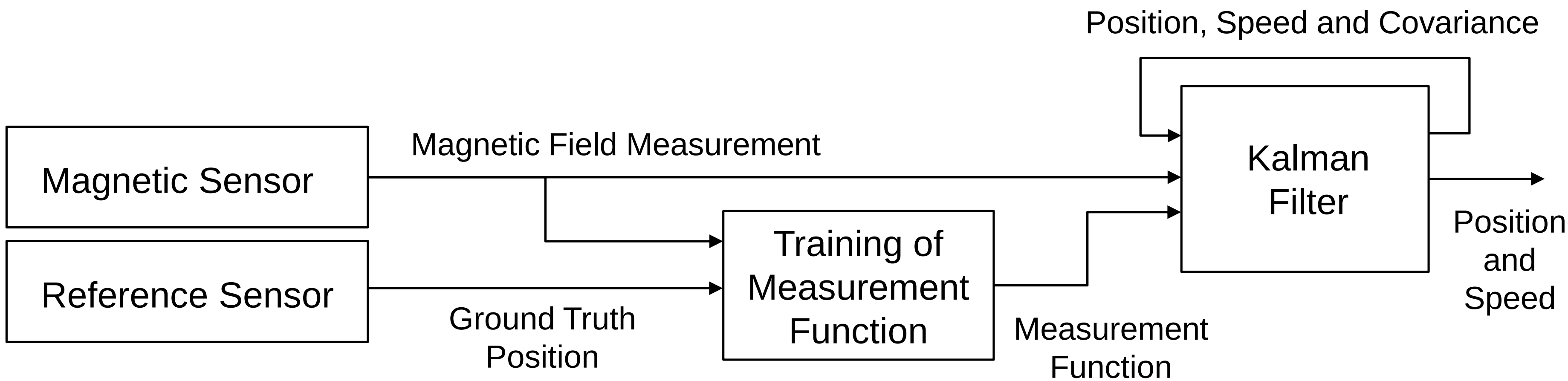
We identify a function mapping the position to the magnetic measurements

- Gaussian processes

Kalman Filter

Using this measurement function we estimate the position and speed from the current magnetic measurement and the previous estimation

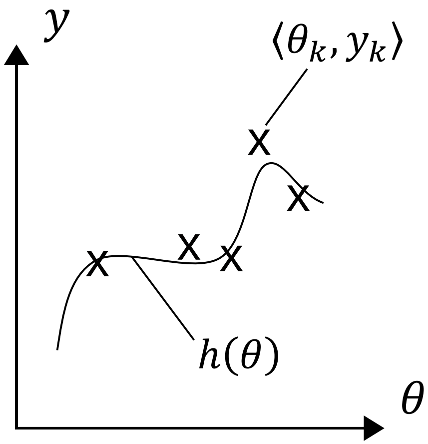
- Extended Kalman Filter
- Unscented Kalman Filter



Training Set and Measurement Model

- 2 regression functions required due to 2-dimensional measurement
  → Here we only consider one measurement dimension
- Training set $\mathbf{D} = \left\langle \underline{\theta}, \underline{y} \right\rangle$
- Measurement equation

$$y_k = h(\theta_k) + e_k \,, \qquad e_k \sim \mathcal{N}(0, {\sigma_n}^2)$$



$\underline{\theta} = [\theta_1, \ldots, \theta_N]^T$: Training input
$\underline{y} = [b_1, \ldots, b_N]^T$: Training output

Regression: Gaussian Processes

- Advantage of GP:
  →Nonparametric regression technique
  →Probability distribution over functions
- Prediction equations for Gaussian processes for a scalar test input θ_*

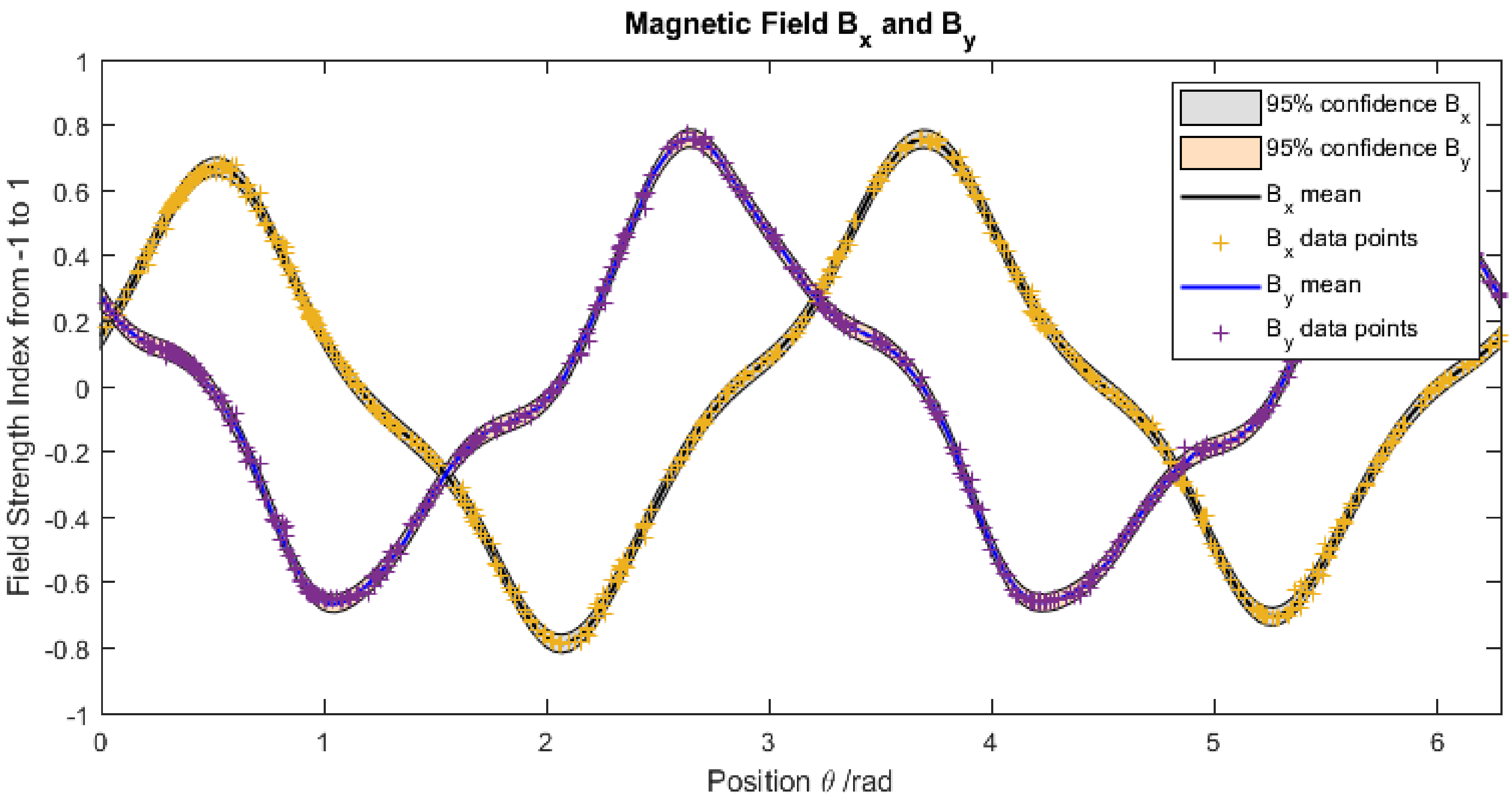
$$\mu_{h_*}(\theta_*) = \mathbf{K}(\theta_*, \underline{\theta})[\mathbf{K}(\underline{\theta}, \underline{\theta}) + {\sigma_n}^2 \mathbf{I}]^{-1} \underline{y}$$

$$\sigma_{\mathrm{h}_*}(\theta_*) = \mathbf{K}(\theta_*, \theta_*) - \mathbf{K}(\theta_*, \underline{\theta})[\mathbf{K}(\underline{\theta}, \underline{\theta}) + {\sigma_n}^2 \mathbf{I}]^{-1} \mathbf{K}(\underline{\theta}, \theta_*)$$

- Covariance matrix $\mathbf{K}(\underline{\theta}, \underline{\theta}')$ specified by kernel function
- Gaussian kernel function for 1-dimensional input

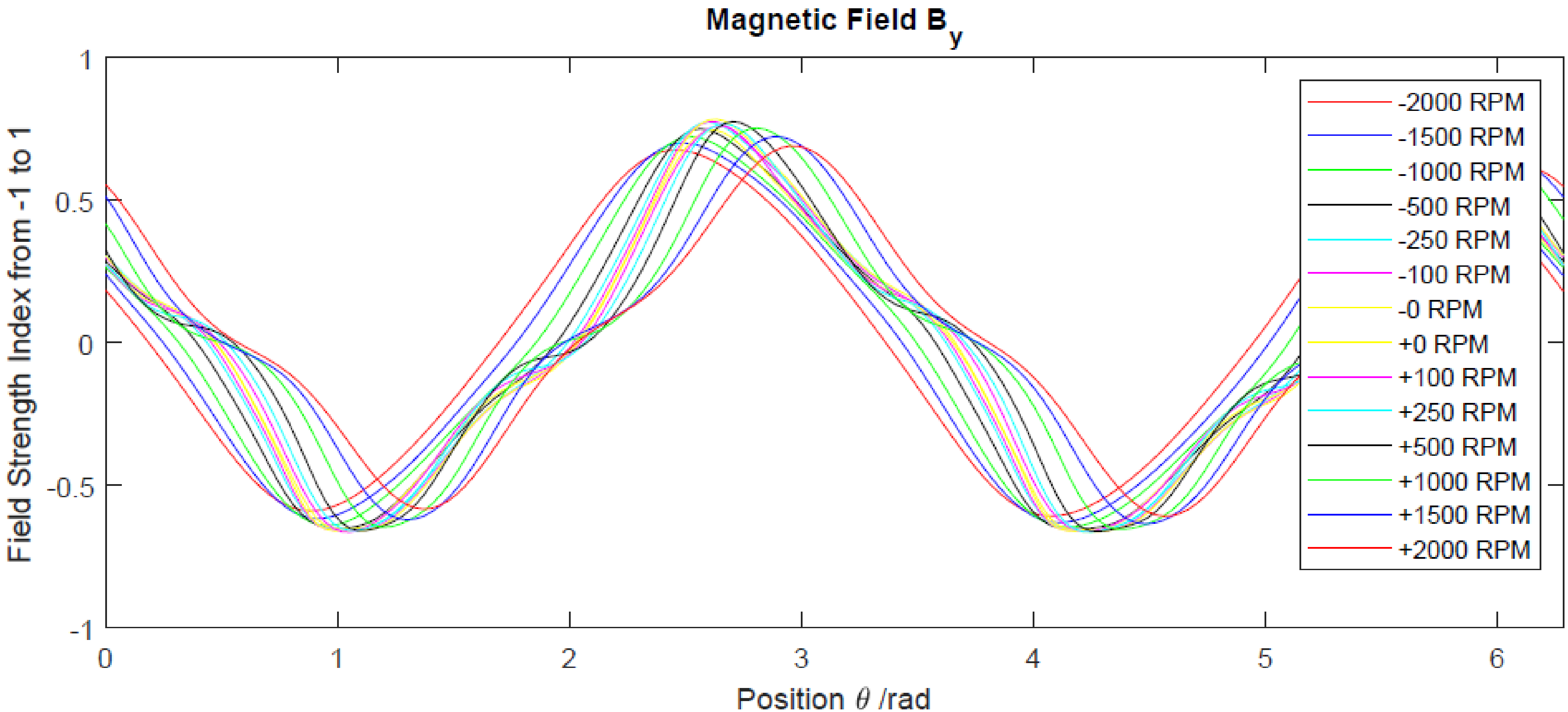
$$k(\theta_n, \theta'_m) = \sigma_f * e^{-\frac{1}{2l^2}(\theta_n - \theta'_m)^2}$$

2. Regression – Gaussian Processes (2)



Operating Condition: 100 RPM, no load torque

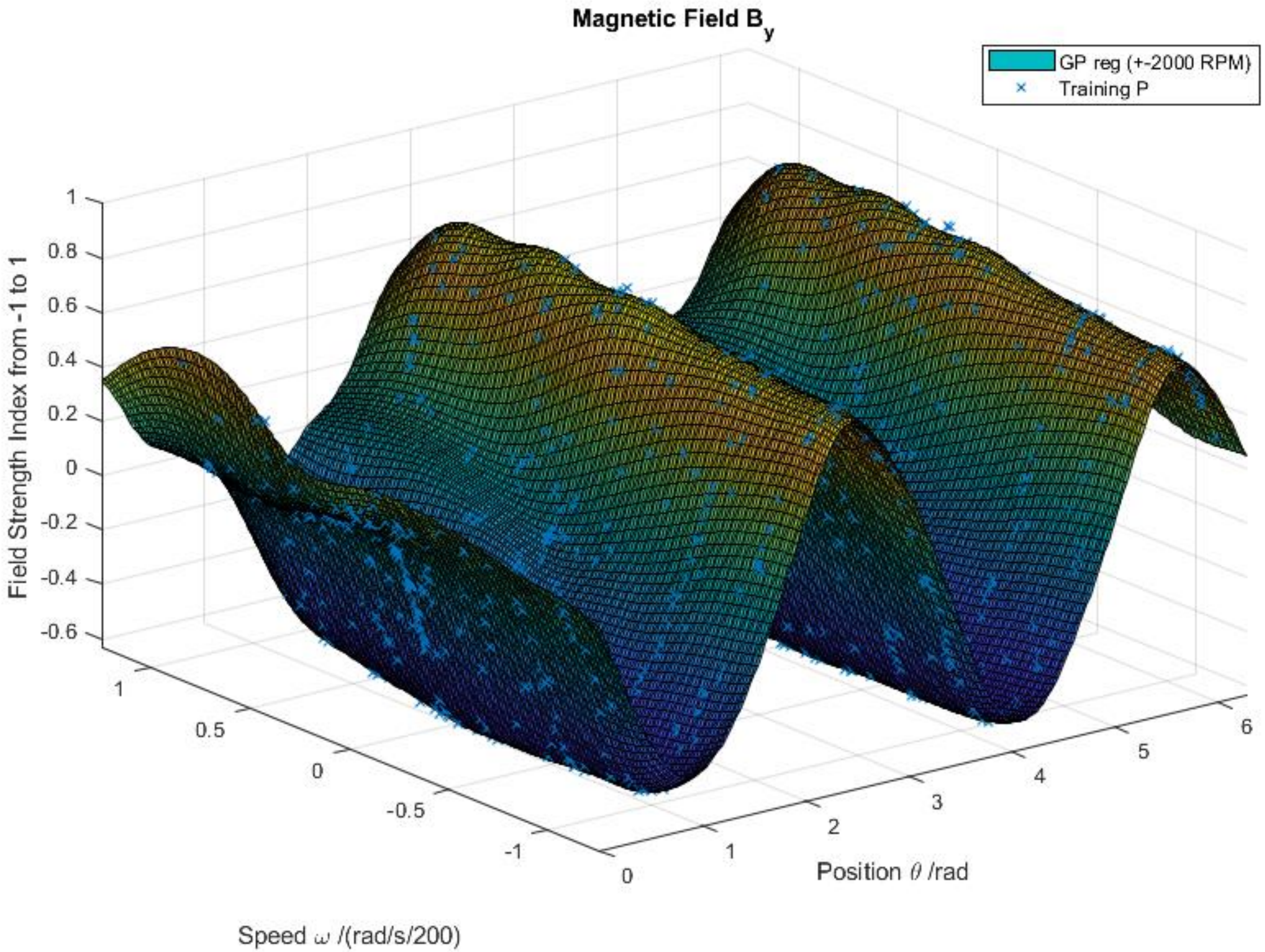
2. Regression – Gaussian Processes (3)



→ **Observed dependency of the magnetic field with respect to the speed**

→ We identify the measurement function with respect to the speed and position $\underline{h}(\theta, \omega)$

Input: Angular position, speed
Output: Magnetic field B_y



The Kalman Filter

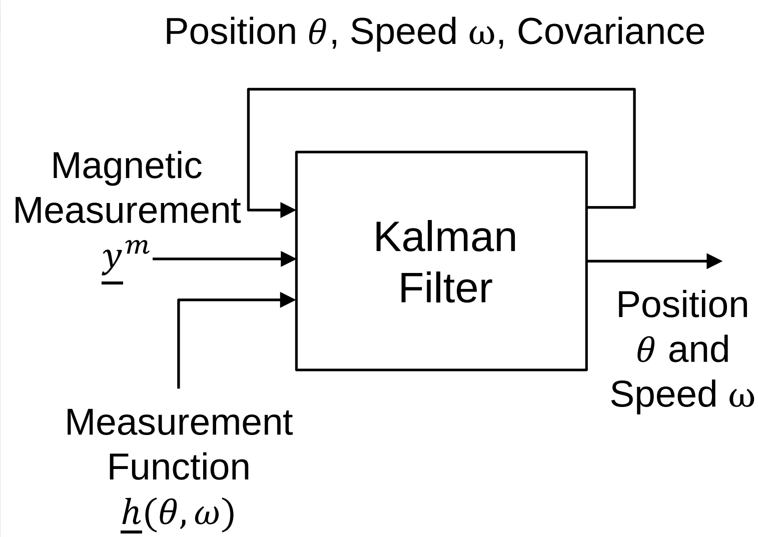
- Measurement equation (non-linear):

$$\underline{y}_k = \underline{h}(\underline{x}_k) + \underline{v}_k$$

- System equation (linear):

$$\underline{x}_k = \begin{pmatrix} \theta_k \\ \omega_k \end{pmatrix} = \mathbf{A}\underline{x}_{k-1} + \underline{w}_{k-1} = \begin{pmatrix} 1 & \Delta T \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \theta_{k-1} \\ \omega_{k-1} \end{pmatrix} + \underline{w}_{k-1}$$

→ Measurement function $\underline{h}(\underline{x}_k)$ is given from regression approach!



Concept – The Extended Kalman Filter

If we have a non-linear relationship in the system/ measurement equation, we can approximate this relationship with a linearization!

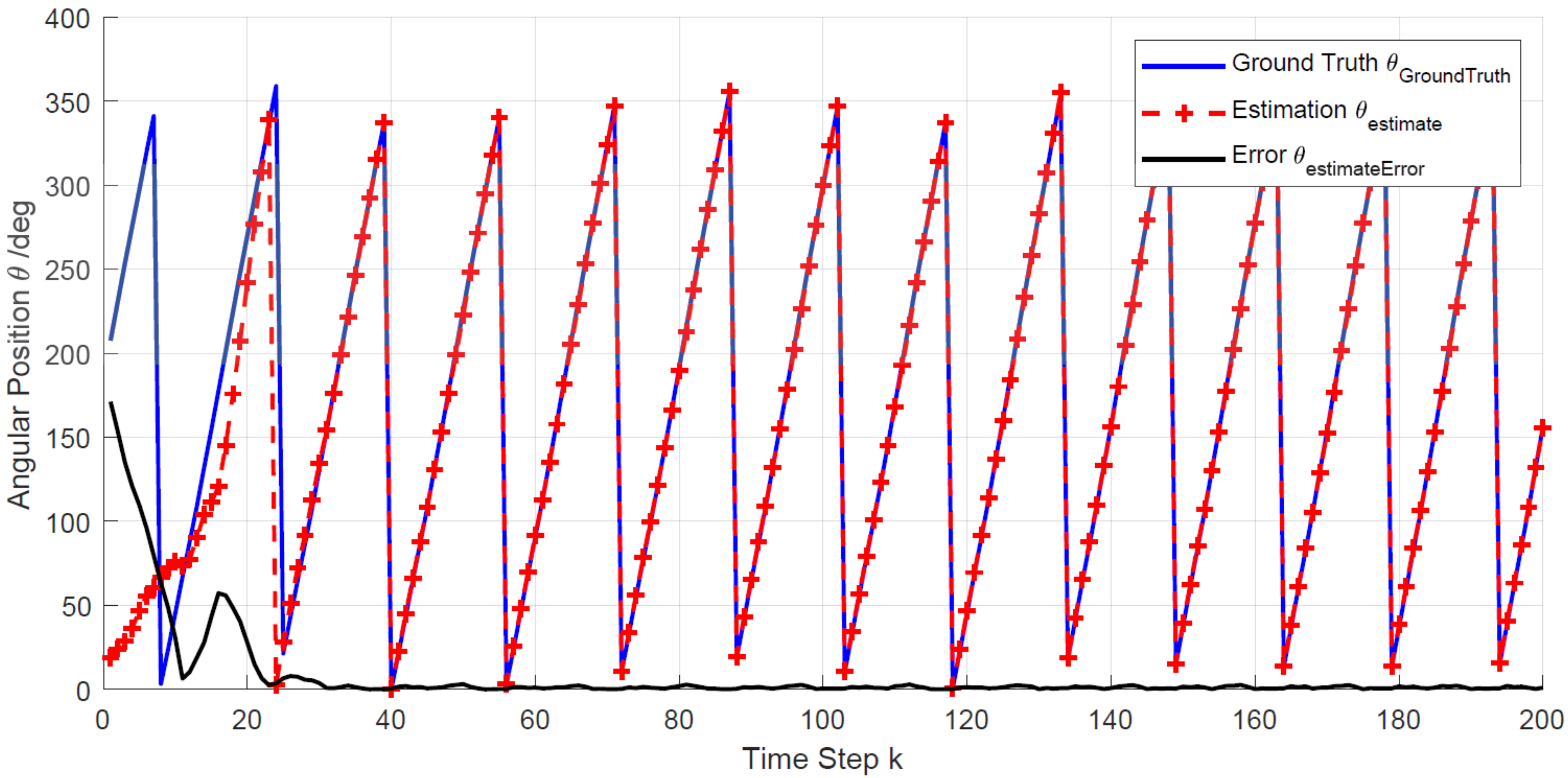
→ Identify Jacobi-matrix for measurement function:

$$\mathbf{H_k} = \frac{\partial \underline{h}(\underline{x}_k)}{\partial \underline{x}}$$

$\underline{v}_k$: Measurement noise with constant covariance $\mathbf{R}$

$\underline{w}_k$: System noise with constant covariance $\mathbf{Q}$

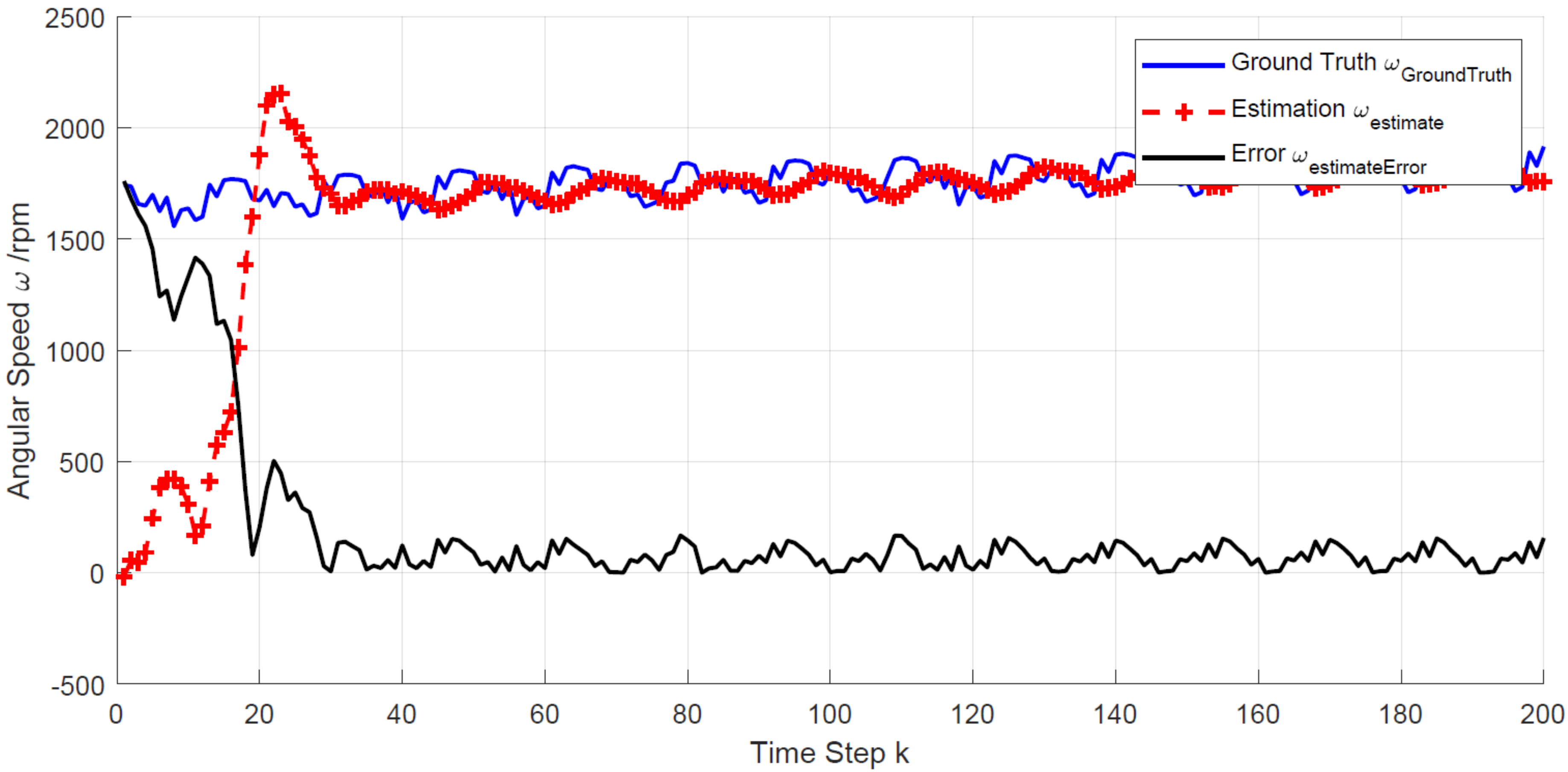
3. Evaluation: GP and EKF – Position Estimation



Operational Condition:

- No load torque (friction brake)
- Angular speeds around 1700 rpm

3. Evaluation: GP and EKF – Speed Estimation



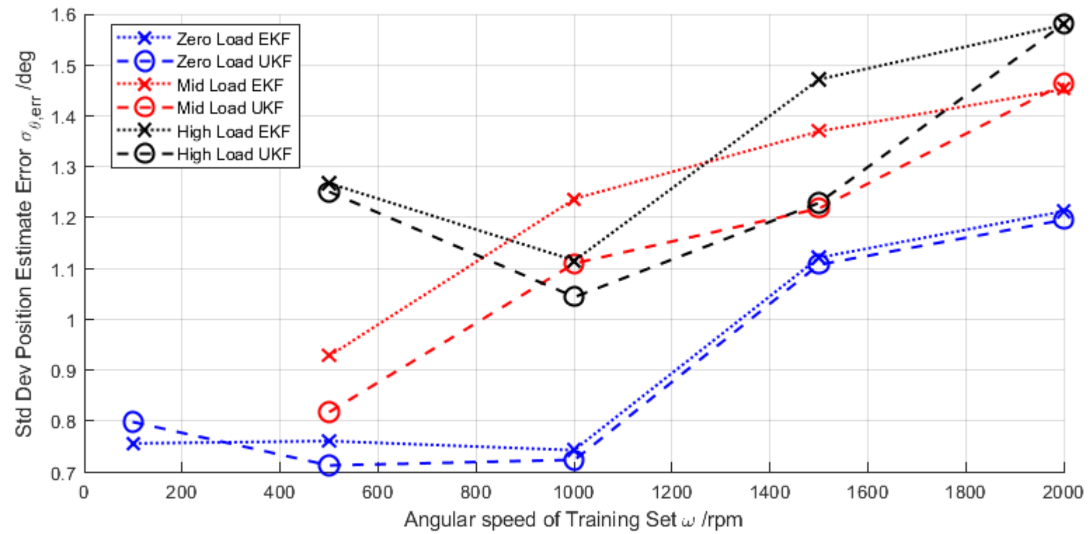
Operational Condition:

- No load torque (friction brake)
- Angular speeds around 1700 rpm

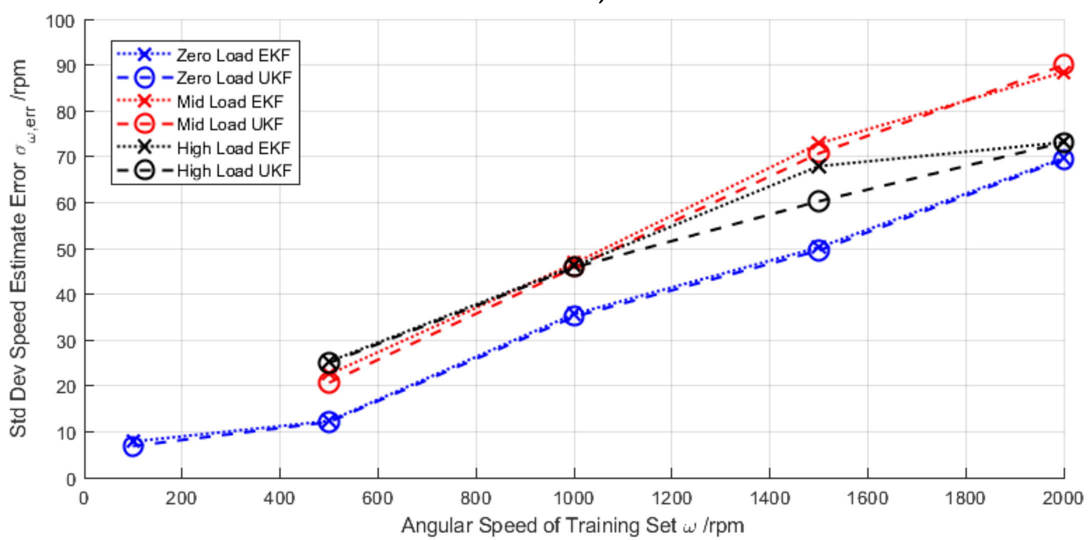
3. Evaluation: Estimation Error for Real Operation

- We performed tests for different angular speeds
  - $\omega_{mot}/\mathrm{rpm} \in [100, \dots, 2000]$
- We applied different load torques on the motor shaft
  - $M_L \in [0, \mathrm{mid}, \mathrm{high}]$
- Compare EKF and UKF for 1000 test points
- Evaluation of the estimation error standard deviation:
  - $\sigma_{\theta,err} = 0.8° - 1.6°$
  - $\sigma_{\omega,err} = 10\mathrm{rpm} - 90\mathrm{rpm}$
- Computing time/ estimation
  - EKF: $T_c = 1.3\ \mathrm{ms}$
  - UKF: $T_c = 1.6\ \mathrm{ms}$

Position estimation error $\sigma_{\theta,err}$, 1000 points



Speed estimation error $\sigma_{\omega,err}$, 1000 points



4. Conclusion

- We developed a new technique to estimate the position and the speed of a BLDC motor
- We observed a dependency of the magnetic field with respect to the angular position and speed
- We successfully integrated a multivariate input GP function into the EKF and the UKF
- Estimation error standard deviation:
  - $\sigma_{\theta,err} = 0.8° - 1.6°$
  - $\sigma_{\omega,err} = 10\text{rpm} - 90\text{rpm}$
- Computing time per estimation step
  - EKF: $T_c = 1.3 \text{ ms}$
  - UKF: $T_c = 1.6 \text{ ms}$

5. Outlook

- A higher estimation accuracy can be achieved by decreasing the time interval between two measurements!
  - Currently: $\Delta T = 2.2\ \mathrm{ms}$
    → only 13.6 measurements per rotation at $2000\ \mathrm{rpm}$
- Ground truth angular speed can be optimized
- A better speed estimation can possibly be achieved by using an array of magnetic sensors
  - **Paper:** Skog, I., Hendeby, G., Gustafsson, F. *Magnetic Odometry – A Model-Based Approach Using A Sensor Array.* FUSION 2018.
- Topic for further research: Why is the magnetic field dependent with respect to the angular speed?
  - Eddy-current in surrounding material could affect the magnetic field

Thank you for your attention

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Sensor-Actuator-Systems

Appendix - References

- Standard reference work for Gaussian processes:
  - [1] C. E. Rasmussen, C. K. I. Williams, *Gaussian Processes for Machine Learning*. The MIT Press, Massachusetts, 2006.
- Standard reference work for optimal state estimation
  - [2] Dan Simon. *Optimal State Estimation*. Wiley Interscience, Hoboken, New Jersey, 2006.
- Integration of Gaussian processes into Bayes filters
  - [3] Jonathan Ko, Dieter Fox. *Bayesian Filtering Using Gaussian Process Prediction and Observation Models*. In Autonomous Robots, Volume 27, pp. 75-90, SpringerScience+Business Media, 2009.

Implementation in Matlab

- Kalman Filter: „The Nonlinear Estimation Toolbox“
- Gaussian Processes: „GP Regression and Classification Toolbox”

Appendix – Noise Terms of the Kalman Filter

System noise $\underline{w}_k \sim \mathcal{N}(0, \mathbf{Q})$

- Zero-mean additive Gaussian noise
- Constant diagonal covariance matrix $\mathbf{Q}$

$$\mathbf{Q} = \begin{pmatrix} (0.01\ \mathrm{rad})^2 & 0 \\ 0 & (6\,\frac{\mathrm{rad}}{\mathrm{s}})^2 \end{pmatrix}$$

→ Using an iterative approach

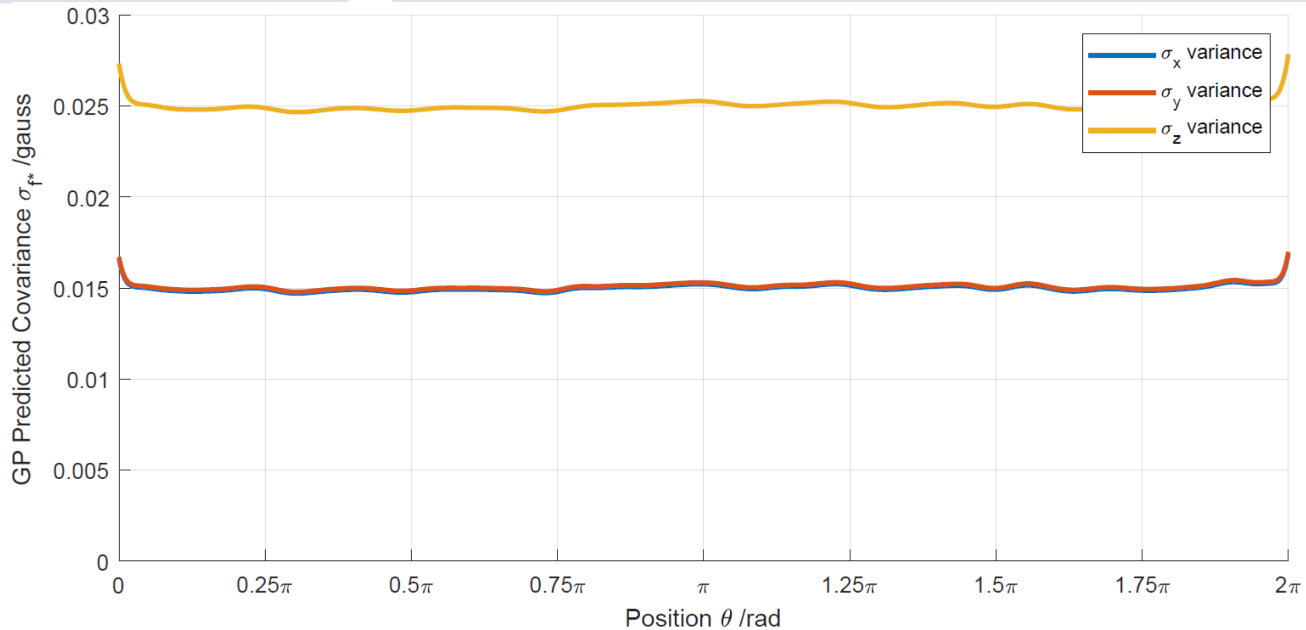
Measurement noise $\underline{v}_k \sim \mathcal{N}(0, \mathbf{R})$

- Zero-mean additive Gaussian noise
- Constant diagonal covariance matrix $\mathbf{R}$

$$\mathbf{R} = \begin{pmatrix} {\sigma_{n,x}}^2 & 0 \\ 0 & {\sigma_{n,y}}^2 \end{pmatrix}$$

→ Using hyperparameters $\sigma_{n,x}$ from GP

Nearly constant predicted covariance! (Example from digital sensor)



Appendix – GP for Multivariate Inputs

Reasons for dependency of the B-field with respect to the speed

1) Latency of the microcontroller ✗
2) Accuracy of sensor is affected by strongly fluctuating magnetic field ?
   → Magnetic bias
3) Material within the area between sensor and rotor can affect magnetic field ?
   → Eddy-currents

GP predictive functions with multivariate inputs

- GP predictive mean function

$$\mu_{h_*}(\underline{x}_*) = \boldsymbol{K}(\underline{x}_*, \boldsymbol{X})[\mathbf{K}(\boldsymbol{X}, \boldsymbol{X}) + \sigma_n{}^2\mathbf{I}]^{-1}\underline{y}$$

- GP predictive covariance function

$$\sigma_{\mathrm{h}_*}(\underline{x}_*) = \boldsymbol{K}(\underline{x}_*, \underline{x}_*) - \boldsymbol{K}(\underline{x}_*, \boldsymbol{X})[\mathbf{K}(\boldsymbol{X}, \boldsymbol{X}) + \sigma_n{}^2\mathbf{I}]^{-1}\mathbf{K}(\boldsymbol{X}, \underline{x}_*)$$

- Gaussian kernel function

$$k(\underline{x}_n, \underline{x}_m) = \sigma_f * e^{-\frac{1}{2l^2}|\underline{x}_n - \underline{x}_m|^2}$$

$\underline{x}_* = (\theta_*, \omega_*)^T$: Test input

$\omega_* = \omega_{true}/200$: Alignment of input space boundaries

σ_n, σ_f, l: Hyper-parameters of GP

Analog Magnetic Sensor - Amplification

- Using potentiometers (0-2000kOhm) in feedback loop of OP-amplifier
- Selection of ~700kOhm for optimal dynamic range

→ Magnetic field as dimensionless quantity from -1 to 1