



Improving Platform Magnetometer Measurements Using Physics-informed Neural Networks

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**SWARM** 

## Motivation

- Calibration of platform magnetometer readings
  - GOCE (2009-2013), GRACE-FO (2018-ongoing)
  - Non-dedicated satellites carrying platform magnetometers
  - Calibrated datasets increase the spatiotemporal coverage
    - MLT, altitude
- Enlarging datasets of magnetic space-based measurements
  interesting to space physics and geomagnetism

# Problem

- Platform magnetometers are only roughly calibrated
  - Part of attitude and orbit control system (AOCS)
  - Typical residuals of 500nT 1000nT (compared to CHAOS-7)
- Our goal: post-launch / in-situ calibration
  - Adjusting artificial disturbances
  - As much information as possible
  - Enable scientific application of the measurements
    - Below 10nT

# **First Approach**

- Applying Machine Learning with long preprocessing pipeline
  - Feed-forward neural network
  - Architecture found through Hyperparameter Optimization
- Inputs include magnetometer measurements, electric currents, temperatures, magnetorquer activations, thrusters, telemetry data like status variables, flags, and others
- The reference model consists of the CHAOS-7 model
  - Empiric model supported by Swarm mission
- Further details in publications (Styp-Rekowski et al. & Michaelis et al.)



### **New Developments**

- Introduce physics-informed neural networks
- Combine the CHAOS-7 and AMPS model for the reference model

## **Next Step: Physics-Informed NN**

- Make the calibration 'physically more correct'
  - Previously strictly data/statistics driven
- Constraint the NN to follow certain physical laws
  - Electric currents may only be used in their physical meaning
  - Ensure more meaningful results
- Improve modeling and calibration of electric current-induced artificial magnetic fields

## **Physics-informed NN**

• Biot-Savart law for dipoles

• 
$$\vec{B}(\vec{r},\vec{m}) = \frac{\mu_0}{4\pi} \left( \frac{3\vec{r}(\vec{m} * \vec{r})}{|\vec{r}|^5} - \frac{\vec{m}}{|\vec{r}|^3} \right)$$

•  $\vec{m} = IN\vec{a}$  (Dipole moment)



Source: https://users.physics.ox.ac.uk/~harnew/lecture s/EM-lecture12-handout-abridged.pdf

- Parameters  $\vec{r}$  and  $\vec{a}$  will be learned
  - Position relative to the inducing current at origin
- Produces a 3dimensional output corresponding to the magnetic field induced by the electric current I
- Assumption: The artificial disturbance can be approximated by a dipole

### **Biot-Savart Neuron**

- Biot-Savart (BiSa) Neuron
- Input is an electric current
- Produces 3-dimensional output
  - Representing the induced magnetic field
- Output is subtracted from calibration result to correct for this induced artificial disturbance



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## **AMPS Model**

- Additionally, used a second model in the ground truth
  - Average magnetic field and polar current system (AMPS) (Laundal et al.)
- Combine CHAOS-7 and AMPS models
  - Ground truth now a composition of models
- Large-scale, average structures of FACs
  - Helps to model mean values



Source: https://klaundal.w.uib.no/files/2017/09/croppe d-cropped-130.png

## Results

- GOCE: Low residual of 6.6nT for low- and mid-latitudes compared to the reference model
- GRACE-FO: Low residual of 3.7nT for low- and mid-latitudes compared to the reference model

### **Result - GRACE-FO1**



#### **Result - GRACE-FO1 vs. Swarm-A**



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## **Result – GRACE-FO**

- Analyze the 'black box' of the PINN
- Biot-Savart neurons are analyzable
  - Learned parameters  $\vec{r}$  and  $\vec{a}$
- Magnetorquers
  - Influence on PlatMag
  - Dipole Moment



#### **Result - GOCE**



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#### **Result - GOCE**



08.04.2024

## Conclusion

- More evaluation to assess the data quality
- Automatic calibration of platform magnetometers
  - Introduced the PINN
    - GOCE: residual of 6.6nT, GRACE-FO: residual of 3.7nT
  - In-situ determination of dipole positions of the satellite system
  - Included large-scale FAC into the reference model
- Preprint published and revision handed in (Styp-Rekowski et al., 2024)
- Current datasets are available in a Swarm-like format
  - VirES Client
  - <u>https://isdc.gfz-potsdam.de/platform-magnetometer/</u>
  - GOCE: <u>https://doi.org/10.5880/GFZ.2.3.2022.002</u>
  - GRACE-FO: <u>https://doi.org/10.5880/GFZ.2.3.2023.001</u>

## References

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- I. Michaelis, K. Styp-Rekowski, J. Rauberg, C. Stolle, and M. Korte. Geomagnetic data from the GOCE satellite mission. Earth Planets Space 74, 135 (2022). <u>https://doi.org/10.1186/s40623-022-01691-6</u>
- Laundal, K. M., Finlay, C. C., Olsen, N. & Reistad, J. P. (2018), Solar wind and seasonal influence on ionospheric currents from Swarm and CHAMP measurements, Journal of Geophysical Research -Space Physics. <u>https://doi.org/10.1029/2018JA025387</u>
- Kevin Styp-Rekowski, Ingo Michaelis, Monika Korte, et al. Physicsinformed Neural Networks for the Improvement of Platform Magnetometer Measurements. Authorea.

# Backup

### **Previous Month Calibration (towards FAST data)**



#### GOCE vs. CryoSat-2



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#### **Conjunctions: GRACE-FO1 with Swarm-A (over 5 years)**

