

Machine-learning approach to magnetic navigation

Ying-Cheng Lai
Arizona State University
1/7/2025

Collaborators:

- Zheng-Meng Zhai, Mohammadamin Moradi, Ling-Wei Kong (ASU current and former PhD students)
- Dr. Aaron Nielsen, Air Force Institute of Technology

Magnetic Navigation - An Alternative to GPS Navigation



Dr. Aaron Canciani, AFIT



Dr. John Raquet, AFIT

- Aerial navigation without GPS - quite challenging!
- Alternative navigation systems for airborne use are limited:
 - ❖ Terrain following systems
 - ❖ star-tracker and computer-vision systems
- **Earth's magnetic anomaly field is globally available at all times – aerial navigation in a GPS-denied environment?**



Original Article | [Full Access](#)

Absolute Positioning Using the Earth's Magnetic Anomaly Field[†]

! [Correction\(s\) for this article](#) ▾

Aaron Canciani, John Raquet

First published: 21 June 2016 | <https://doi.org/10.1002/navi.138> | Citations: 32

Airborne Magnetic Anomaly Navigation

January 2017 · [IEEE Transactions on Aerospace and Electronic Systems](#)

DOI: [10.1109/TAES.2017.2649238](https://doi.org/10.1109/TAES.2017.2649238)

Aaron Canciani · John Raquet

Earth's Magnetic Field

1. Field generated from inside the earth:

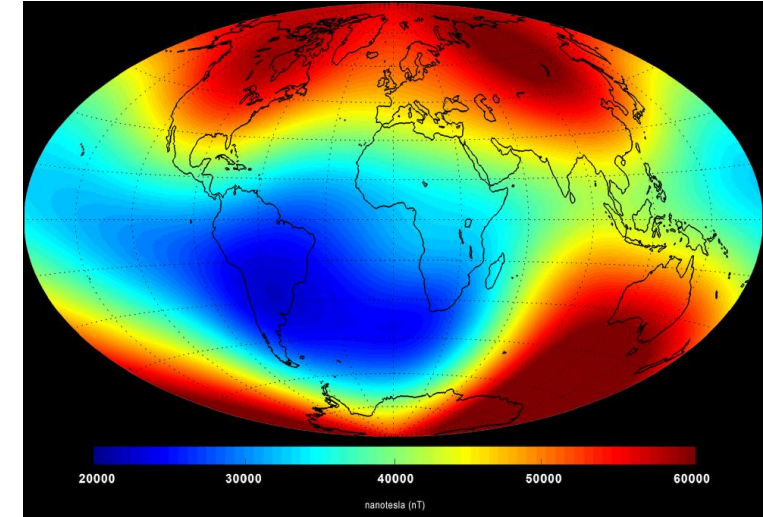
- Core field - 20-60 mT: dominant, responsible for the working of compasses
- **Anomaly field** - about 100 nT: due to the permanent or induced magnetization of the rocks in the earth's crust

Key feature of the anomaly field:

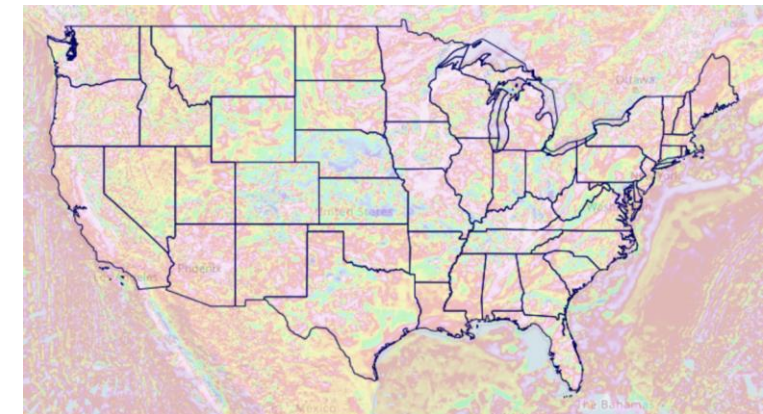
- **Strength depends on the location – possible for positioning and navigation**
- **When collected from, e.g., an airplane, the anomaly field is effectively a time series signal**

2. Magnetic field generated outside of the earth:

- Temporally varying field - about 10 nT: from the ionosphere, magnetosphere, and the coupling currents between the two



NASA Earth Observatory, “Measuring Earth’s Magnetism,” 2014. <https://earthobservatory.nasa.gov/images/84266/measuring-earths-magnetism>

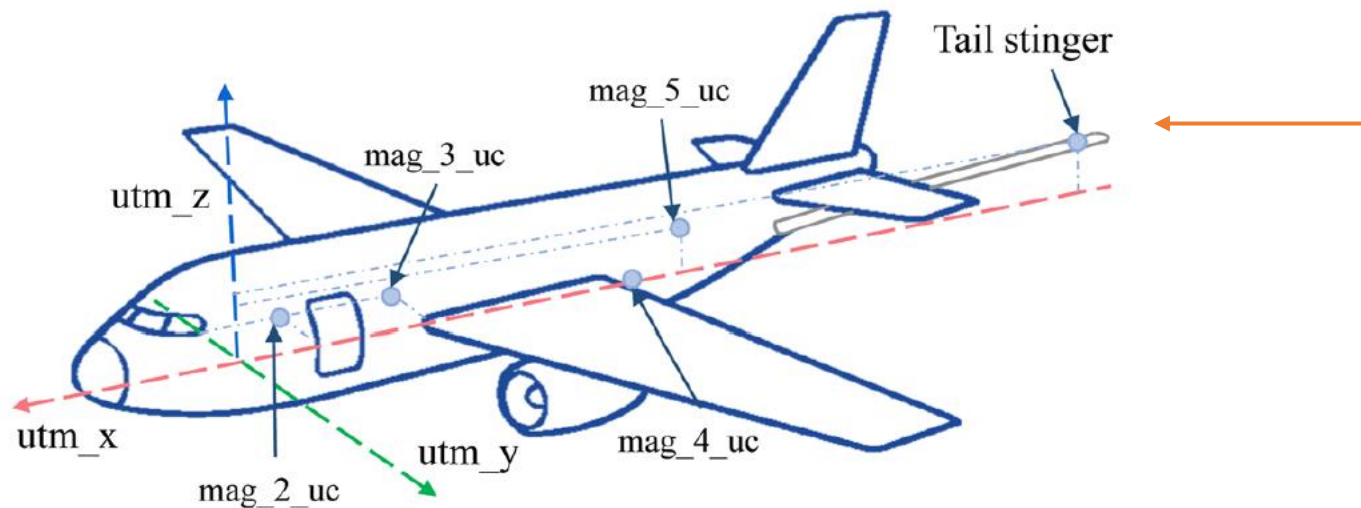


U.S. Geological Survey, “Magnetic anomaly maps and data for North America,” 2021. <https://mrdata.usgs.gov/magnetic/>

How to Obtain the Earth Magnetic Field \vec{B}_e from Aircraft Measurements?

Total measured field: $\vec{B}_m = \vec{B}_e + \vec{B}_{aircraft} = \vec{B}_{core} + \vec{B}_{anomaly} + \vec{B}_{tv} + \vec{B}_{aircraft}$

- \vec{B}_{core} - calculated from the International Geomagnetic Reference Field (IGRF) coefficients
- \vec{B}_{tv} - mostly from the diurnal variations and space weather – can be removed using ground-based reference measurements
- $\vec{B}_{aircraft}$ - total field generated by the aircraft



- **Calibration: Tolles-Lawson (TL) model** to estimate $\vec{B}_{aircraft}$
- Applied to the reading of the magnetometer at the tail stinger \rightarrow real value of the earth field \vec{B}_e

Estimate of Earth's Anomaly Magnetic Field – Ground Truth



- Recall:

$$\vec{B}_e = \vec{B}_{core} + \vec{B}_{anomaly} + \vec{B}_{tv}$$

- TL calibration gives an estimate of \vec{B}_e :

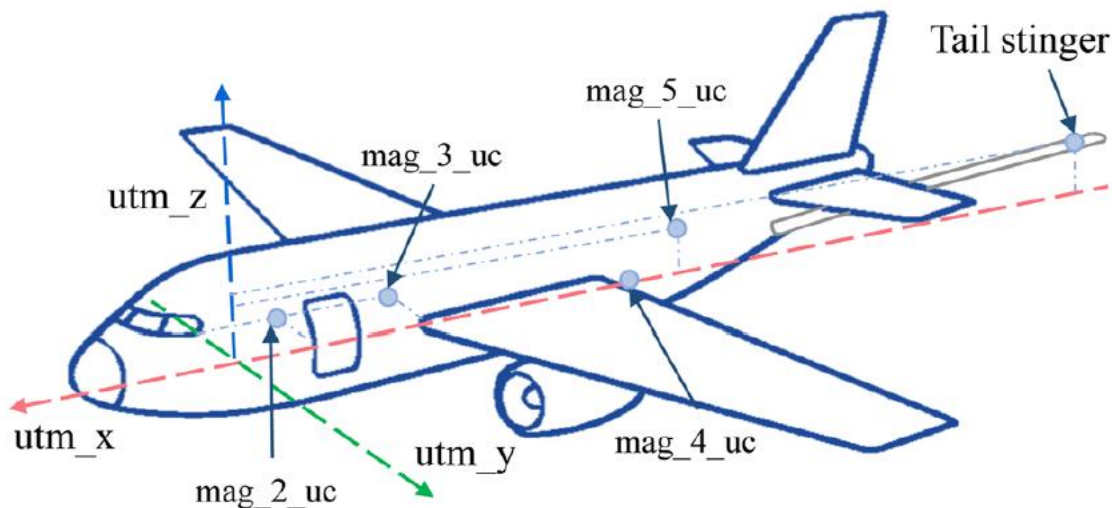
$$\hat{\vec{B}}_e = \vec{B}_{e,TL}$$

$$\rightarrow \vec{B}_{anomaly} \approx \vec{B}_{e,TL} - \vec{B}_{core} - \vec{B}_{tv}$$

- TL calibration works well only when the flying aircraft is in a magnetically quiet mode and all the magnetometer measurements are performed on a tail stinger outside the cabin.*
- For normal flights, these conditions are not met.*
- Magnetic signals collected inside the cockpit are noisy due to the electronics – a weak signal embedded in overwhelmingly strong noise!***
- Use TL model to obtain the ground truth for training neural networks

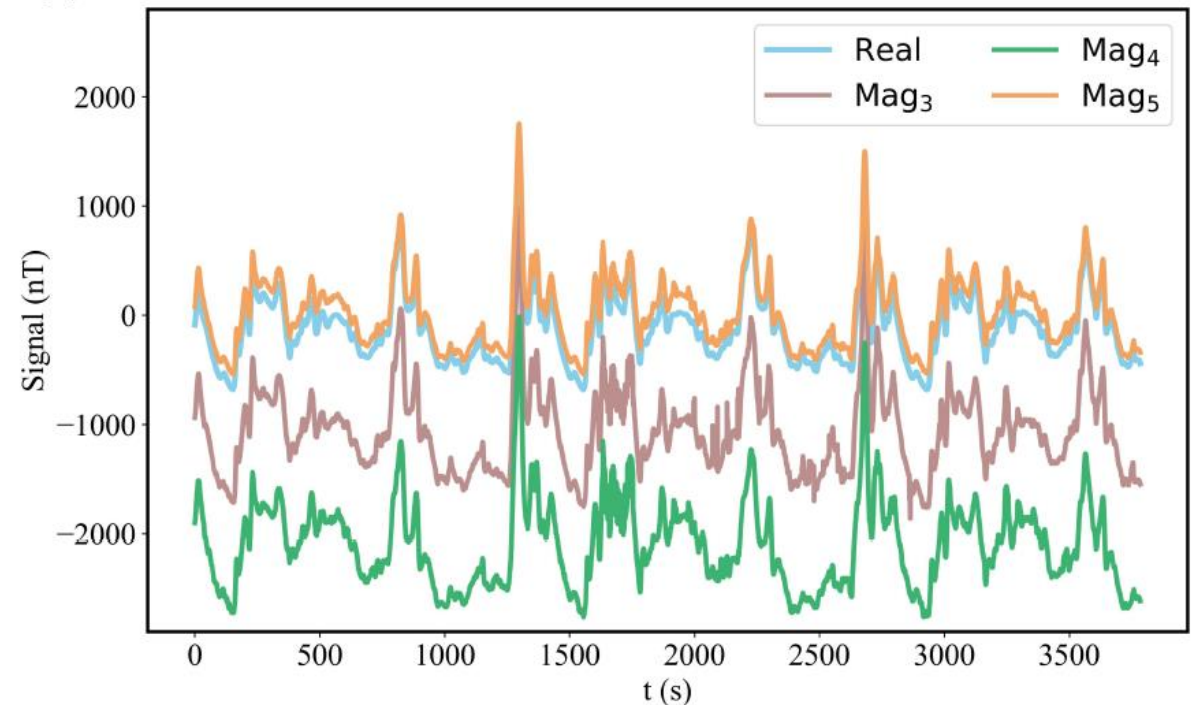
Data Source and Structure

- Source: Open Call for developing machine-learning approaches to signal enhancement for magnetic navigation (MagNav) Challenge organized in 2020 by the Air Force-MIT Artificial Intelligence Accelerator
- Four other magnetometers placed at different positions in the cabin
- A large number of available flight lines



github.com/MIT-AI-Accelerator/MagNav.jl

(d) Examples of results from TL calibration:



$$|\vec{B}_{e, TL}| = |\vec{B}_m| - B_{TL}$$

TABLE II. [Line number summary for flight 1003](#)

Line number	Description	Training length (s)	Validation/Test length (s)
1003.02	Eastern Ontario Free-Fly 400m	2246.5	748.8
1003.03	Climb to 800m	61.3	20.4
1003.04	Eastern Ontario Free-Fly 800m	2877.7	959.2
1003.05	Transit at 800m	246.7	82.2
1003.06	Descend to 400m	83.5	27.8
1003.07	Transit to Renfrew Free-Fly	58.9	19.6
1003.08	Renfrew Free-Fly 400m	2581.9	860.6
1003.09	Climb to 800m	82.3	27.4

TABLE V. [Line number summary for flight 1006](#)

Line number	Description	Training length (s)	Validation/Test length (s)
1006.03	Climb to 17,000ft	448.3	149.4
1006.04	Compensation maneuvers at 17,000ft	2547.7	849.2
1006.05	Descent to 10,000ft	317.5	105.8
1006.06	Compensation maneuvers at 10,000ft	369.1	123.0
1006.07	Transit/Descent to Eastern Ontario	732.1	244.0
1006.08	Compensation maneuvers in Eastern Ontario at 400m	479.5	159.8

1. Reservoir computing
2. Time-delayed feedforward neural networks

PHYSICAL REVIEW APPLIED **19**, 034030 (2023)

Detecting Weak Physical Signal from Noise: A Machine-Learning Approach with Applications to Magnetic-Anomaly-Guided Navigation

Zheng-Meng Zhai¹,¹ Mohammadamin Moradi¹,¹ Ling-Wei Kong¹,¹ and Ying-Cheng Lai^{1,2,*}

¹*School of Electrical, Computer and Energy Engineering, Arizona State University, Tempe, Arizona 85287, USA*

²*Department of Physics, Arizona State University, Tempe, Arizona 85287, USA*

Features Collected During Flight



102 features altogether from, e.g., current and voltage sensors and readings from the INS system

Examples
of some
“**most
important**”
features:

Fluxgates B, C,
D along x , y , and
 z axes have been
used in TL
calibration (Air
Force – MIT
MagNav
Challenge)

TABLE I. Importance ranking of the features selected by a greedy algorithm

Features	Units	Description
flux_c_t	nT	Flux C: fluxgate total
cur_ac_lo	A	Current sensor: air conditioner fan low
ins_alt	m	INS computed elevation
flux_c_z	nT	Flux C: fluxgate z axis
flux_a_t	nT	Flux A: fluxgate total
vol_back_p	V	Voltage sensor: resolver board(+)
vol_back_n	V	Voltage sensor: resolver board(-)
ins_lat	rad	INS computed latitude
cur_com_1	A	Current sensor: aircraft radio 1
flux_c_y	nT	Flux C: fluxgate y axis
vol_acpwr	V	Voltage sensor: aircraft power
ins_wander	rad	INS computed wander angle
cur_flap	A	Current sensor: flap motor
vol_bat_2	A	Current sensor: battery 2
ins_roll	deg	INS computed aircraft roll

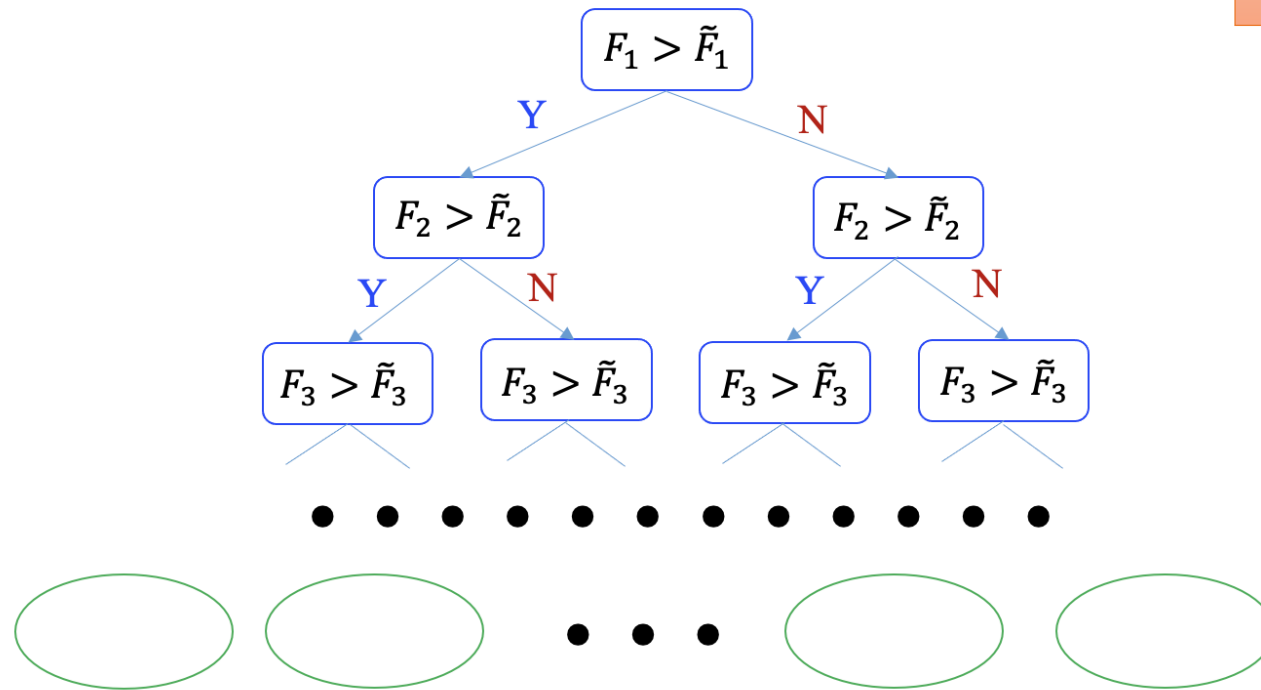


**Random
Forest**

A Decision Tree

Parameters to be trained:

$\tilde{F}_1, \tilde{F}_2, \tilde{F}_3, \dots$

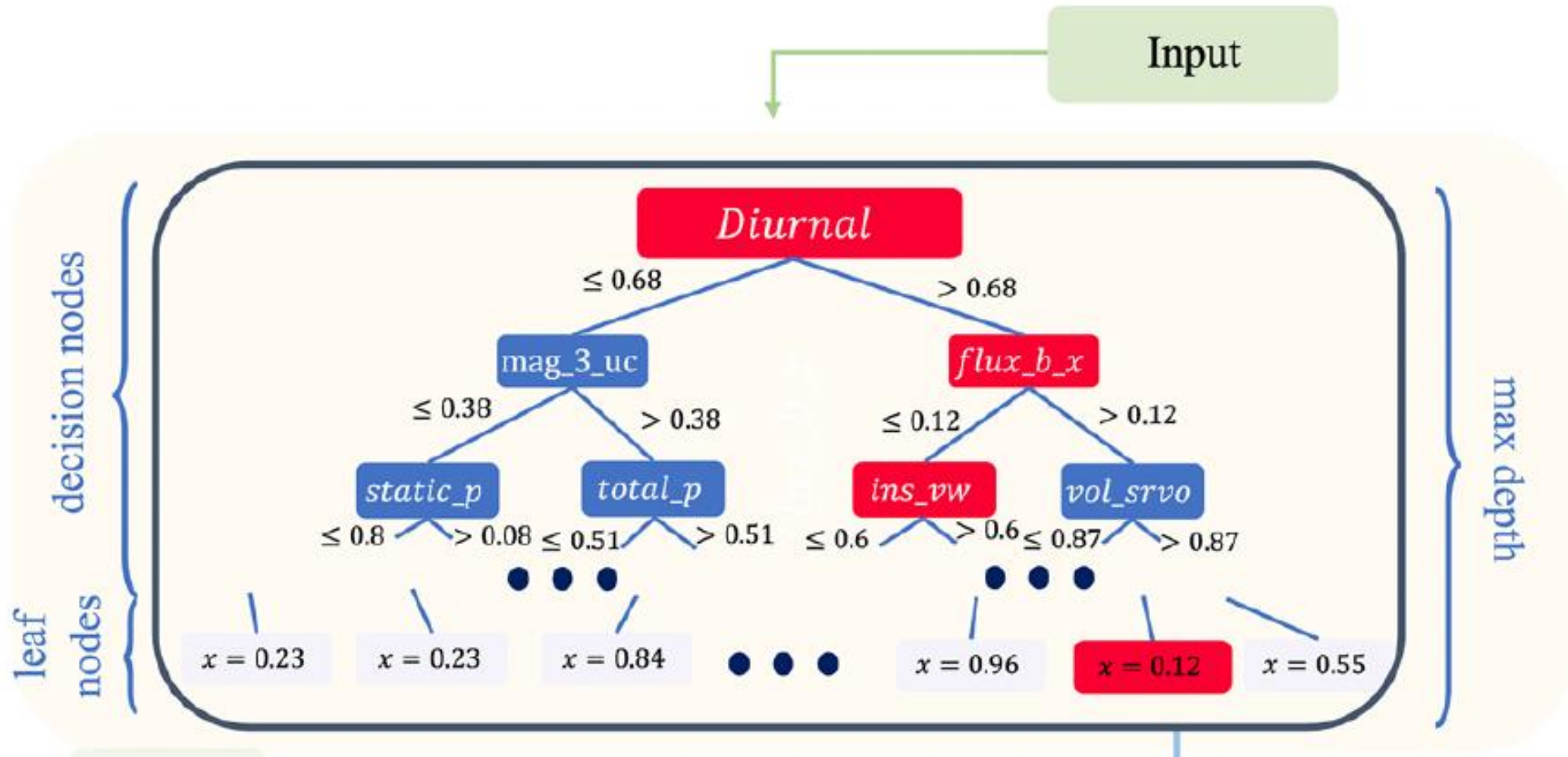


Wish to detect:

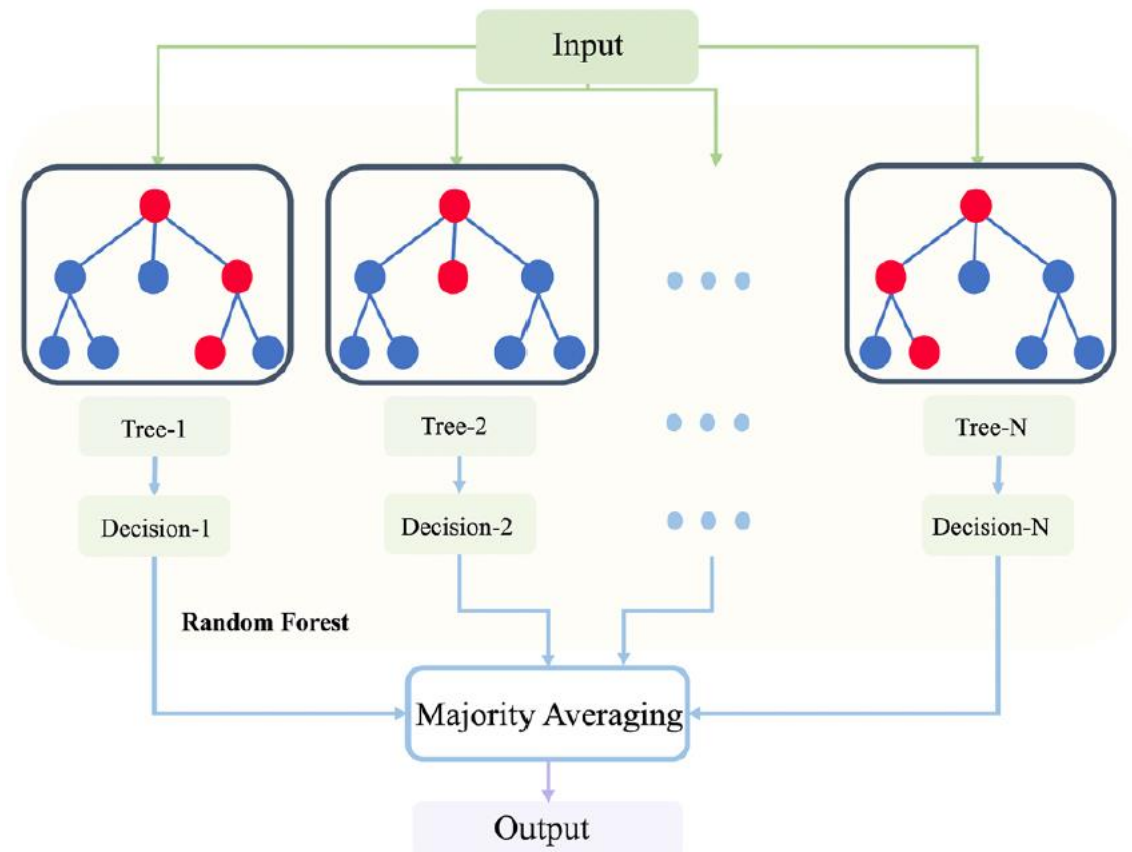
1. Anomaly magnetic field
2. Actual aircraft position

Labels: a large collection of possible values of the signals to be detected in a suitable range (values in the training set + random values)

An Example



Random Forest



Random Forest:

- An ensemble of decision trees;
- Each tree is trained using a different subset of data

Training:

- Training a tree with a randomly selected set of features and a fraction of the available training data;
- Adding the trained tree to the “Forest”
- Adding more trained trees to the “Forest”

Prediction:

- Combining all predictions from the trees in the “Forest”

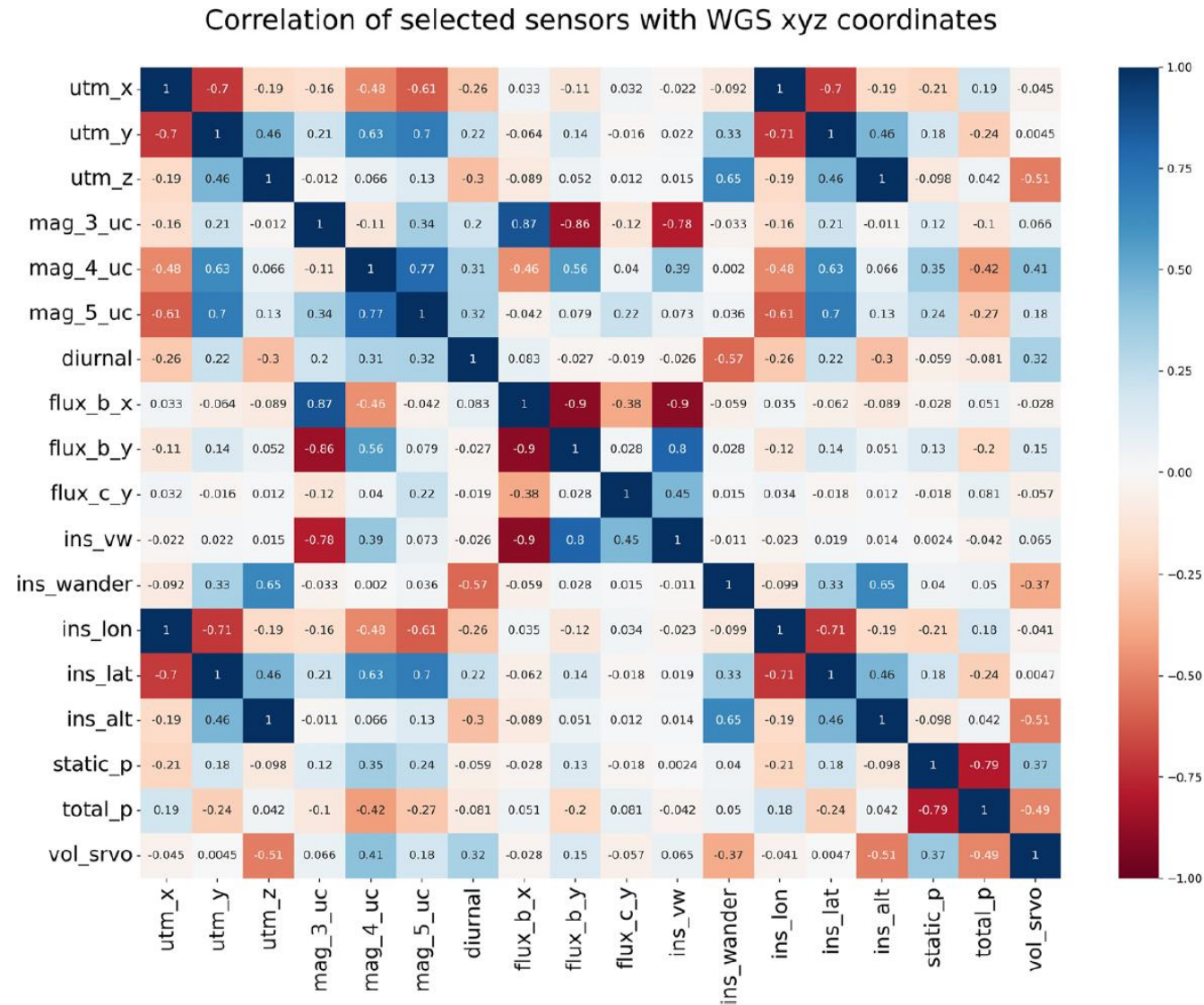
Feature Selection Step 1 – Eliminating those with Small Variance



TABLE I. Standard deviations of the features of the entire flight dataset.

Feat. with lowest std	Std	Feat. with highest std	Std
<i>cur_flap</i>	0.0077	<i>total_p</i>	0.3438
<i>mag_2_uc</i>	0.0282	<i>cur_ac_lo</i>	0.3345
<i>cur_com_1</i>	0.0441	<i>static_p</i>	0.3344
<i>ins_acc_z</i>	0.0545	<i>baro</i>	0.3340
<i>nrml_acc</i>	0.0569	<i>ins_alt</i>	0.3323
<i>roll_rate</i>	0.0590	<i>utm_z</i>	0.3322
<i>ltrl_acc</i>	0.0715	<i>msl</i>	0.3321
<i>pitch_rate</i>	0.0718	<i>diurnal</i>	0.3123
<i>mag_1_igrf</i>	0.0738	<i>ins_vw</i>	0.3063
<i>cur_srvo_o</i>	0.0798	<i>ins_vn</i>	0.2963

Feature Selection Step 2 – Feature Correlations



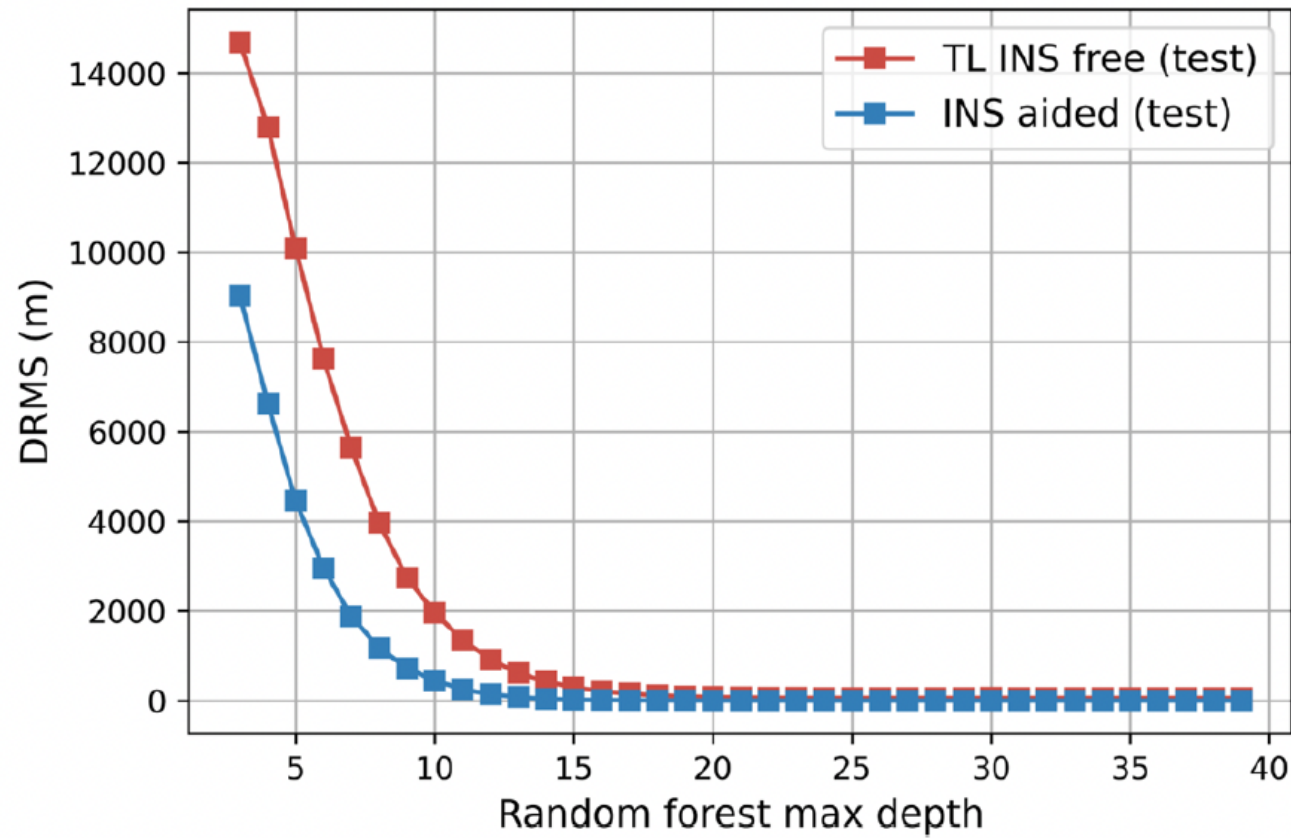
Disregarding the features with high correlations

Examples of Feature Selection Results



Feat	Description	TL INS free	INS aided
<i>mag_3_uc</i>	Uncomp. mag. sensor 3	✓	✓
<i>mag_4_uc</i>	Uncomp. mag. sensor 4	✓	✓
<i>mag_5_uc</i>	Uncomp. mag. sensor 5	✓	✓
<i>mag_3_c</i>	Comp. mag. sensor 3	✗	✗
<i>mag_4_c</i>	Comp. mag. sensor 4	✗	✗
<i>mag_5_c</i>	Comp. mag. sensor 5	✗	✗
<i>diurnal</i>	Measured diurnal	✓	✓
<i>flux_b_x</i>	Fluxgate B x axis	✓	✓
<i>flux_b_y</i>	Fluxgate B y axis	✓	✓
<i>flux_c_y</i>	Fluxgate C y axis	✓	✓
<i>ins_vw</i>	INS west velocity	✗	✓
<i>ins_wander</i>	INS wander angle	✗	✓
<i>static_p</i>	Avionics static pressure	✓	✓
<i>total_p</i>	Avionics total pressure	✓	✓
<i>vol_srvo</i>	Volt. sensors: servos	✗	✓

How Many Trees Are Needed in Random Forest?



We used 100 trees

Detecting Anomaly Magnetic Field

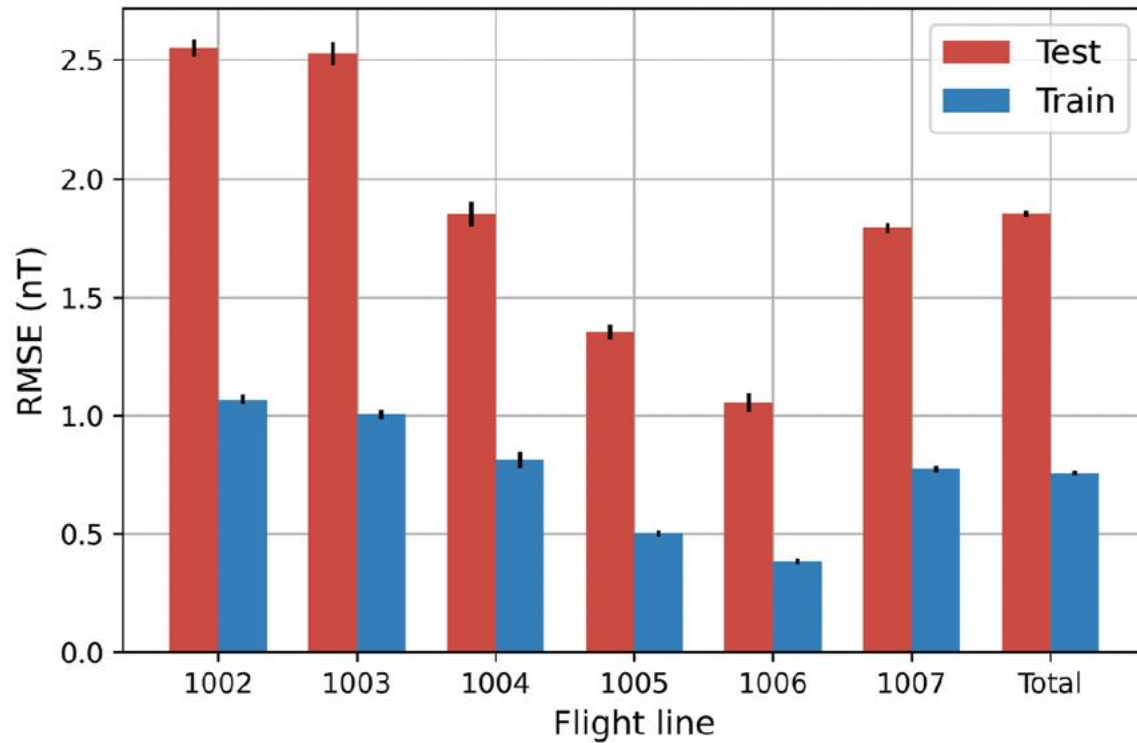
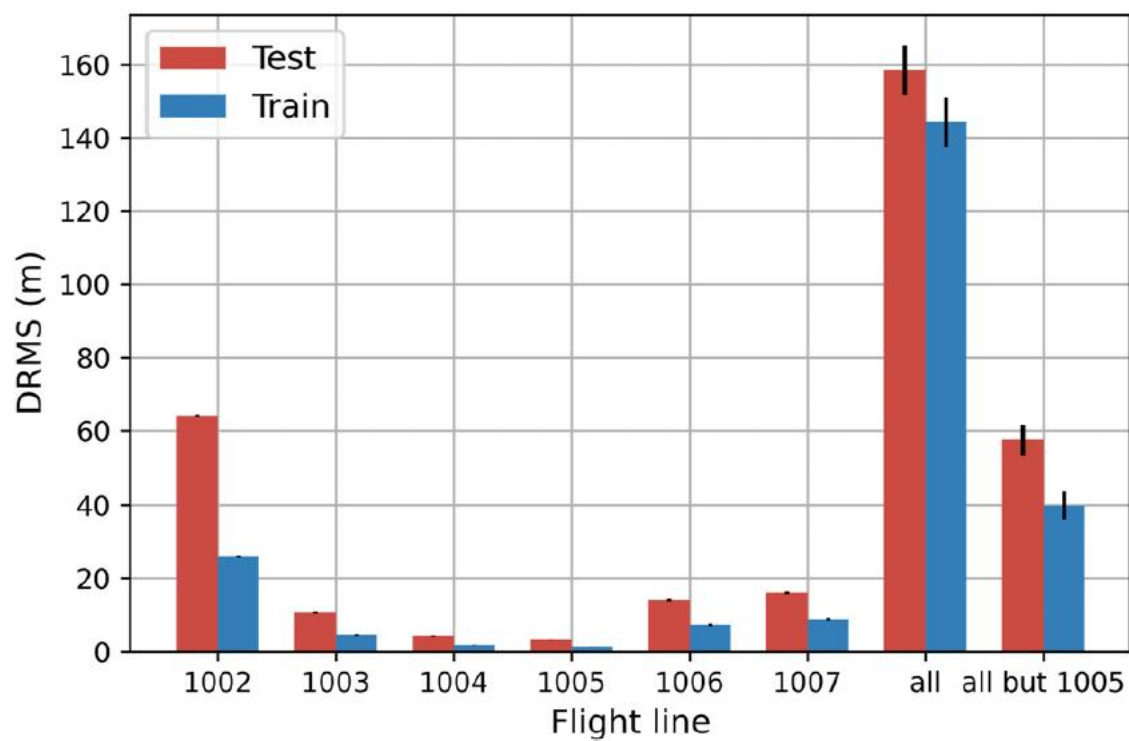


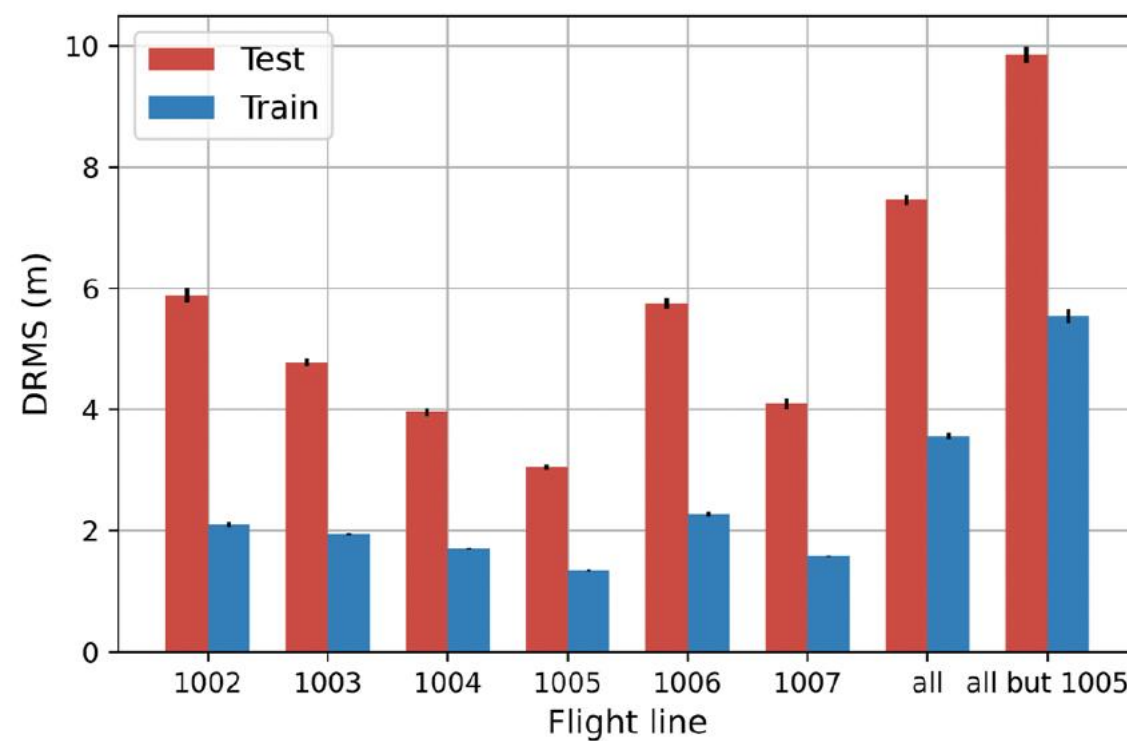
TABLE III. Performance comparison among KNN, decision-tree, and random-forest methods in terms of RMSEs using selected features to detect the weak anomaly magnetic field signal (in units of nT).

Flight line	Random forest train	Random forest test	KNN train	KNN test	Decision tree train	Decision tree test
1002	1.05	2.57	40.94	53.23	1.92	5.01
1003	1.05	2.60	19.29	25.68	1.17	3.94
1004	0.82	1.83	15.43	19.98	0.36	3.33
1005	0.50	1.31	9.46	12.74	0.58	3.16
1006	0.36	0.95	12.29	16.35	0.91	2.23
1007	0.80	1.84	18.18	23.34	1.27	3.68
All	0.93	2.58	26.24	33.79	4.01	6.10

Positioning



INS Free



INS Aided

Positioning – Performance of Random Forest



Flight line	Use PCA	Use selected features	Random forest Train	Random forest Test	KNN Train	KNN Test	Decision tree Train	Decision tree Test
1002	✗	✓	2.12	6.00	30.62	42.14	1.34	8.50
1003	✗	✓	1.94	4.75	37.21	53.11	2.46	9.61
1004	✗	✓	1.70	3.82	33.15	47.63	0.68	7.76
1005	✗	✓	1.35	3.07	19.83	29.11	0.13	7.19
1006	✗	✓	2.02	5.48	25.85	36.78	13.52	20.84
1007	✗	✓	1.55	4.05	38.89	53.26	0.41	7.71
All	✗	✓	2.54	6.51	115.96	159.9	48.48	53.90

Method	Test mean	Test std	Train mean	Train std
TL INS Free	41.08	2.50	29.26	2.46
INS Aided	5.60	0.03	2.51	0.03

Random forests for detecting weak signals and extracting physical information: A case study of magnetic navigation

Cite as: APL Mach. Learn. 2, 016118 (2024); doi: [10.1063/5.0189564](https://doi.org/10.1063/5.0189564)

Submitted: 29 November 2023 • Accepted: 20 February 2024 •

Published Online: 12 March 2024



Mohammadamin Moradi,¹ Zheng-Meng Zhai,¹ Aaron Nielsen,² and Ying-Cheng Lai^{1,3,a)}

- The relation between the error in the detected earth's anomaly magnetic field and positioning precision is nonlinear
- An error below 6.5 nT corresponds to the positioning error of less than 45 m
- Empirically, the position error is approximately about 10 - 40 m when the magnetic signal error is around 4 nT
- The mean magnetic signal errors from both reservoir computing and time-delayed feed forward neural networks is about 4 nT
- The mean errors from Random Forest is below 4 nT
- The mean position errors from Random Forest is below 10 meters

Ongoing work:

Developing **Transfer Learning** methods to deal with the situations where tail stinger measurements are not available - collaboration with Dr. Aaron Nielsen from Air Force Institute of Technology