Physics-Informed Calibration of Aeromagnetic Compensation in Magnetic Navigation Systems using Liquid Time-Constant Networks

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Magnetic Anomaly Navigation (MagNav)

- MagNav is a proven, viable **fallback to GPS**[1,2]
- Airborne MagNav estimates positioning by correlating **aircraft magnetometer readings** to **anomaly maps** of the Earths crustal magnetic field.
- Airborne MagNav is **highly resistant** to:
  - jamming/spoofing attacks
  - atmospheric weather conditions
- **Stochastic** and **deterministic effects** from external magnetic fields **hinder** classical **calibration** attempts[3].

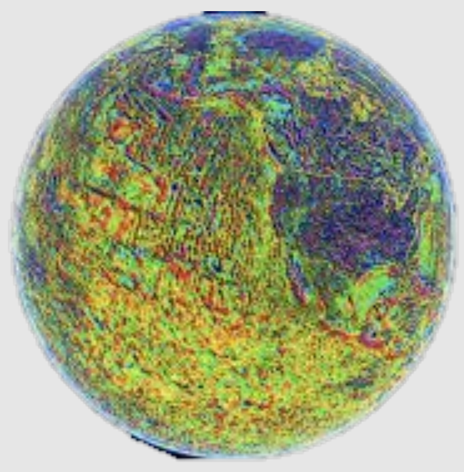

Fig 1. Magnetic Anomaly Map

Motivation

- Inertial navigation position measurements **drift** over time due to **accumulated estimated errors**.

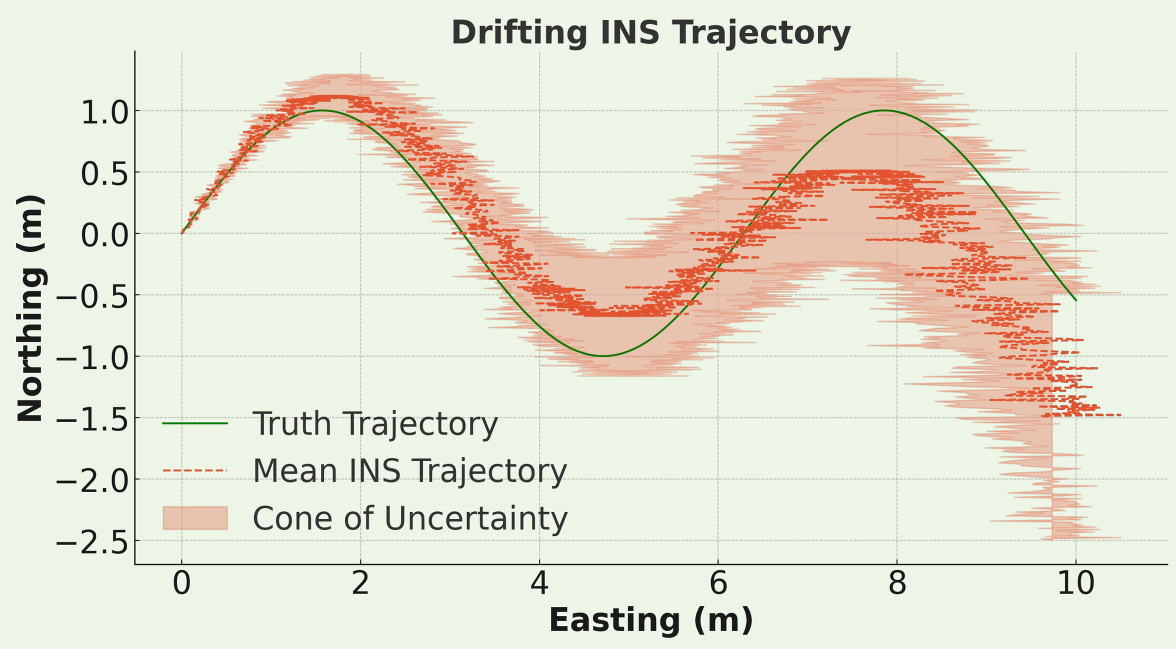

Fig 2. Example Flight Trajectory vs. INS Trajectory with Drift

- MagNav measurements exhibit **nonlinear, spatiotemporal dynamics** that are **difficult** to model due to **noisy, corrupted magnetic fields**.

Q: How can we capture complex, nonlinear, spatiotemporal dynamics of airborne MagNav from a weak, noisy signal?

Closed-Form Continuous Liquid Time-Constant Networks (LTC-CfC)

- **LTCs**, a type of RNN, use **ODE-solvers** for high-dim, sequential tasks.
- LTCs uncover **nonlinear dynamics** using **neural circuit policies**[4] to solve the system:

$$\frac{d\mathbf{x}}{dt} = w_\tau + f(\mathbf{x}, \mathbf{I}, \theta)\mathbf{x}(t) + Af(\mathbf{x}, \mathbf{I}, \theta)$$

- A **CfC** delivers higher efficiency and achieves faster, adaptive, causal, & continuous-time solutions **without an ODE-solver**[5].

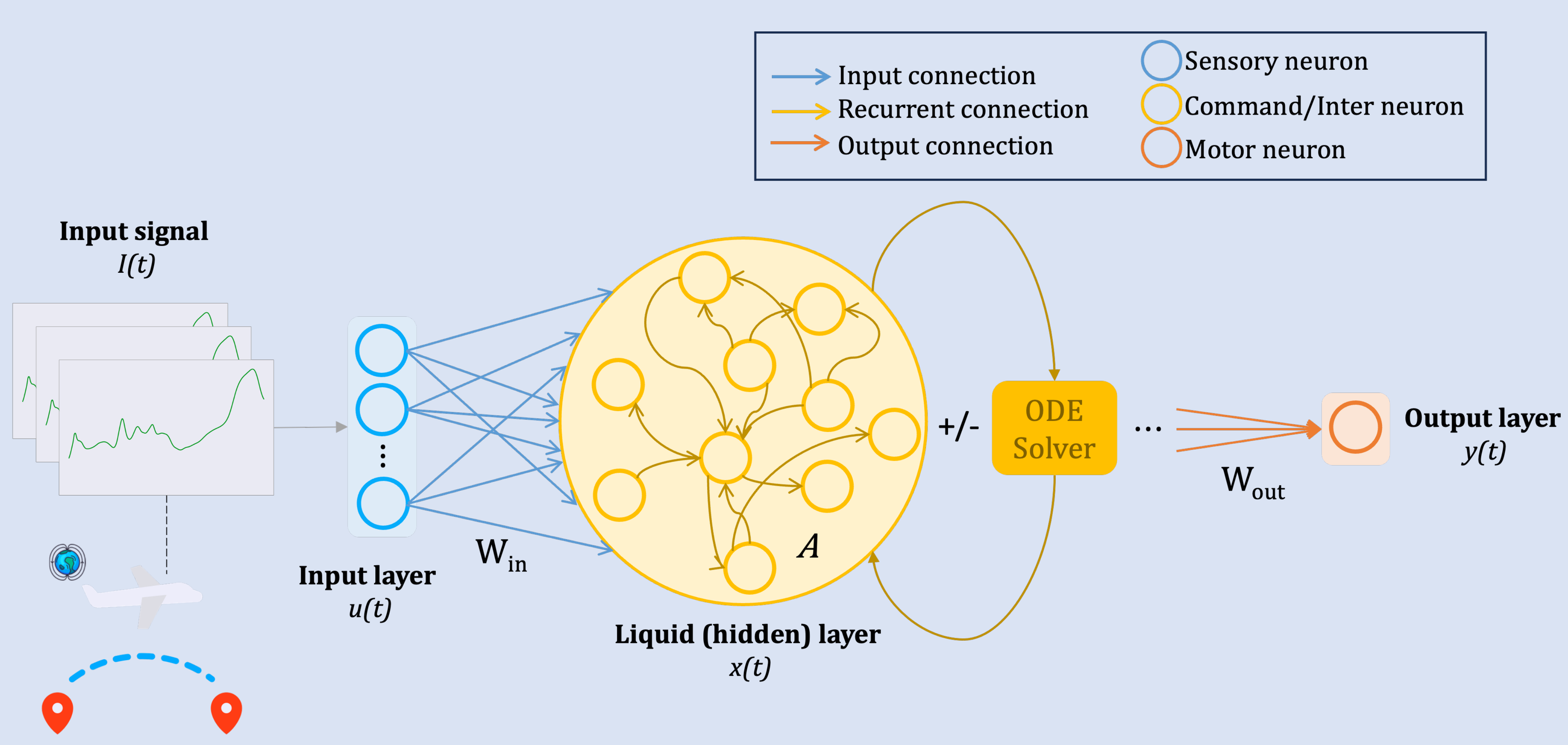

Fig 3. Liquid Time-Constant Network Architecture

Dataset & Setup

Dataset: United States Air Force-MIT Signal Enhancement for Magnetic Navigation Challenge Dataset [open-source][3].

Aim: remove aircraft magnetic field from total magnetic field (**i.e., aeromagnetic compensation**) to **derive** a **clean signal** for MagNav.

Features: compensated magnetometer measurements, aircraft positional+INS measurements, & electrical measurements.

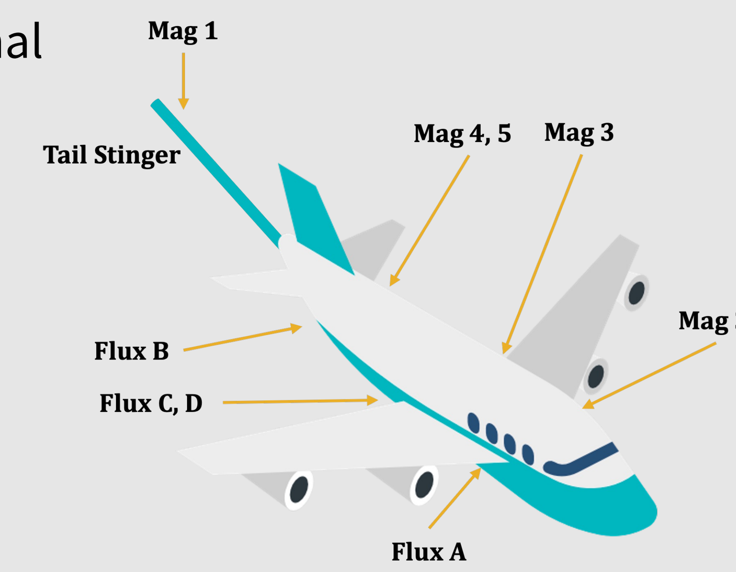

Fig 4. MagNav Challenge magnetometer locations

Results

- LTC demonstrates **~58% deduction** in **compensation error [RMSE].**
- LTC-CfC shows **~64% reduction compensation error** vs. classical model.

Model	Flt1003 [RMSE nT]	Flt1007 [RMSE nT]
Tolles-Lawson (baseline)	58.85	45.13
LSTM	41.79	42.18
MLP	30.47	26.23
CNN	26.05	30.56
LTC	20.31	22.89
LTC-CfC (ours)	18.20	19.14

Tab 1. Model comparison of aerocompensation calibration error (RMSE nT) for flights 1003 and 1007.

Our method **successfully detects weak anomaly fields** with significant **accuracy**.

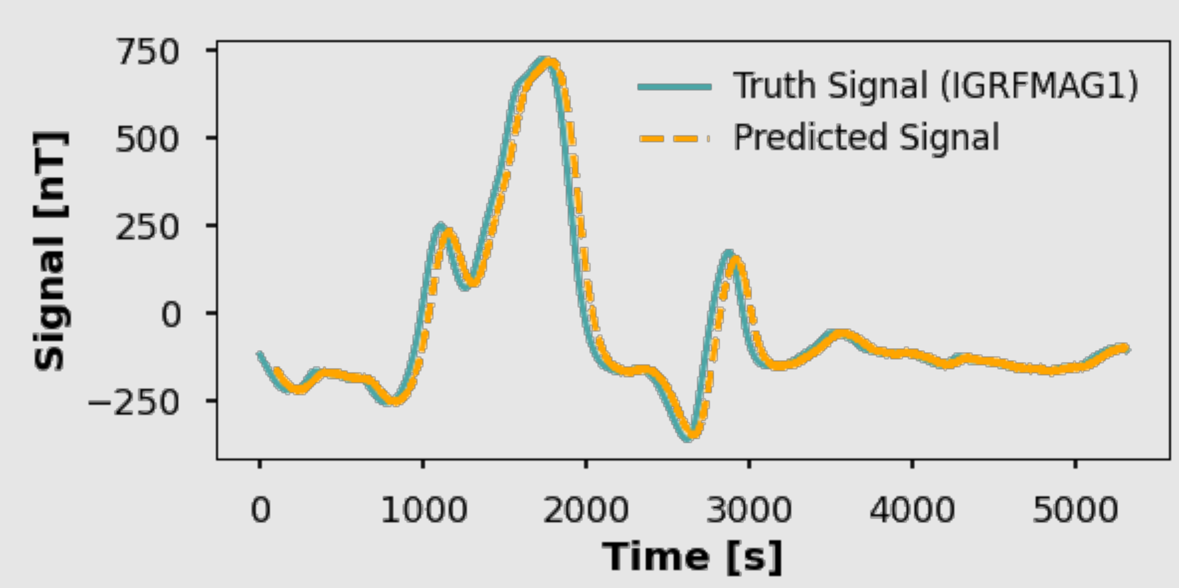

Fig 5. Truth vs. predicted signal [nT] for flight 1007

Conclusion & Broader Impact

1: **Novel, physics-informed model** that models higher-order, nonlinear dynamics in aeromagnetic compensation.

2: Offers **magnetic effects corrections**, **LTCs with ODE-solvers/closed-form** & **additive compensation correction** for MagNav signals.

3: **Separates weak magnetic anomaly fields** from noisy **magnetic interference** for **accurate positional estimation** in airborne MagNav.

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