GP41B-01

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AI-Driven Magnetic Navigation: Predicting Position from Anomalies

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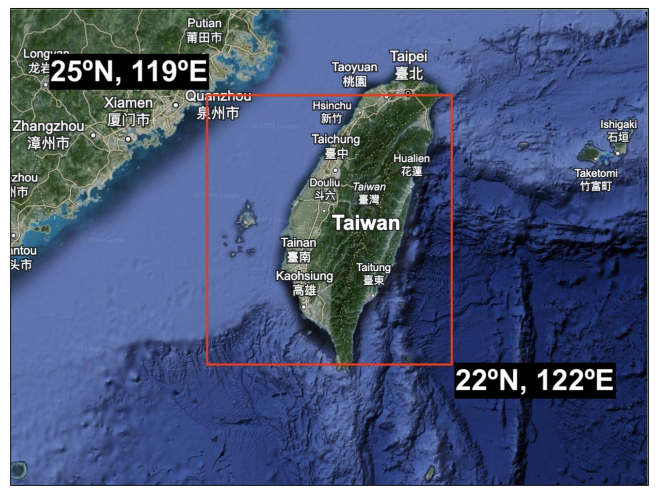
Question

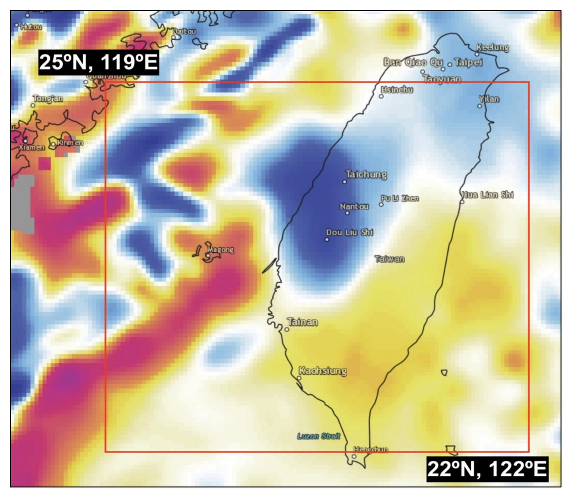
- In the absence of GPS and inertial navigation instruments, we ask to what extent can machine-learning models leverage magnetic anomaly readings to accurately determine an aircraft's longitude and latitude.
- We consider the cold-start variant of this problem: the aircraft's initial position is unknown.

Introduction

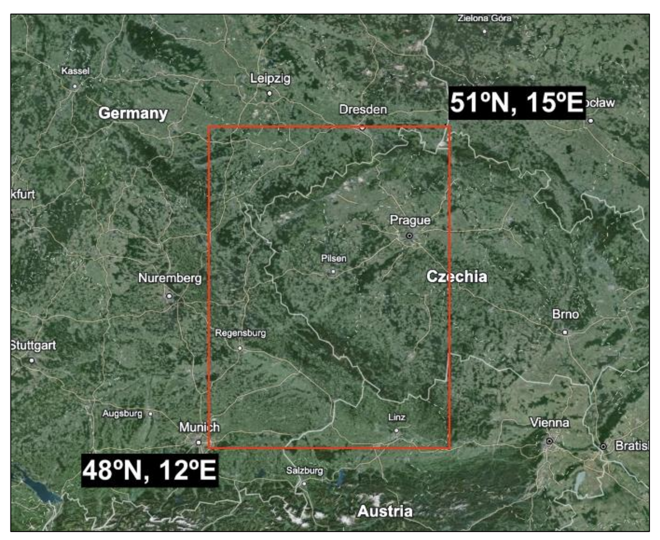
- Aerial navigation without GPS is challenging - most approaches fail in various conditions.
- Magnetic navigation (MagNav) can be used over oceans, in poor weather conditions, and is difficult for adversaries to jam.
- We seek to expand the literature by adding a machine-learning approach.
- We assume ideal conditions, such as straight flight paths and constant altitude; even under perfect conditions it is unclear if machine-learning performs well.
- We investigated the MLP, LSTM, and 1D CNN architectures.
- This work was conducted at NOAA's David Skaggs Research Center in Boulder, CO.

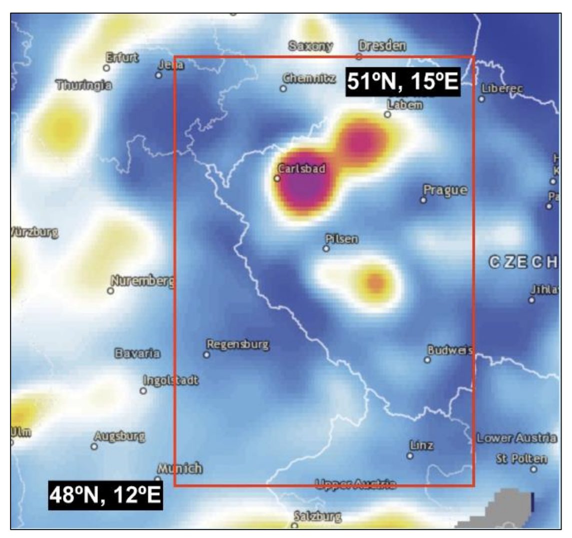
Taiwan Dataset



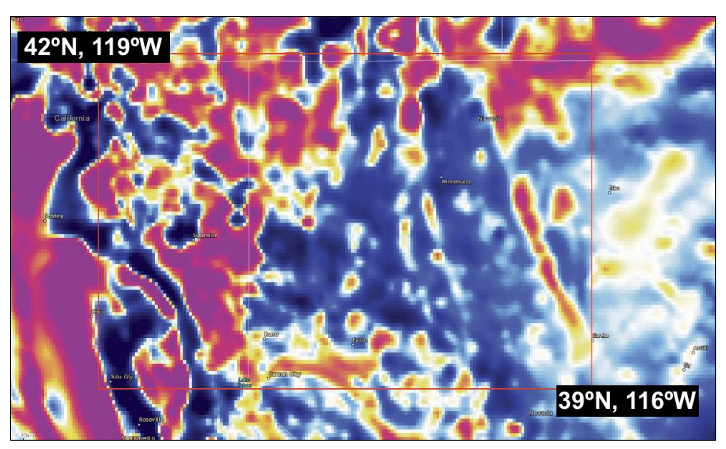


European 2 Dataset





U.S. West Coast Dataset



Acknowledgements

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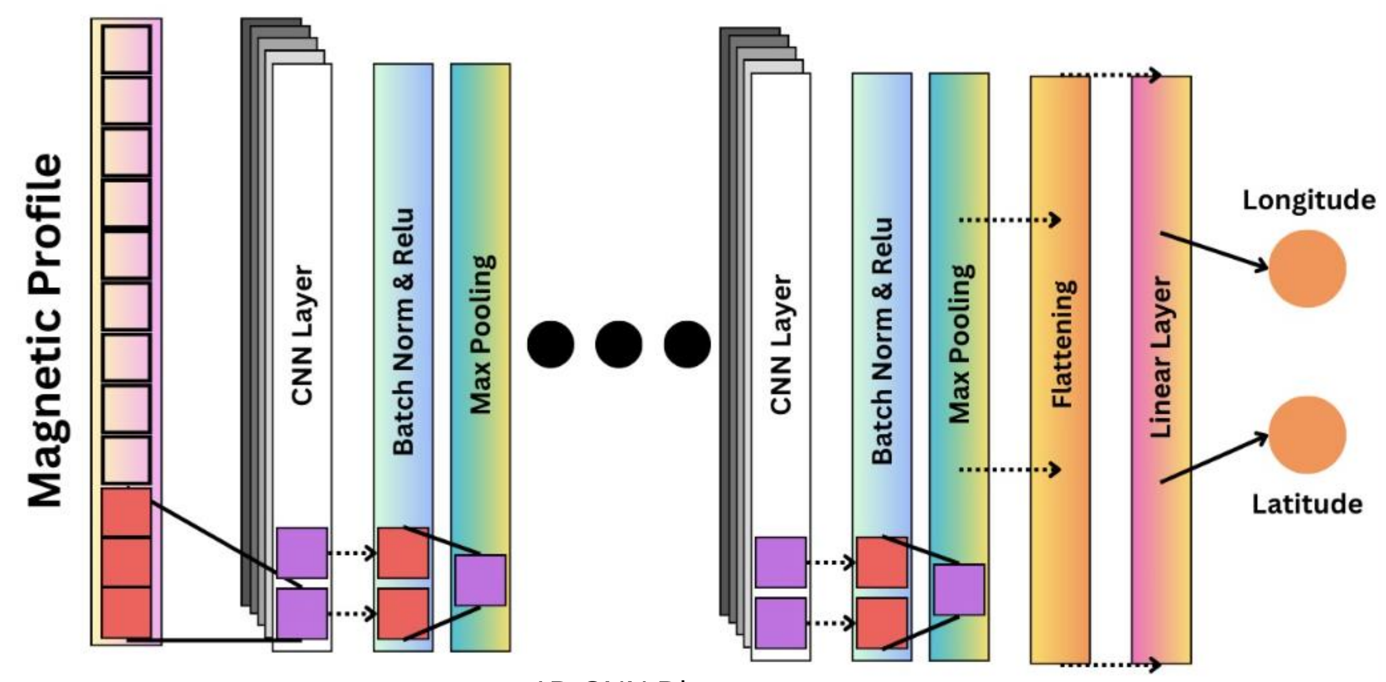
Procedure

- 32 profiles are drawn from each sampled point in the cropped EMAG2 (Earth Magnetic Anomaly Grid 2-arc-minute resolution, Meyer et al., 2017) region. These profiles are straight paths at an altitude of 4 kilometers from sea-level.
- Training (80% of dataset), validation (10% of dataset), and test (10% of dataset) sets are generated.
- The machine-learning models are trained on the training data and evaluated on the validation data. The best model is evaluated on the test data at the end.
- To account for noisy measurements, the above process is repeated. The exception is that the profiles are corrupted by Gaussian noise with standard deviations ranging from [1, 3.5].

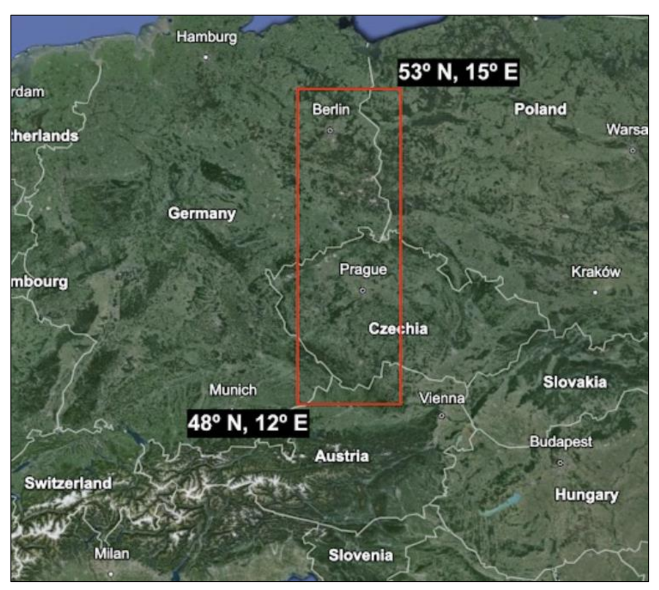


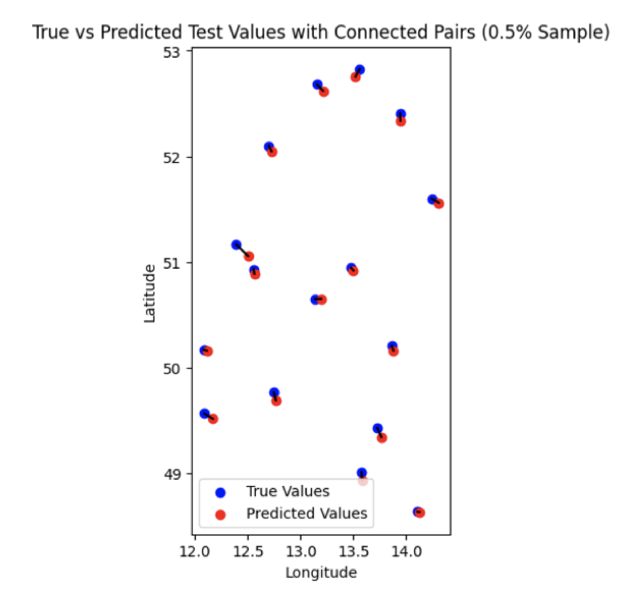
1D CNN Diagram

Prediction

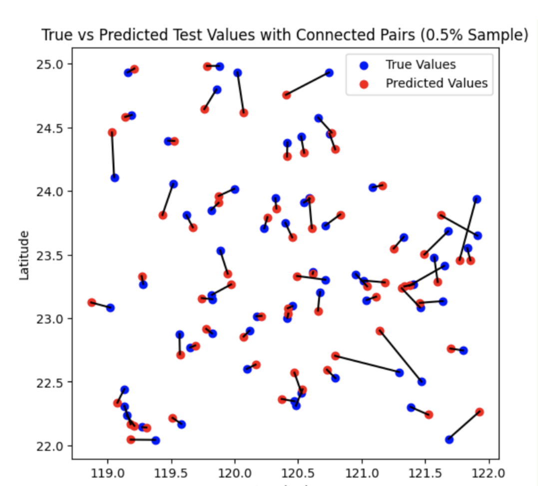
- Over three regions that span 3 longitude and 3 latitude lines, we find that a machine-learning model is capable of learning the profile space and producing position predictions within several kilometers of the true position.
- The LSTM and CNN models appear most promising, as they are designed to take advantage of the temporal and spatial relationship between magnetic measurements.
- With noisy measurements, we suspect that the models will still be able to make predictions that are typically within several kilometers of the true position.

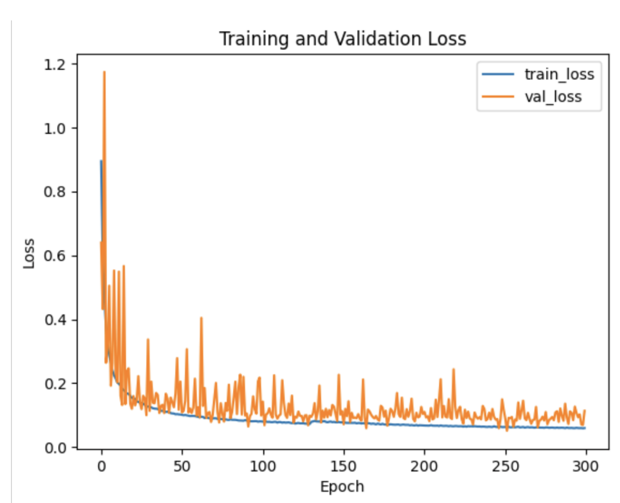
EU1 Results - Visualization





Taiwan Results - Visualization



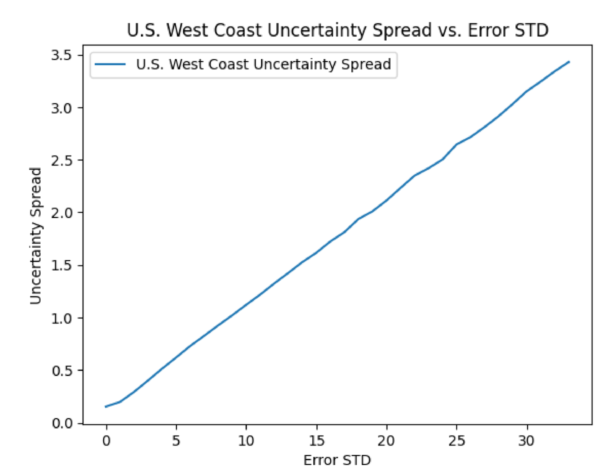


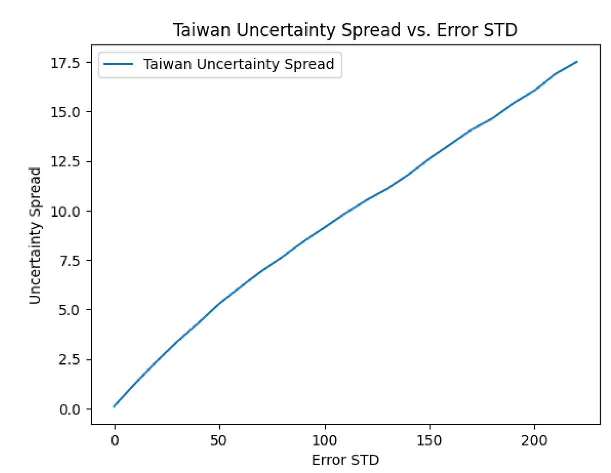
Results

- EU1 region: MAE loss 0.042, or **~2.9 mi** error in position on average.
- Taiwan region: MAE loss 0.10, **or ~6.8 m**i error in position on average.
- West Coast region: MAE loss 0.18, or **~10.5 mi** error in position on average.
- EU2 region: MAE loss 0.07, or **~5.5 mi** error in position on average.
- Recall: the map resolution is **2.5 miles**!

Map Uncertainty Propagation Analysis

- To assess uncertainty propagation in a neural network model for the Taiwan Strait, we introduced a Monte Carlo simulation approach. Starting with a trained model, we generated magnetic profiles by adding Gaussian noise (mean = 0, std = σ, the map's error in nT) to the original profile.
- Predictions from these noisy profiles were compared to true locations, and the spread (standard deviation) of the errors, measured in kilometers, quantified the propagated error from the magnetic map.
- Extending this method to multiple random locations further characterizes spatial variability in uncertainty, providing a robust framework for error analysis in geophysical applications.
- EU region: EMAG2 STD Map Error of **209 nT**. Spread = **15.7634 nT**
- Taiwan region: EMAG2 STD Map error of **212 nT**. Spread = **17.0731 nT**
- West Coast region: EMAG2 STD Map error **of 33 nT**. Spread = **3.4671 nT**





Conclusion

- 1D CNNs show promise to tackle the "cold-start" magnetic navigation challenge.
- Future work involves handling noisy measurements.
- Other questions include probing what path length is necessary for accurate predictions.
- A main factor in accuracy may be model capacity, given an adequate amount of profiles are present.

References

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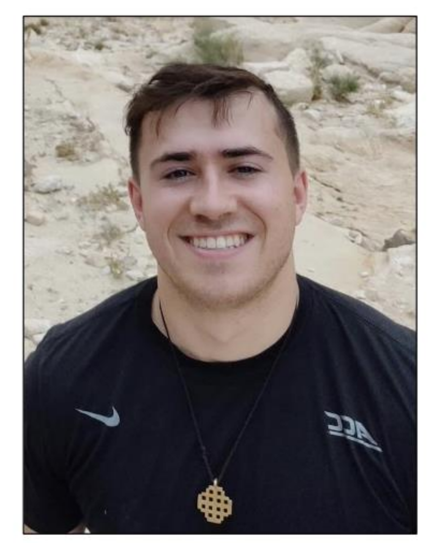

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