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Machine Learning Algorithms for Spacecraft Magnetic Field Interference Cancellation: Enabling Satellite Magnetometry w/o a Boom

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Abstract

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We present a novel approach and algorithm to the problem of time-varying magnetic field interference cancellation using distributed magnetometers and spacecraft telemetry with particular emphasis on the constrained computational and power requirements of CubeSats. The traditional approach to enable space-based low-amplitude and low-noise magnetometry is to develop a spacecraft magnetic cleanliness design and place the magnetometer sensor at the end of a boom far enough away from the bus to minimize remaining stray magnetic fields. In addition, secondary magnetometers are often placed partway along the boom to apply magnetic field gradiometry to clean the data (e.g., NASA MMS has 8 meter booms with a sensor half-way down and another at the end). We employ a different approach taking advantage of low-cost chip-based magnetometers that can be placed throughout the satellite bus instead of utilizing a boom. The spacecraft magnetic field interference cancellation problem that we solve involves estimation of noise when the number of interfering sources far exceeds the number of sensors required to decouple the noise from the signal. The proposed approach models this as a contextual bandit learning problem and the proposed algorithm learns to identify the optimal low-noise combination of distributed magnetometers based on indirect information gained on spacecraft currents through telemetry. The algorithmic behaviors are tested with synthetically modeled spacecraft data and on real world data generated in a lab-based setting with telemetry and currents collected from the GRIFEX CubeSat and provides a way for accurate magnetic field measurements with CubeSats without booms.

Enabling Magnetometer

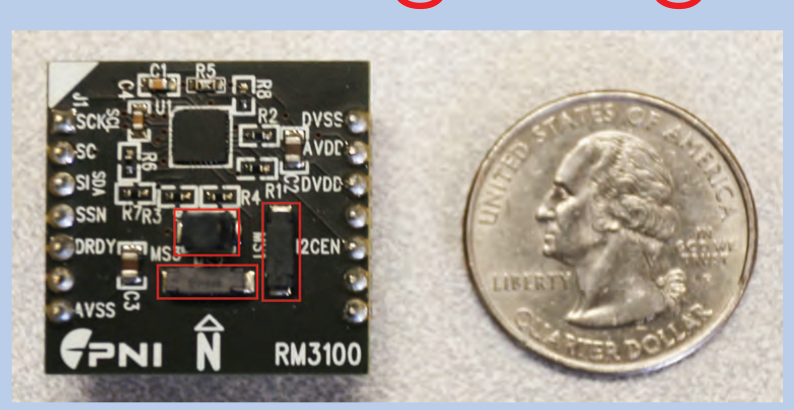
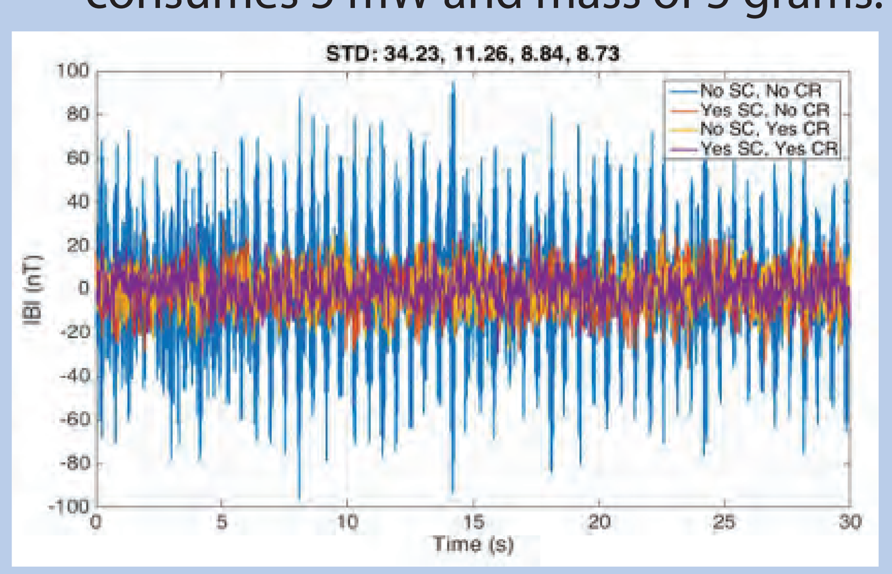


Fig 1. The PNI mag compared to a US quarter. The 3-axis sensors are highlighted in red.

Fig 2. Modified sensor has noise floor of a fluxgate. resolution of about 1 nT, consumes 5 mW and mass of 5 grams.



Simple Regret Minimization and Contextual Bandit Algorithm

Contextual Bandits are a sub-class of Multi-Armed Bandits where the player has access to side information that helps refine policy in arm identification. Simple regret minimization deals with the idea of splitting the exploration and exploitation phases in bandits, where the algorithm is allowed to perform pure exploration either for a period of time or until sufficiently confident enough and identify the best arm at the end of the given period.

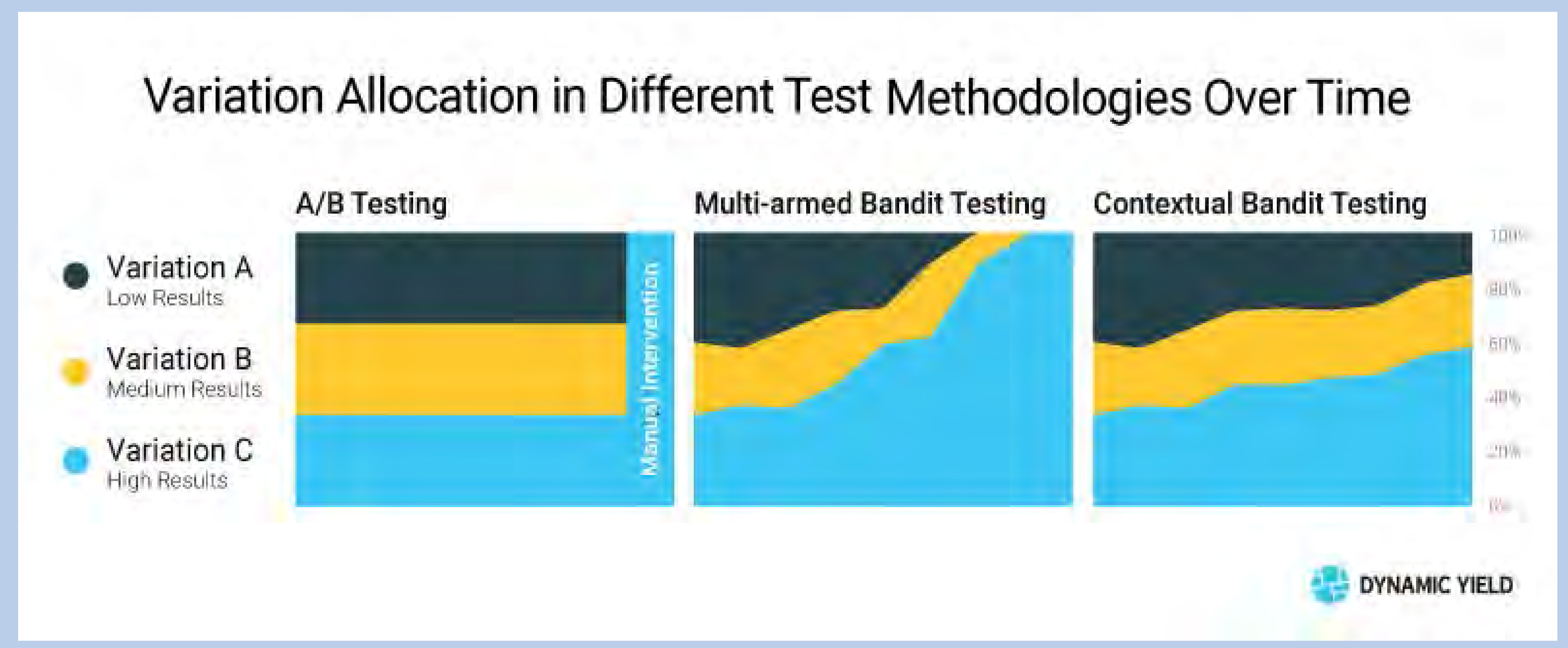


Fig 3. Machine Learning algorithms used in web-page optimization and sales are adapted to find the best combinations of magnetometers with information from telemetry to minimize noise.

Experiment

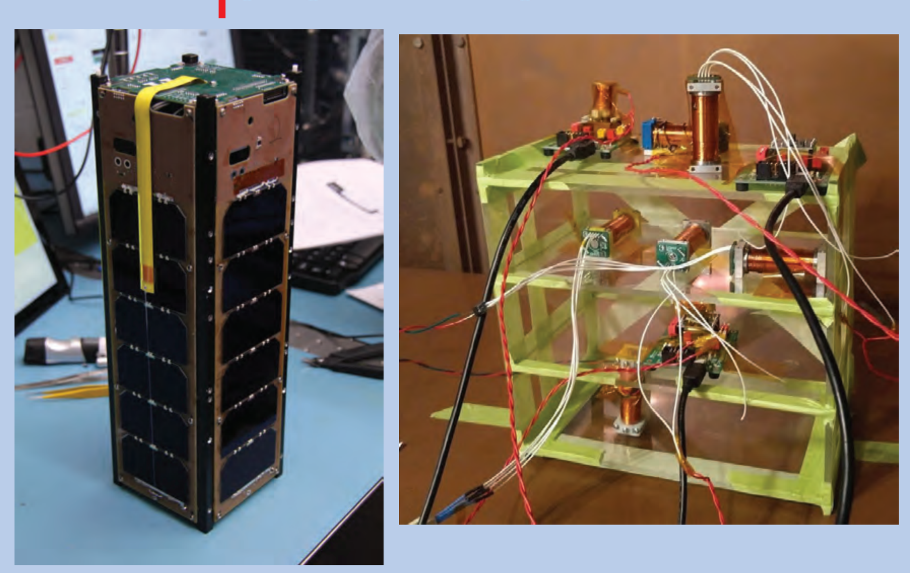


Fig. 4. The GRIFFEX CubeSat provided solar panel current and temperature data and we created a 4U CubeSat model with 8 coils representing reaction wheels, solar panels and electrical power system (EPS) with 3 mags.

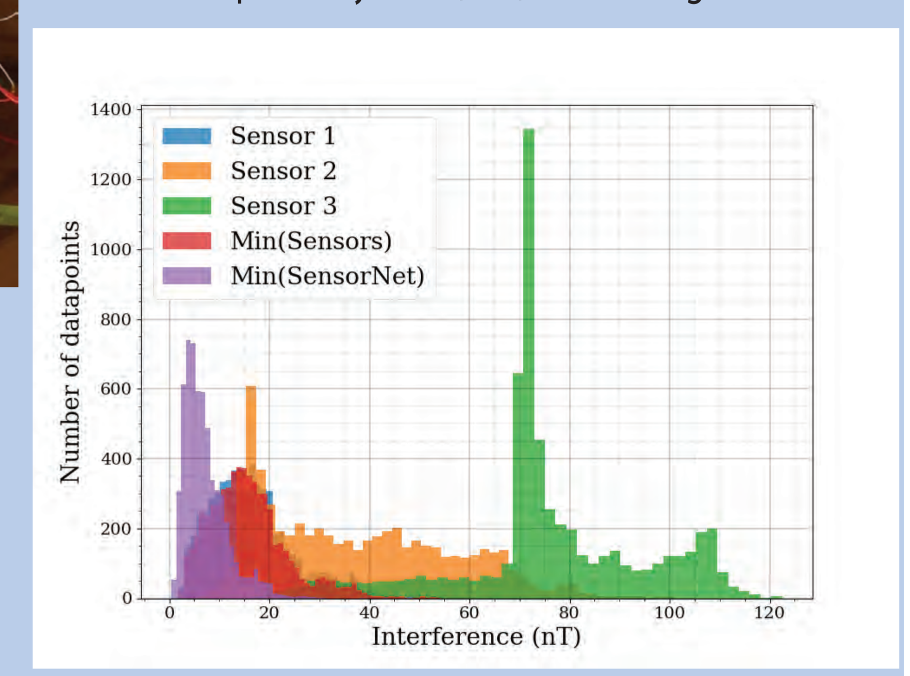


Fig. 5. Distribution of interference levels for individual magnetometers, best mag, and sensor combination results.

Both simulated and a laboratory experiment were conducted to test the algorithm. Fig 3 shows the lab set up and Fig 4 shows the results. Note the purple distribution.

Alogorithm Results

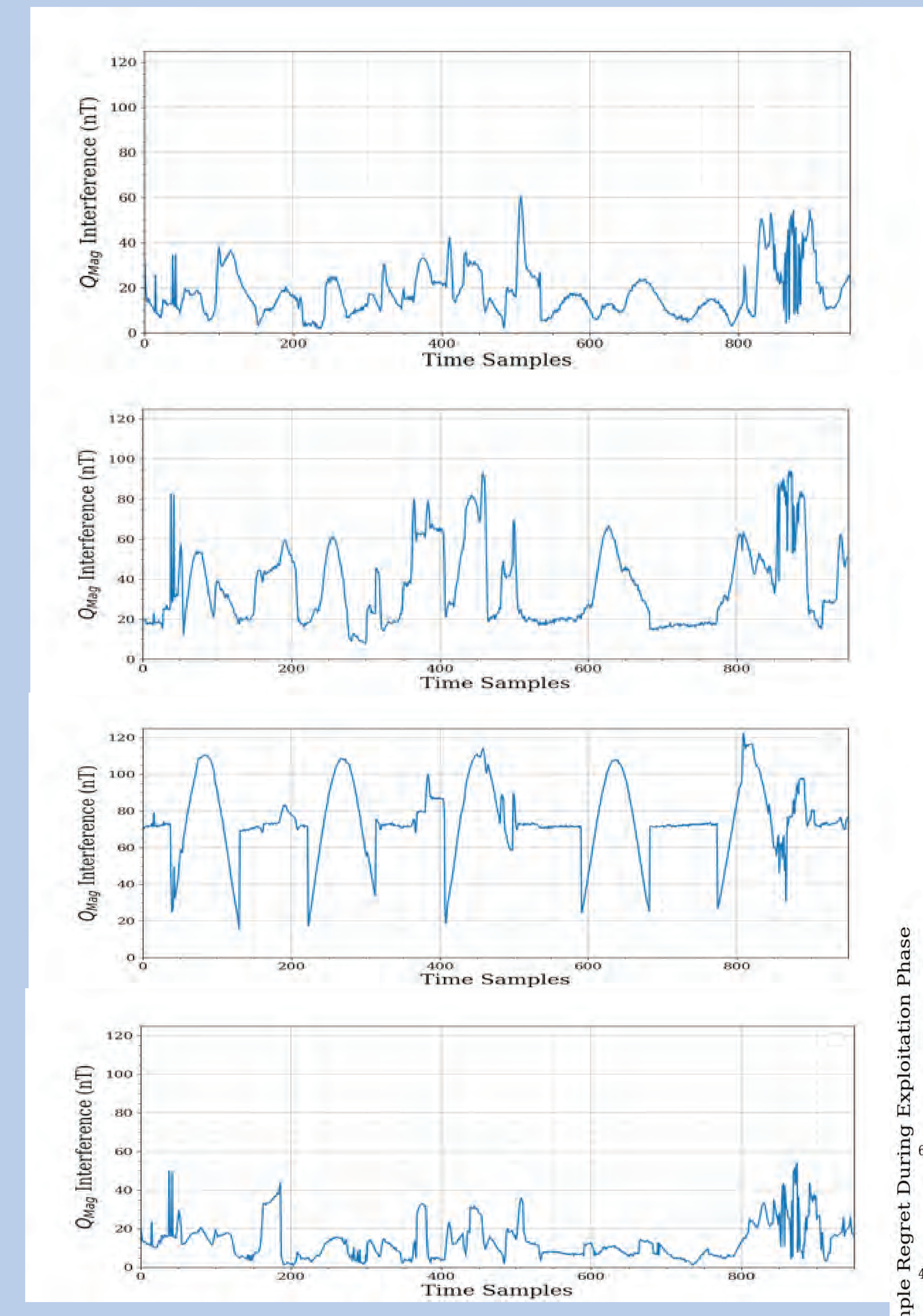


Fig. 6. Raw magnetometer magnitude data from 3 sensors with residual interference data from Contextual Bandit Algorithm.

The 8 noise coils were fed with noise profiles from EPS. solar panels and reaction wheels and geomagnetic field data observed from a spinning spacecraft using the POMME magnetic field model were added in addition to random noise profiles. The algorithm found the best sensor that had the minimum noise.

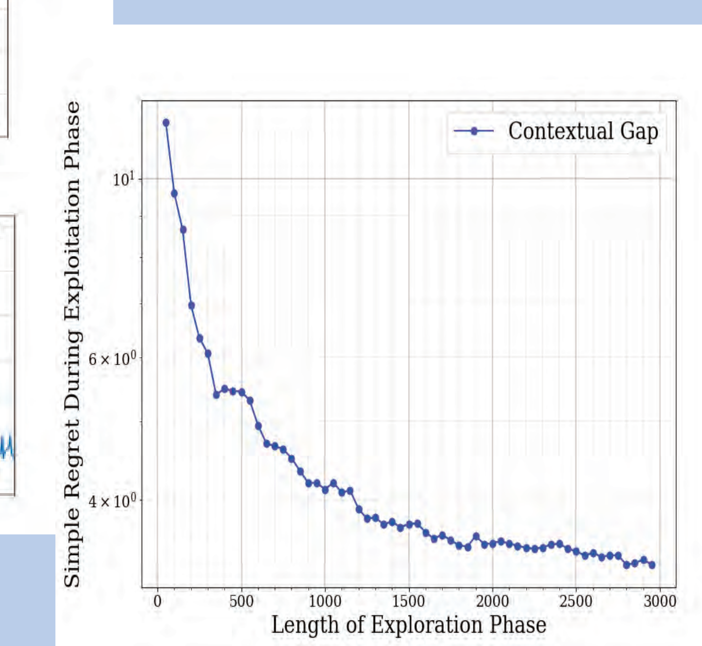


Fig. 7. Minimization of Regret as a function of Exploration Phase duration showing that with increased data, the Contextual Gap Algorithm was able to identify combinations of sensors that minimized interference. Note that regret does not go to zero indicating the the optimum sensor combination is imperfect.

Conclusions

The results show that a Machine Learning approach can be used in combination with low-SWAP+C magnetometers [Regoli et al., 2017] to identify and cancel s/c magnetic interference [Sheinker and Moldwin 2016] on CubeSats. Sharma [2018] describes the mathematics, algorithm and results in detail.

References

Sharma, Srinagesh, (2018) Machine Learning Applications in Spacecraft State and Environment Estimation, PhD Dissertation, (paper under review).

Regoli et al., (2017) Investigation of a low-cost magneto-inductive magnetometer for space science applications Geoscientific Instrumentation, Methods & Data Sys Disc.

Sheinker, A., and M. B. Moldwin, (2016) Adaptive Interference Cancellation Using a Pair of Magnetometers, IEEE Transactions on Aerospace and Electronic Systems, 52, 1.