NG45B-0548 Algorithm Development for Magnetic Field topology Reconstruction in a 3-D Simulation Box Using Machine Learning

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Abstract

At present we cannot image full structure of the interplanetary magnetic field using a few spacecraft. However, constellations with larger and larger number of spacecraft are becoming increasingly common with several possible missions to be launched in near future. Thus with a view towards the future, we carried out a study to reconstruct the 3-D topology and morphology of the interplanetary magnetic field from observations made by such a constellation with finite number of spacecraft. Using Gaussian Processes in machine learning for different configurations of number and arrangement of spacecraft, we showed that we need a baseline of 24 spacecraft to successfully carry out such a process. A complete 3-D image of the magnetic field will significantly advance our understanding of turbulence in space plasmas and and shed light on the exact process of turbulence cascade. We also report on the change of quality of reconstructed images for different number of spacecraft and configuration.

Introduction

With increasing numbers of spacecraft and even constellations currently being developed, traditional single spacecraft analysis techniques no longer provide feasible methods.

Classical extrapolation techniques like first order Taylor expansion or Grad-Shafranov techniques, though are useful at one scale, fail to fully capture the complexity of the interplanetary magnetic field (IMF) because of its inherent multiscale nature. New tools are thus required to efficiently ingest multipoint data to produce magnetic field reconstruction.

Over last decade or so, machine learning has become increasingly relevant in data analysis techniques. In this study we thus present an initial proof of concept of an algorithm development using Gaussian Processes (GP) Regression in machine learning.

Methodology and Results

In order to demonstrate the feasibility of the algorithm, we fly a 2-D constellation of spacecraft, in two different configurations (see Figure 1), through a fully kinetic 3-D PIC simulation data. The size of simulation box is 42 times the ion-inertial length (d_i) in each direction. Each spacecraft make an observation at a cadence of ~ 13 Hz. We assume a typical solar wind speed of 500 km/s. This, under the assumption that Taylor's hypothesis is valid, corresponds to consecutive data points separated by approximately $0.33d_i$. We then train the GP model on these data to get a model which can predict the value of magnetic field at every point in the 3-D volume spanned by the spacecraft coonstellation.

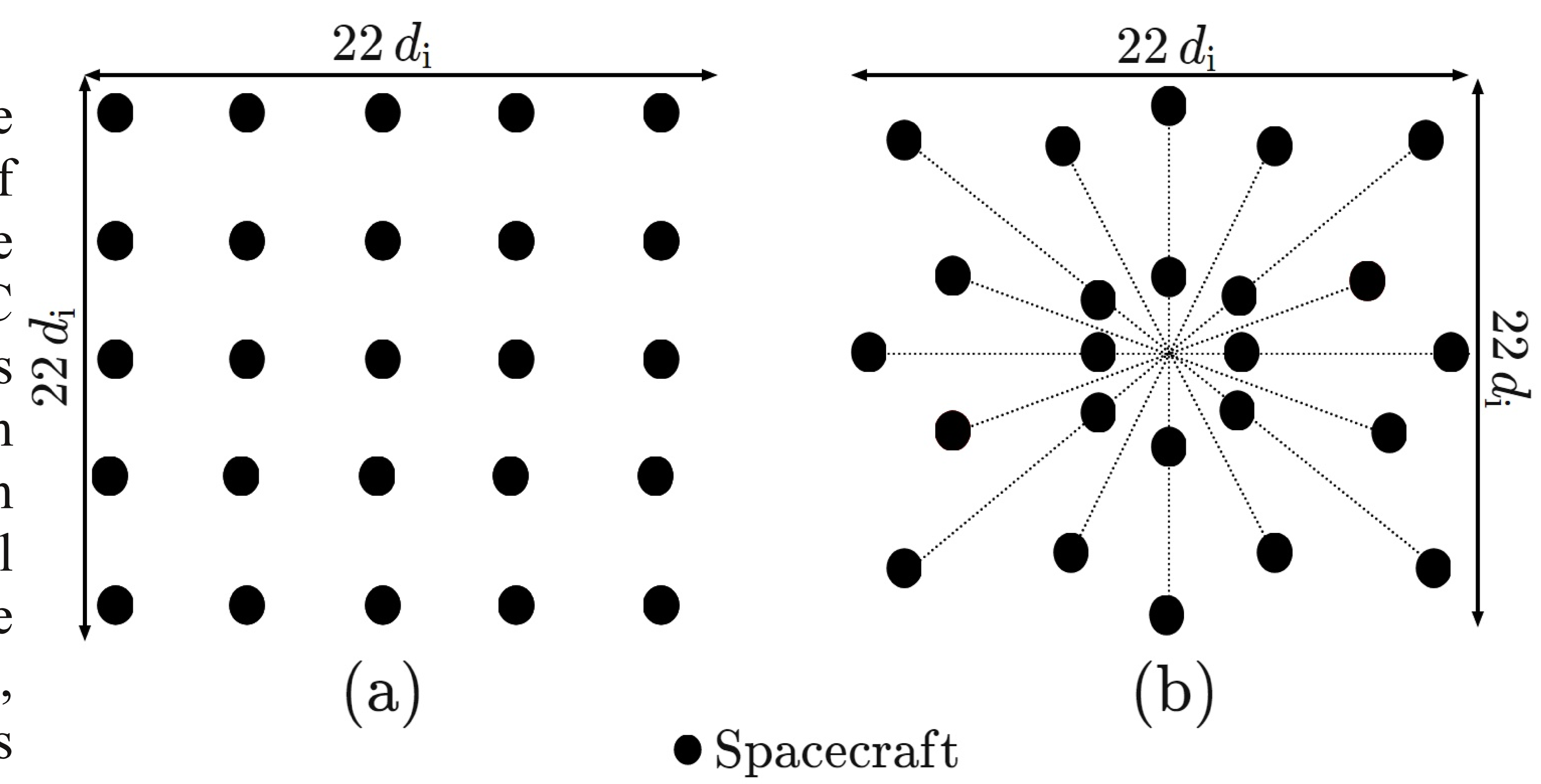

Figure 1: The two configurations of spacecraft.

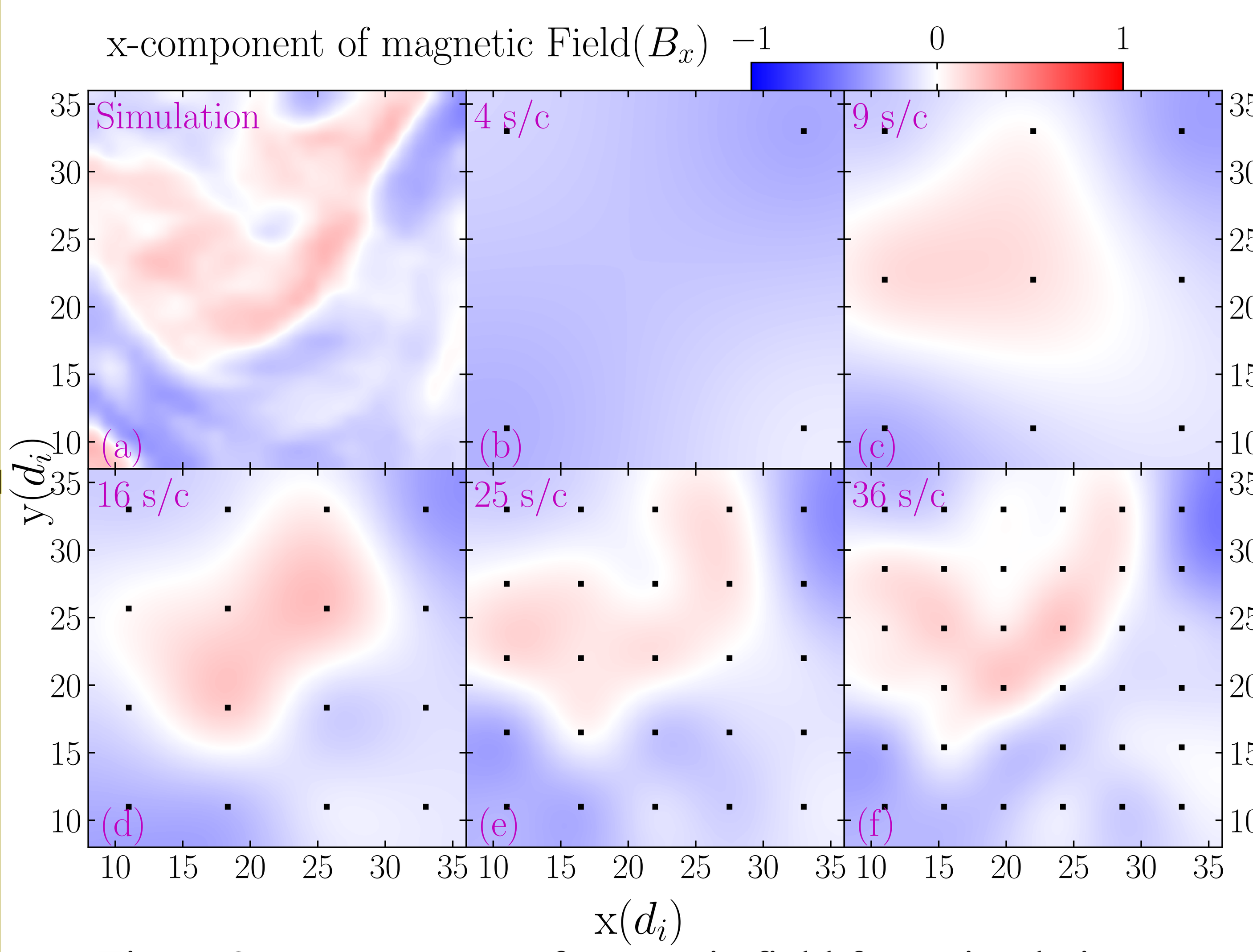

Figure 2: x-component of magnetic field from simulation .

Panel a of Figure 2 and 3 shows the magnetic field from simulated data. In Figure 2 panels b to f (and panel b to h in Figure 3) show the reconstructed magnetic field using different number of spacecarft in square (circular) configuration. For both configuration of spacecraft 4 and 8 spacecraft can barely capture any structure. It is only when we have 16 spacecraft in the constellation that structure resembling the simulation data emerges. The quality of reconstructed image improves significantly as we increase the number of spacecraft from 16 to 24. Further increment in number of spacecraft though improves the quality, the change doesn't seem to be substantial enough. Though further error analysis is required to make a final conclusion.

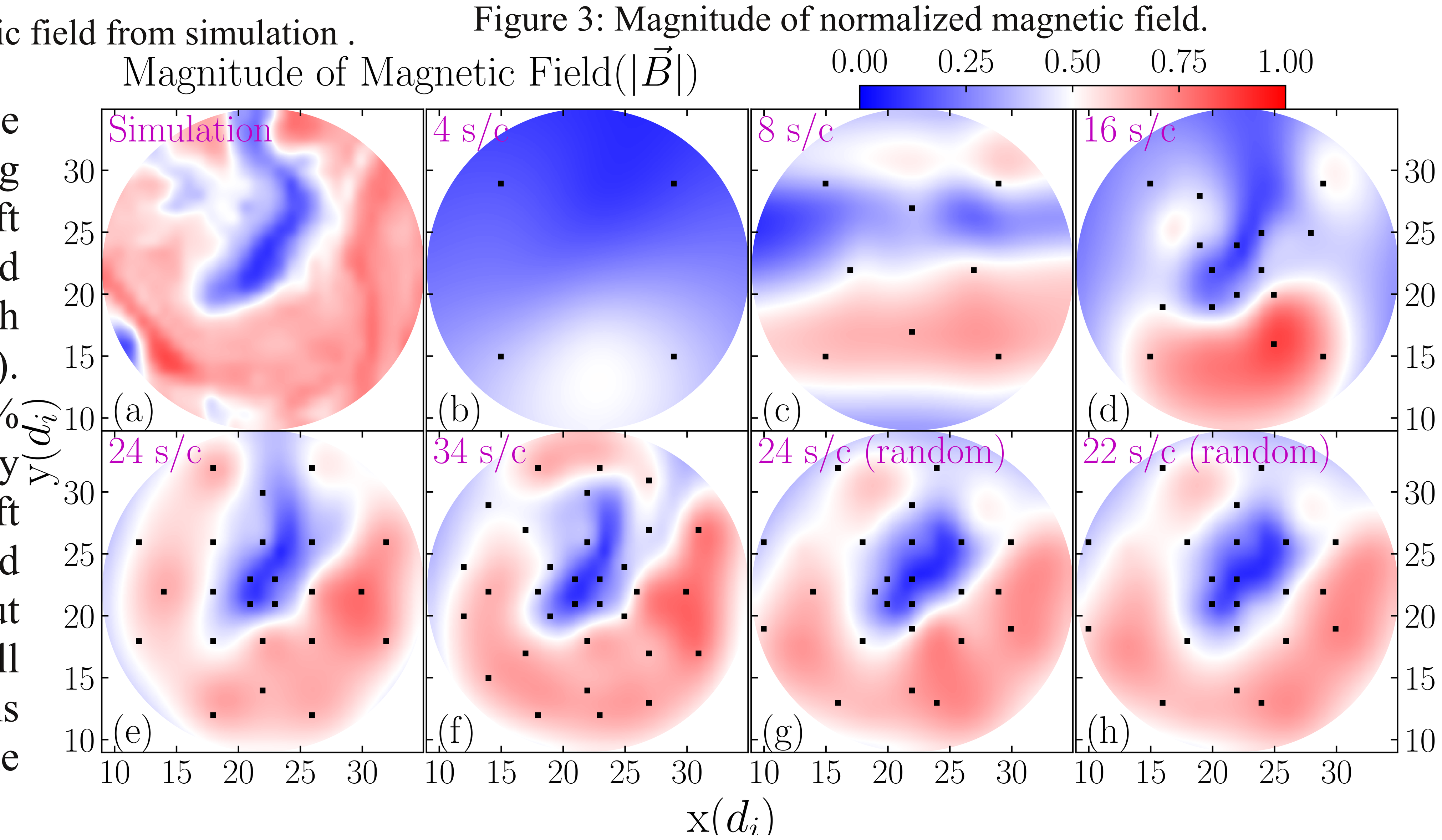

Figure 3: Magnitude of normalized magnetic field.

We further tested the predictive power of algorithm by varying the location of each spacecraft randomly in a circle of $2d_i$ around the mean position of each spacecraft (panel g in Figure 3). We also simulated roughly 10% failure rate of the spacecraft by randomly removing 2 spacecraft from constellation. We observed that though the shape of output image changes a bit, the overall quality of reconstruction remains same, which shows the robustness of the algorithm.

Conclusion and Discussion

- Traditional methods of data extrapolation are not sophisticated enough to capture the multiscale nature of solar wind using data from multiple spacecraft.
- We presented a proof of concept study of reconstruction of IMF using Gaussian Processes in machine learning.
- Based on observations thus made, we establish that a baseline of 24 spacecraft is required to reconstruct IMF with reliable accuracy.
- Though further study is required to understand the effect of spacecraft separation and arrangement on the quality of reconstructed image.
- The present algorithm does not take into account the zero divergence condition of magnetic field. We thus need to carry out divergence cleaning of the reconstructed magnetic field.
- We are also in process of developing a quantitative way of comparing various reconstructed images.

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