Using Self-consistency to Determine Uncertainty in Particle Accelerator Diagnostic Measurements

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Abstract

Control of a particle accelerator relies on interpreting input diagnostics, and tuning the accelerator settings to achieve desired diagnostic values. Particle accelerator diagnostics can fail, slowly or abruptly, and currently a human operator is tasked with evaluating this. For truly autonomous operation of particle accelerators, we must be able to determine the reliability of a diagnostic using nothing more than the set of all diagnostic data. We present a method of quantifying the scale of error in diagnostic measurements based on gaussian process (GP) regression and the intuition that each diagnostic measurement from a beam position monitor (BPM) should be predictable given the set of all other BPM measurements.

Methods

This work is based on the assumption that the measurements from perfect diagnostics are all related, so that given the set of other all the other diagnostic measurements, we can accurately predict each diagnostic's measurement. If we can make this prediction exactly in a theoretical picture, then we can use errors in fitting this relation to errors in the diagnostic measurements.

Thus, given a set of diagnostic measurements $\{X_n\}$, we can infer the diagnostic measurement from a functional relation with all the other diagnostic measurements:

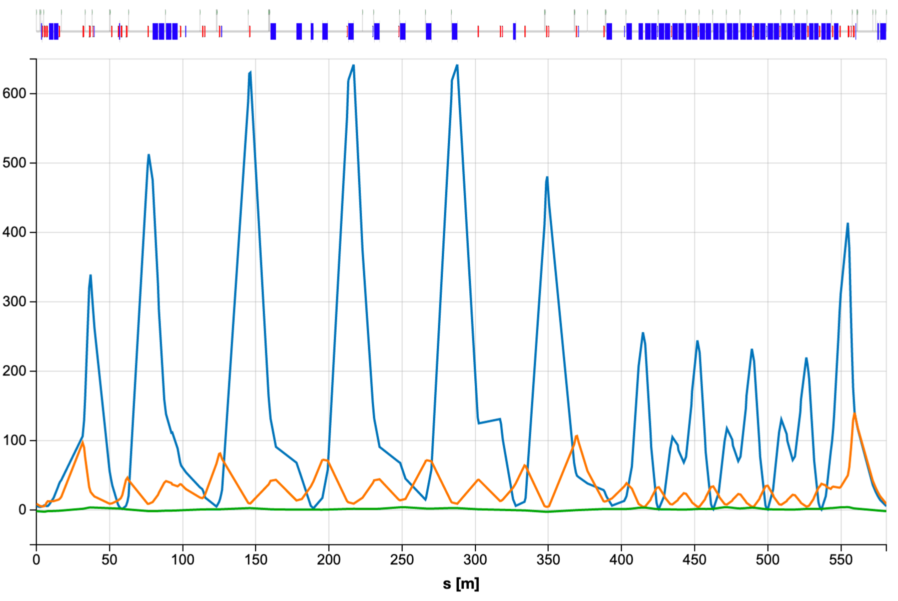
$$X_i = f_i(\{X_{n \neq i}\})$$

This is the diagnostic self-consistency assumption.

We will test this assumption using simulation data to determine where it is valid using gaussian process regression. We then add normally distributed noise with a randomly assigned RMS value to each BPM's data, and fit a GP model to this data on a training set. We compare the predictions of the GP model to the actual data in a holdout set, compute the RMS error of those predictions, and compare to the RMS noise level for each BPM.

ATR Beamline

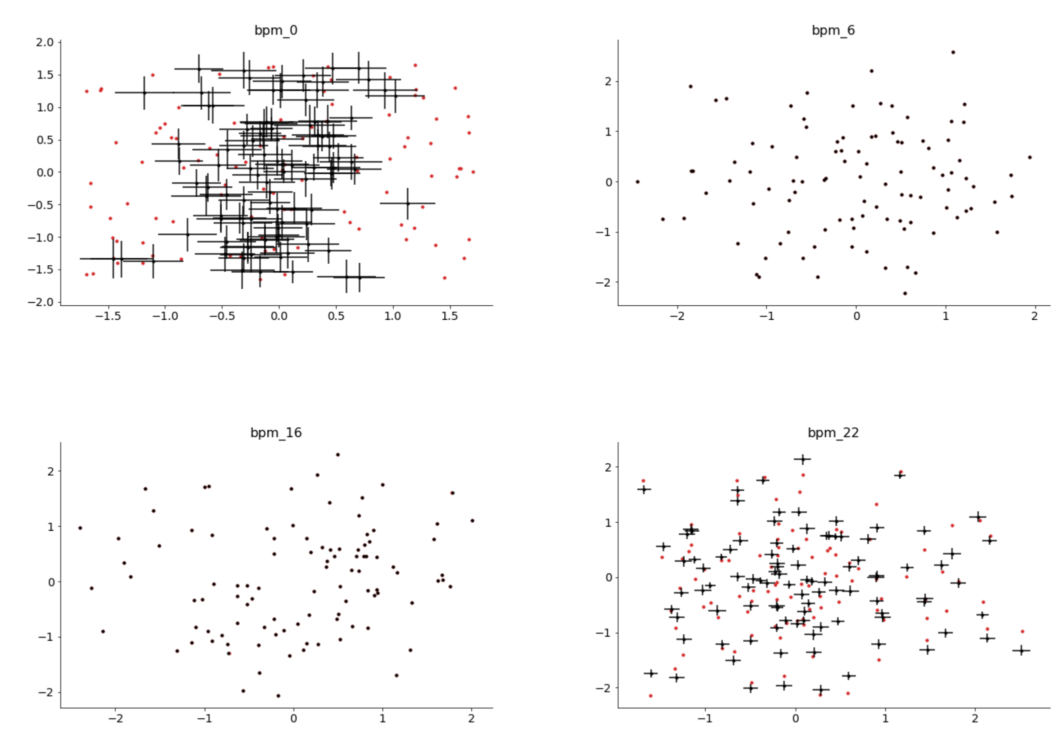
We use the ATR beamline at Brookhaven National Laboratory as our test beamline. This beamline has 22 BPMs. We simulate the beam dynamics using MAD-X.



Twiss parameters and schematic of the ATR beamline

Baseline Model

To establish whether diagnostic self-consistency exists, we start by looking at simulation data with no noise – if BPM data is correlated self-consistently, then we expect a GP model to fit the data perfectly.

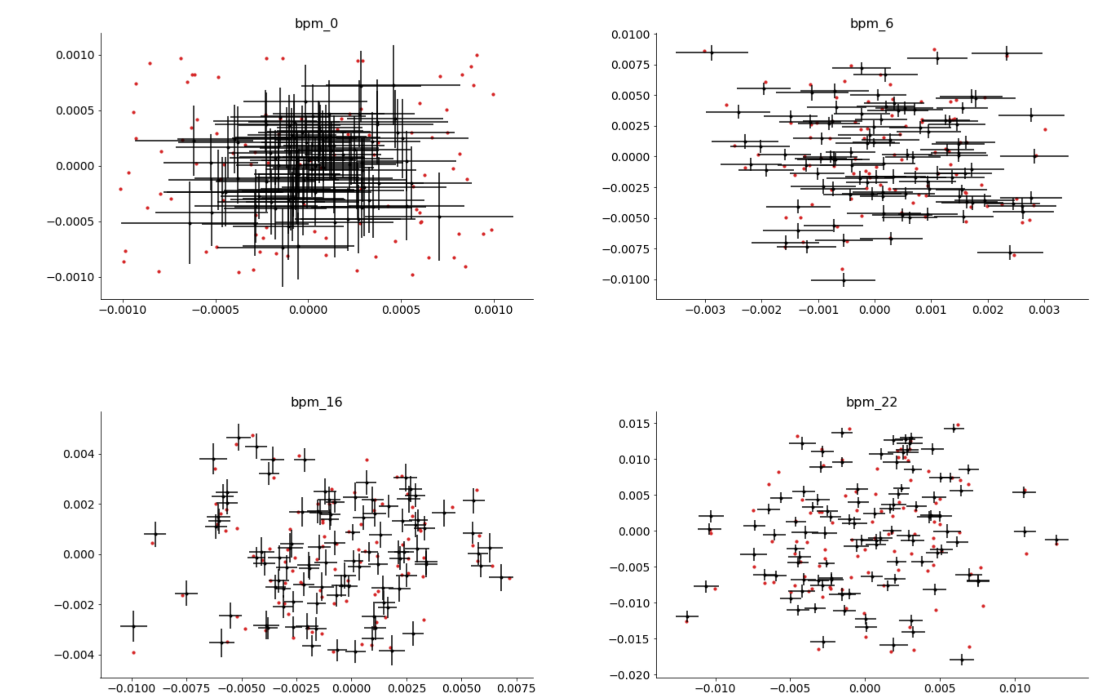


GP model predictions from self-consistency (black points with uncertainty bars) vs. data from MAD-X simulations (red points).

We find this diagnostic self-consistency for most of the BPMs, with outliers detectable from the simulations.

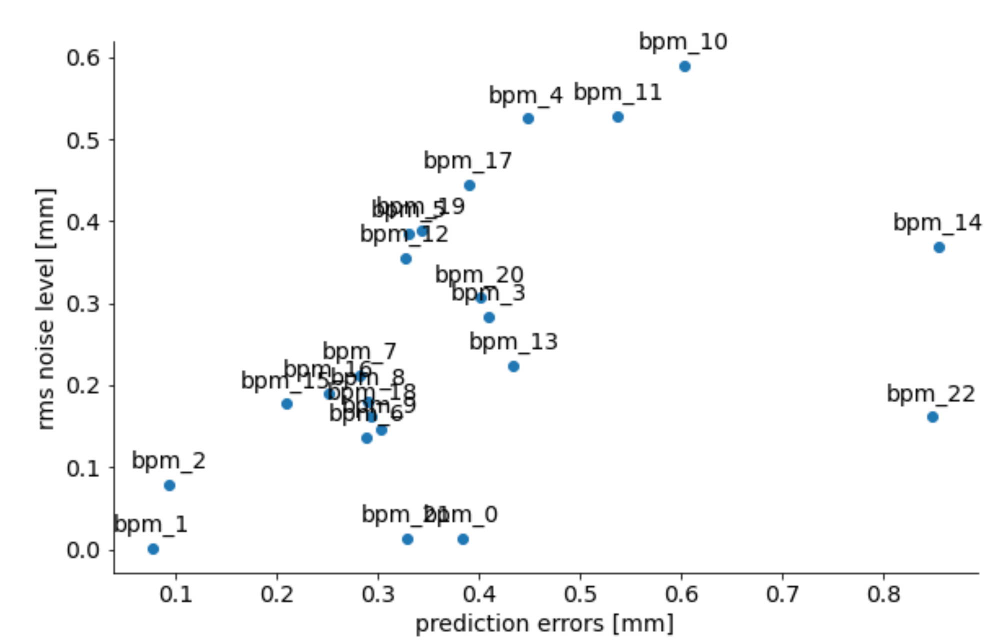
Self-consistency with Noise

To test how the diagnostic self-consistency appears with noise, we assigned each BPM a random RMS noise level and added noise to each BPM's measurements, then repeated the self-consistency computation.



GP model predictions from self-consistency (black points with uncertainty bars) vs. data with noise (red points).

The self-consistency was fit to a training set of the BPM data, and then predictions were taken from a holdout set of BPM data using the trained GP model. We quantified the noise level by taking the RMS error in the prediction for each BPM's holdout dataset, and compared to the



RMS prediction errors from GP model predictions versus RMS gaussian noise level, showing linear trend for most BPMs

Outside of outlier BPMs which can be detected in simulations of the ideal case, the RMS noise levels are an excellent predictor of the diagnostic uncertainty, suggesting that this approach could be used to quantify diagnostic uncertainty.

Conclusions & Future Work

We have demonstrated that a self-consistency requirement can be used in an ideal model case to quantify the RMS uncertainty in BPM measurements for BPMs which satisfied the self-consistency condition in simulations. This assumes that the noise is gaussian and uncorrelated.

Future work must look at two different conditions:

1. The artificially added noise is non-gaussian (i.e. $1/f$ noise); correlated; then both; to show that the predictions are robust in more complex systems
2. The technique must be applied to archival particle accelerator data to see if it can predict diagnostics that were in the process of failing, which is a proxy measure for uncertainty.

Once we establish the technique is robust, we must find a way to integrate the resulting RMS measures into a *reliability metric* that can be used when automatically tuning a particle accelerator. This could be, for example, used as a prior on the inputs for a Bayesian optimization scheme, or a weight on the rate parameter in a gradient-based optimization scheme.

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