LINEAR OPTICS CORRECTION OF STORAGE RING WITH CLOSED ORBIT DATA BASED ON MACHINE LEARNING

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Abstract

The LOCO algorithm based on orbit response matrix (ORM), which is the change in orbit at beam position monitors (BPMs) with changes in steering magnets, has been widely used for linear optics correction in storage rings. It computes the orbit response matrix and fits it to the experiment data linearly as making quadrupole strengths and others as free parameters. In order to solve the difficulty on convergence of ORM method when the change of focusing optics or the effect of nonlinear optics on the closed orbit is large, we propose a method based on machine learning. The closed orbit of the design lattice produced by each steering magnet at BPMs is calculated using ELEGANT simulation code which fully includes non-linear components and is fitted to the measured closed orbit data in the experiment. This method can nonlinearly compute the correction parameters of the lattice by minimizing the discrepancies between measured and predicted closed orbits. We have applied this method to the lattice of UVSOR_III.

INTRODUCTION

In order to have a successful operation of particle accelerators, the study of linear optics to understand and remove or compensate the source of the optics perturbations is required. Linear optics from closed orbit (LOCO) method, which based on the orbit transform matrix (ORM) is a powerful method to fit the measured data to a lattice model to determine the quadrupole errors in the machine [1-3]. The orbit response matrix consists of orbit deviations at beam position monitor (BPM) locations when the orbit correctors are changed, one at a time. Each column of the orbit response matrix corresponds to the response of one corrector.

One limitation of the LOCO method is its sensitivity to the linear dependency on quadrupole strength, rendering it unsuitable for machines with strong nonlinear parameters.

This new method is similar to LOCO in that it also measures closed orbits, may be referred to as nonlinear optics from closed orbit (nLOCO). In the case of fast calculation, we use a machine learning method based on Bayesian optimization method to obtain the fitted model parameters to the measurements quickly.

In this study, we introduce an innovative approach for linear optics correction, incorporating nonlinear components through the computation of closed orbit shifts using a particle tracking simulation code. We refer to this novel method as "nonlinear optics from closed orbit" (nLOCO), and it shares similarities with LOCO in its focus on closed orbit measurements. To speed up the parameter fitting process, we use a machine learning technique based on Bayesian optimization. This allows us to obtain fitting parameters in situations requiring rapid calculations.

In this paper, we will describe the nLOCO method in more detail in section III. In Sec. IV, simulation results are shown for UVSOR_III. The conclusion is given in Sec. IV.

THE LOCO METHOD

The closed orbit correction can be calculated by the LOCO method which originally relies on orbit response matrix method (ORM). ORM is based on the linear orbit response equation for a small change of j-th dipole kick angle θ_j [4]:

$$x_i = M_{ij}\theta_j$$

where x_i is the measured position at monitor i, M_{ij} is the element in the response matrix. Therefore, the ORM matrix can be both measured and calculated theoretically if the linear optics is known. Therefore, it is an appropriate way to judge the agreement between the design and real machine is described by a merit function [5],

$$\chi^2(p) = \sum_{i\,j}\left(\frac{M_{ij}^{meas} - M_{ij}^{model}}{\sigma_i}\right)^2$$

where σ_i is the measured noise level on the ith BPM. The goal is minimization of χ^2 which is the difference between measured and model response matrix. The minimization process can be achieved by varying some model parameters based on singular value decomposition (SVD) algorithm.

However, the convergence of fitting is very much limited within linear dependence of χ^2 on quadrupole strengths, orbit kickers, and BPM gain. The assumption of this linearity is usually invalid in real cases. Therefore, one should iterate the fitting algorithm. To include the nonlinearity, we propose a new method in the next section.

THE NLOCO METHOD

Modeling

The closed orbit shift can be measured experimentally and calculated theoretically at each BPM when one orbit corrector is changed to give an angular kick to the beam. In order to make a judge between measured closed orbit and model one, we introduce a function which is the difference between the measurement and the model closed orbit,

$$\Delta C^2 = \sum_{i\,j}\left(\left(\Delta x_{ij}^{meas} - \Delta x_{ij}^{model}\right)^2 + \left(\Delta y_{ij}^{meas} - \Delta y_{ij}^{model}\right)^2\right)$$

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where Δx_{ij} and Δy_{ij} are horizontal and vertical closed orbit shift at ith BPM for an angular kick of jth steering magnet, respectively.

In this method, the closed orbit of the model is calculated by using a single particle simulation code such as ELEGANT [6] which can consider not only nonlinear components on the electron beam, but also correct the betatron tune for each fitting parameters set. Dispersion functions is included as fitting data; $\Delta E/E$, as is done for the LOCO method. The electron energy shifts proportional to the dispersion at the steering magnet when a horizontal steering magnet strength is changed.

$$\frac{\Delta E_j}{E} = \frac{\theta_{xj}\,\eta_{xj}}{\alpha_C L_0}$$

where η_{xj} is the horizontal dispersion at the steering magnet, α_C is the momentum compaction, and L_0 is the storage ring circumference defined by RF frequency.

In order to fit the model closed orbit to the measurement, the minimization of the function ΔC^2 is required. The minimization can be achieved by surveying the model parameters such as strength of quadrupoles, BPM gains and steering magnet calibrations. In general, the minimization process by surveying each parameter while using a particle tracking simulation code is computationally expensive in terms of CPU time (time consuming).

Bayesian Optimization Method

To optimize a black-box function there are a large variety of optimization algorithms in use [7-9]. For the functions which are noiseless and do not require significant time, local optimization methods can be used with very strong performance. While for expensive functions which take a long time to evaluate, there are some global optimization algorithms which can approach the global optima in better performance on time limited and noisy measurements. Recently Bayesian optimization method has been attracted in accelerator community [10, 11].

Bayesian optimization is a framework to optimize a costly function which may perform a large number of evaluations. It consists of two elements; a surrogate model which is a mathematical model to approximate the real objective function and an acquisition function which describes the strategy to determine the next points in input space to measure. The surrogate model is usually generated through Gaussian process regression that returns a probability distribution of possible functions compatible with previous evaluations and is much faster and/or cheaper to evaluate. The model can predict the most probable value of objective function at an unexplored location and provides an uncertainty for this prediction. Then the model predictions and their uncertainties are combined into an acquisition function to determine the next parameters to sample. After the evaluation, the model is refined with the newly gathered information. This process is repeated iteratively to find the optimum parameters that optimize the objective function.

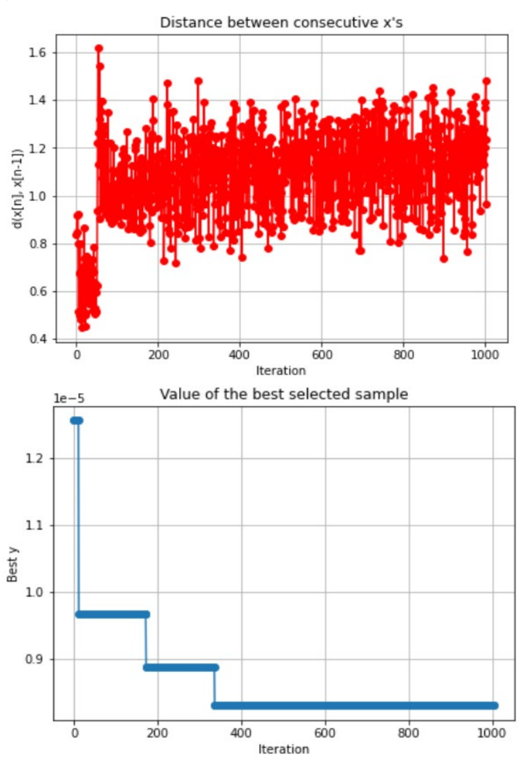

Figure 1: Convergence plots of bayesian optimization method.

APPLICATION

The lattice of UVSOR_III [12, 13] is formed by 8 identical dipoles, 32 quadrupoles grouped in 4 families and 5 sextupoles families. The ring has 8 straight sections and six of them are occupied with undulators of various kinds is significant at the beam energy 750 MeV. Beam diagnostics used for lattice corrections consists of 24 BPMs.

The nLOCO has been applied on the lattice design and beam diagnosis to discover quadrupole gradients of UVSOR_III storage ring. The fitting parameters for UVSOR_III are 40 quadrupole strengths, 48 horizontal and vertical BPM gains (2 × 24), and 35 steering magnets calibration. There is a total of 123 fitting parameters. The most straight forward way to fit the parameters is completely surveying the fitting parameters. If we examine at least 5 values for each parameter, the number of running the simulation code will be around 5^{123}, which is very expensive in CPU time. To decrease the number of running simulation code, we used Bayesian optimization method through GPyOPT algorithm [14] to have better performance on time. This algorithm can calculate the optimum fitting parameters by modelling the data points with Gaussian process regression and using acquisition functions to filter out the maximum information about the location of the minimum of function ΔC^2. Therefore, it can approach to optimum fitted parameters in small number of iterations as shown in Fig. 1. In this calculation, ΔC^2, the difference between evaluated closed orbit by ELEGANT and measurement one, is objective function for each trial solution. For the acquisition function which is defined as the target for selecting next trial solution, we chose the lower confidence bound (LCB) with GP model as a prior function. Figure 1 (up) represents the distance between consecutive's evaluations in terms of the number of times has evaluated the objective function ΔC^2. Figure 1 (botom) shows that Bayesian optimization method can approach the fitted parameters after 500 iterations (it takes around 7 hours). While the surveying method to find the fitted parameters needs at least 5^{132} of running simulation code which requires some processor days to complete.

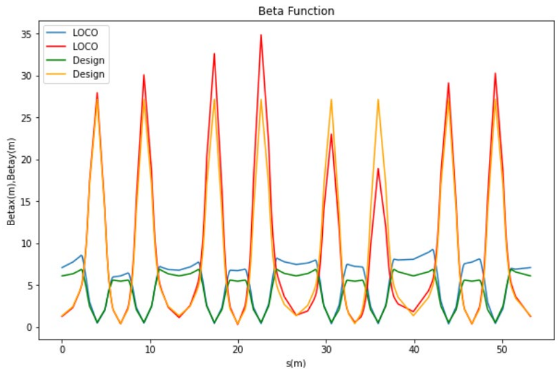

Figure 2: beta function before (green and yellow) and after (blue and red) correction with nLOCO.

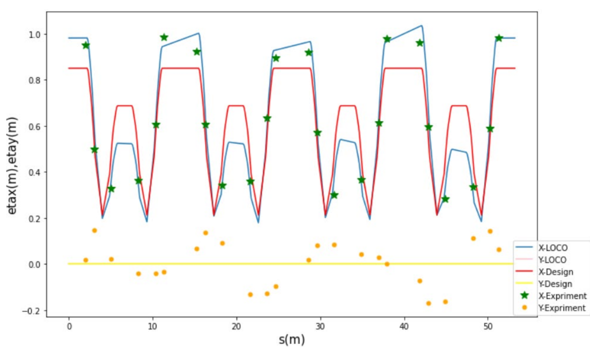

Figure 3: Comparison of measured (green star) and model dispersion function before correction (red), after correction (blue).

Figure 2 compares the designed betateron function for before and after applying nLOCO. Figure 3 shows the dispersion function measurement compared with the model before and after fit by nLOCO. Clearly the measured dispersion function differs significantly from the designed one. After correction by nLOCO method, the model is fitted to the measurements. The initial ΔC^2 which is 1.2×10^{-5}, is reduced to 8.19×10^{-6}, after 400 run iteration numbers. The gradient of each quadrupole magnet has been shown in Fig. 4.

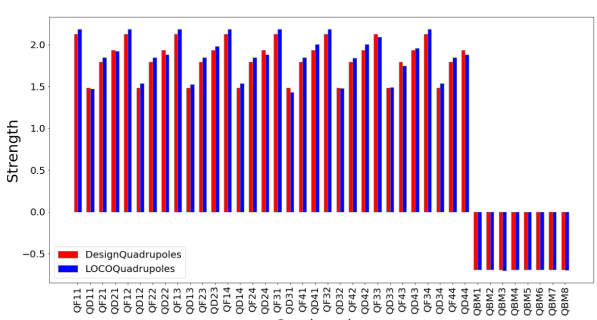

Figure 4: Quadrupole strengths designed (red) after nLOCO (blue).

CONCLUSION

We propose a new method to measure the linear optics and coupling of a storage ring with BPM data. This method called nLOCO is an effective and robust solution to nonlinear fitting problems with hundreds of variable fitting parameters. In this method, a particle tracking simulations code has been used to include the nonlinear components. To have better performance on time, we used Bayesian optimization method to minimize the difference between the measurements and the model closed orbit fast. BPM gains and calibration of the correctors are included in the fitting.

A simulation was done with the UVSOR_III storage ring lattice to find out the gradient of each quadrupole strength error, correct the beta function and dispersion. It can also obtain the calibrations of BPM and corrector.

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