Beam Based Alignment Using a Neural Network

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Abstract

Beams usually do not travel through the magnet centers due to errors in storage rings. The beam deviatingfrom the quadrupole centers is affected by additional dipole fields due to magnetic field feed-down. The beambased alignment (BBA) is often performed to find a golden orbit, on which the beam circulates around thequadrupole center axes. For storage rings with a large number of quadrupoles, the conventional BBA procedureis time-consuming, especially in the commissioning phase due to the necessary iterative process. Additionally,the conventional BBA method can be affected by strong coupling and nonlinearity of the storage ring optics.In this work, a novel method based on a neural network is proposed to find the golden orbit in a much shortertime with reasonable accuracy. This golden orbit can be directly used for operation, or can be adopted as thestarting point for the conventional BBA. The method is demonstrated in the HLS-II storage ring for the firsttime, through simulation and online experiments. The results of the experiments show that the golden orbitobtained using this new method is consistent with that from the conventional BBA. The development of thisnew method and corresponding experiments are reported in this paper.

Full Text

Preamble

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In storage rings, beams typically do not travel through magnet centers due to various errors. When a beam deviates from quadrupole centers, it experiences additional dipole fields arising from magnetic field feed-down effects. Beam-based alignment (BBA) is routinely performed to identify a golden orbit—one where the beam circulates along the axes of all quadrupole centers. For storage rings with numerous quadrupoles, the conventional BBA procedure becomes extremely time-consuming, particularly during commissioning when iterative processes are necessary. Furthermore, the conventional BBA method can be adversely affected by strong coupling and optical nonlinearities in the storage ring.

This work proposes a novel neural network-based method to determine the golden orbit in significantly less time while maintaining reasonable accuracy. The resulting golden orbit can be used directly for operation or serve as an improved starting point for conventional BBA. We demonstrate this method for the first time in the HLS-II storage ring through both simulation and online experiments. Experimental results confirm that the golden orbit obtained using this new approach agrees well with that from conventional BBA. The development of this method and the corresponding experiments are reported herein.

Keywords: Golden orbit, Beam-based alignment, Neural network, Storage ring.

Introduction

Ideally, beams in storage rings should circulate on an orbit passing through the axes of all magnet centers, known as the golden orbit. However, various errors—including misalignment, magnet imperfections, and power supply regulation errors—cause the beam orbit to deviate from this ideal path. When beams traverse magnets with orbit offsets, they encounter undesired magnetic fields through a phenomenon called feed-down. Specifically, feed-down from a quadrupole with an orbit offset generates an additional dipole field. To minimize this effect, beam-based alignment can be employed to determine the golden orbit for machine operation, a technique widely used during storage ring commissioning.

For large-circumference storage rings, such as most diffraction-limited storage rings (DLSRs), the numerous quadrupoles make conventional BBA methods particularly time-consuming. Recently, a fast BBA method was developed at the ALBA light source using AC excitation of orbit correctors and rapid beam position data acquisition. At HLS-II, we have developed a machine learning (ML) based method to find the golden orbit without requiring hardware upgrades.

Neural networks (NNs) have achieved remarkable success across various fields of artificial intelligence and have been increasingly applied to particle accelerators. At the Advanced Light Source (ALS), an NN model maintains vertical beam size while insertion device gaps vary. NN models have also dramatically reduced simulation times for beam dynamics optimization. At the Shanghai Synchrotron Radiation Facility (SSRF), convolutional neural networks (CNNs) have been adopted for image processing to extract bunch longitudinal phase information. These applications demonstrate the great potential of NNs for improving accelerator performance.

In this paper, we present a new BBA method that employs an NN model to predict the storage ring' s golden orbit. To initiate the experiment, different closed orbits are generated by randomly varying the strength of all orbit correctors. Beams with various orbit deviations in quadrupoles experience different degrees of influence from feed-down effects, which can be evaluated by measuring orbit changes caused by quadrupole strength variations. Since a beam on the ideal golden orbit should not be disturbed by quadrupole strength changes, an NN model can be trained to identify the orbit least affected by such variations. The model uses orbit differences due to quadrupole changes as input data, with the corresponding pre-adjustment orbits as output data. The golden orbit is then predicted by setting the input value to zero.

We validate this new BBA method in the HLS-II storage ring through simulation and online experiments. Results show that the golden orbit obtained from the NN model agrees with that from several iterations of the conventional method. The NN-derived golden orbit can be used directly for operation or as a starting point to accelerate conventional BBA, which normally requires multiple iterations. Overall, this new method significantly reduces time compared to conventional BBA, especially during initial commissioning.

The following sections detail the conventional and NN-based BBA methods (Section II), present simulation results for the HLS-II storage ring (Section III), describe online experiments using both methods (Section IV), and summarize the work (Section V).

II. Beam-Based Alignment

A. Conventional BBA Method

The purpose of BBA is to find a reference orbit where the beam passes through the centers of all quadrupoles in a storage ring, using beam position monitors (BPMs) and orbit corrector magnets (OCMs). A quadrupole generates dipole fields with strengths $B_x = B_0\rho_{0K_{0y}}0$ and $B_y = B_0\rho_{0K_{0x}}0$, where $B_0\rho_0$ is the magnetic rigidity, K_0 is the normalized quadrupole strength, and x_0 and y_0 are the beam offsets relative to the quadrupole center in the horizontal and vertical planes, respectively. Changing the quadrupole strength by ΔK causes a dipole field variation of $\Delta B_x = B_0\rho_0\Delta K y_0$ and $\Delta B_y = B_0\rho_0\Delta K x_0$, resulting in a kick that leads to an orbit change at an observation point s given by

$$\Delta u(s) = \Delta K u(s_0)\frac{\sqrt{\beta(s)\beta(s_0)}}{2\sin(\pi\nu)}\cos(|\phi(s) - \phi(s_0)| - \pi\nu),$$

where L_0 is the quadrupole length, ν is the betatron tune, $\beta(s_0)$ and $\beta(s)$ are the beta functions at the quadrupole and observation point locations, $\phi(s_0)$ and $\phi(s)$ are the phase advances at those locations, and u represents beam positions in the horizontal and vertical planes. This equation shows that the beam orbit depends on both quadrupole strength variation and beam position within the quadrupoles. To avoid this effect, the orbit feedback system' s reference orbit is typically set to the centers of all quadrupoles with $u = 0$, which can be determined using BBA techniques.

The quadrupole center is measured using its nearest BPM. When the beam passes through the quadrupole center, the associated BPM reading is v_0. According to the equation above, changing the quadrupole strength by ΔK produces an orbit change of $\Delta u = \Delta K F(v - v_0)$, where v is the target BPM reading before the quadrupole strength change and F is a coefficient easily obtained from the equation. To measure the quadrupole center, the beam is positioned at several different locations at its associated BPM. At each position, the quadrupole strength is changed by the same ΔK and the corresponding orbit change is recorded. Applying a linear fit to this relationship yields the quadrupole center v_0. Conventional BBA always determines horizontal and vertical offsets separately, implicitly treating coefficient F as constant—meaning beam optics remain unchanged during the BBA process.

In reality, changes in quadrupole strength and closed orbit distortion can affect beam optics. During initial commissioning, the beam orbit and optics may differ significantly from the ideal model, introducing strong nonlinearity and coupling. In such cases, conventional BBA requires several iterations to eliminate nonlinear effects and obtain accurate quadrupole centers. A multi-layer neural network capable of handling nonlinear problems can be adopted for the BBA process.

B. BBA Using a Neural Network

BBA is based on the principle that off-axis beams are affected by quadrupole strength changes. The golden orbit can therefore be evaluated from the relationship between orbit changes and initial beam orbits before quadrupole variation. This relationship can be learned by training a neural network using orbit changes as input data and initial orbits as output data. By setting the orbit change to zero, the corresponding initial beam orbit becomes the predicted golden orbit. This concept is illustrated in Fig. 1 [Figure 1: see original paper].

To obtain training data for the NN model, simulations or online experiments proceed as follows: randomly excite all corrector magnets to form an initial closed orbit; record all BPM readings; change all quadrupoles by the same amount to form a new closed orbit; record changes in all BPM readings; restore quadrupole and corrector strengths to original values; and repeat these procedures.

A typical dense neural network consists of one input layer, several hidden layers, and one output layer, as shown in Fig. 2 [Figure 2: see original paper]. Nodes (neurons) transfer data between adjacent layers through connections represented by arrows. Each connection represents a linear transformation combined with an activation function to introduce nonlinearity when needed. A loss function describes network performance, while an optimizer function adjusts transmission parameters by minimizing the loss value.

III. Simulation Study for the HLS-II Storage Ring

Simulation was conducted to evaluate the validity of the new NN-based BBA method before online experiments. The Accelerator Toolbox (AT) was used for simulation, while TensorFlow provided a flexible platform for building and training the NN model.

The HLS-II storage ring has two super periods with a circumference of 66.1 m. The layout for one super period is shown in Fig. 3 [Figure 3: see original paper]. The orbit system consists of 32 BPMs and 32 correctors combined with sextupoles. Thirty-two quadrupoles are installed, whose real centers must be measured through BBA.

Random rotation and shift errors were applied to simulate element and girder misalignment, generated from a normal distribution truncated at three standard deviations. Based on the design report, error settings for all magnets, girders, and BPMs are listed in Table 1 . Magnet strength errors were also applied, and BPM random measurement error was set to 0.5 µm.

A. Conventional BBA Method

In conventional BBA measurement for one quadrupole, the beam is moved to three different positions using corrector magnets. At each position, the change in beam orbit from all BPM readings is recorded after varying the target quadrupole strength by a certain ΔK. The orbit changes can be linearly fitted as a function of beam position in the target quadrupole. An immobile point is found by identifying the position where BPM changes vanish. The quadrupole center is then obtained by combining all immobile points from each BPM. A complete BBA routine repeats this process for all quadrupoles in both planes. To improve accuracy, measurements can be repeated after moving the beam to the orbit obtained from the previous BBA iteration—a scheme typically needed during machine commissioning. Fig. 5 [Figure 5: see original paper] shows simulated measurements of horizontal and vertical centers for one quadrupole in HLS-II. At least three conventional BBA iterations are needed to reduce the standard deviation of the fitted Gaussian function for the quadrupole center to several microns, comparable to BPM measurement resolution.

B. BBA Using an NN Model

In simulation, correctors were randomly set with kick variations generated from a normal distribution with 0.05 mrad standard deviation (truncated at three standard deviations). For each random orbit, all quadrupoles were simultaneously changed by $\Delta K = -0.02\ \mathrm{m}^{-2}$. The corresponding initial beam orbit and orbit changes were recorded from all BPMs.

The simulation generated 10,000 samples, each containing 64 initial orbit data points and 64 orbit change data points (32 horizontal and 32 vertical). These samples were used to train the neural network. Fig. 6 [Figure 6: see original paper] shows the random initial beam orbits within a range of $(-5, 5)$ mm. Fig. 7 [Figure 7: see original paper] shows the orbit changes after quadrupole adjustment, ranging within $(-1.5, 1.3)$ mm horizontally and $(-0.8, 0.8)$ mm vertically.

To obtain the golden orbit, an NN model was trained using these data. The 64 sets of orbit change data served as model input, while the 64 sets of corresponding initial orbit data served as output. The network had three hidden layers with 128, 256, and 128 neurons, respectively. The hyperbolic tangent (tanh) activation function provided nonlinearity. The Adam optimizer trained the model using mean squared error (MSE) loss: $\text{loss} = \text{mean}((r_{\text{model}} - r_{\text{real}})^2)$.

Fig. 8 [Figure 8: see original paper] compares golden orbits from conventional BBA and NN-based BBA, showing good consistency and validating the new technique. Online experiments in the HLS-II storage ring followed.

IV. Online Experiment in the HLS-II Storage Ring

Conventional BBA has been applied to the HLS-II storage ring, with results for one quadrupole shown in Fig. 9 [Figure 9: see original paper]. Fitting errors for most quadrupoles are within 20 µm.

A. Training Data Acquisition

Similar to simulation, training data were obtained from the actual storage ring. Before the experiment, magnet strengths were set according to earlier commissioning results, though the beam was not yet on the golden orbit connecting quadrupole centers.

During the online experiment, the orbit feedback system was disabled and correctors were randomly set to generate different orbits. As a compromise between beam stability and data diversity, all correctors were adjusted within ± 0.8 A relative to the starting point. This range ensured no beam loss while maintaining distinguishable orbit changes, as shown in Fig. 10 [Figure 10: see original paper]. The HLS-II horizontal tune is approximately 4.44, while the vertical tune is 2.36 –further from the half-integer. Increasing quadrupole strength simultaneously raises the horizontal tune, which can easily reach the half-integer resonance and cause beam loss. Therefore, all quadrupole strengths were decreased by -0.02 m^{-2} (normalized focusing strength). After recording orbit changes, quadrupole strengths were restored to original values. The HLS-II orbit corrector power supplies have a 15 ms time constant, while quadrupole power supplies have a 30 ms time constant, enabling one complete measurement loop within 1 second. For data acquisition accuracy, each loop' s measurement time was set to 2 seconds.

The online experiment was conducted during machine study time, generating 21,000 samples for neural network training. Fig. 10 shows the randomly generated initial beam orbits before quadrupole variation, distributed within approximately $(-10, 10)$ mm with the densest distribution around zero. Fig. 11 [Figure 11: see original paper] shows the orbit change distribution after quadrupole adjustment, ranging within $(-3, 2)$ mm horizontally and $(-1.5, 1.5)$ mm vertically.

B. NN Model Training Using Online Data

This subsection explores the relationship between initial orbit and post-adjustment orbit change using a dense neural network. Similar to simulation, 64 sets of orbit change data served as model input, and 64 sets of corresponding initial orbit data served as output. To determine data size requirements, two models were trained with different sample sizes. Model I used all 21,000 samples (5/6 for training, 1/6 for validation). Model II used only 3,000 training samples and 600 validation samples (3,600 total). Both models used the Adam optimizer and MSE loss function.

Model performance was evaluated by calculating the mean absolute error (MAE) between measured and predicted validation sample values for each BPM: MAE $= \text{mean}(|r_{\text{measured}} - r_{\text{predicted}}|)$. Fig. 12 [Figure 12: see original paper] shows that Model I errors are smaller than Model II errors. Horizontally, the overall average absolute error is approximately 99 µm for Model I and 125 µm for Model II. Vertically, it' s approximately 62 µm for Model I and 71 µm for Model II. Increasing training samples improves model accuracy.

C. Golden Orbit from the NN Model

In NN training, orbit changes caused by quadrupole variation serve as input data, with corresponding initial orbits as output data. A beam on the golden orbit should experience minimal orbit distortion (ideally zero) from quadrupole strength changes. Therefore, setting the NN input to zero yields the predicted golden orbit.

To estimate accuracy, this golden orbit was compared with that from conventional BBA, as shown in Fig. 13 [Figure 13: see original paper]. The subfigures show differences between the novel and conventional methods, demonstrating good consistency. Horizontally, the average difference between conventional BBA and model prediction is approximately 46 µm for Model I and 53 µm for Model II. Vertically, it' s approximately 42 µm for Model I and 39 µm for Model II. Although Model I' s training error is significantly smaller than Model II' s, the predicted golden orbits show only small deviations between the two models.

In the HLS-II storage ring, the typical experimental period for conventional BBA is around 5 hours. During commissioning, this process must be repeated several times for precise results. Model II uses only 3,600 samples, requiring about 2 hours of online measurement. As discussed, the online measurement time for this new method is independent of total quadrupole number, unlike conventional BBA where larger rings require more time. The NN-derived golden orbit can serve as a starting point for conventional BBA, reducing iterative processes and experimental time.

V. Summary

A novel method has been developed to search for the golden orbit of a storage ring. This approach trains a neural network model using simulated or online data from different closed orbits and their corresponding changes when all quadrupole strengths are varied simultaneously. Online experiments can be completed quickly, especially for large storage rings. Comparison with conventional BBA shows good consistency.

NN-based BBA is particularly suitable for storage ring commissioning, where beam optics differ significantly from the ideal model and closed orbits deviate from magnet centers. In such cases, the linear process of conventional BBA becomes inaccurate. Additionally, conventional BBA treats horizontal and vertical orbits separately, while real machine coupling is non-negligible, especially when insufficiently corrected. The NN-based method handles both transverse planes simultaneously, naturally solving coupling issues. Furthermore, the new BBA method better accommodates storage rings with strong nonlinear effects, common in DLSRs. With strong nonlinearity, conventional BBA may work only in limited regions due to assumed orbit response linearity. Since NNs excel at solving nonlinear problems, this NN-based BBA method is expected to be more effective for DLSRs. From another perspective, this technique better handles cases where quadrupoles are powered in series, as it doesn' t require varying each quadrupole' s strength individually. Small light sources and boosters are anticipated to benefit from this new BBA method.

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Note: Figure translations are in progress. See original paper for figures.