Simulation of the Global Orbit Feedback System for Pohang Light Source

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Abstract

This paper describes the simulation of the global orbit feedback system using the singular value decomposition (SVD) method, the error minimization method, and the neural network method. Instead of facing unacceptable correction result raised occasionally in the matrix inversion, we choose the error minimization method for the global orbit feedback. This method provides minimum orbit errors while avoiding unacceptable corrections, and keeps the orbit within the dynamic aperture of the storage ring. The simulation shows that a selection of BPMs is very sensitive in the reduction of rms orbit distortions, and the random choice gives better results than any other cases. Especially, the most effective combination is the randomly selected BPMs and the equal number of correctors located in high β_x region. In a good case, we can reduce the orbit distortion by an order of magnitude. For the correction of the orbit drift, the neural network method gives less fluctuated orbits than the error minimization method.

1 INTRODUCTION

A long-term drift of the closed orbit is routinely observed in the PLS. Between the beam injections in every 12 hours, the closed orbit is drifted to 40 $\sim$ 100 μm. Since the horizontal beam size is about 200 μm, this drift corresponds to 20% $\sim$ 50% of the beam size, which needs to be corrected to less than 10%. In order to cure this long-term drift, we need a feedback system which can be achieved without the modification of corrector power supplies and expensive DSPs and realtime hardware [1].

2 THEORY

The response matrix $\mathbf{R}$ can be obtained from measurements by reading beam position changes at BPMs while varying the strengths of the correctors by following relation:

$$|\triangle \mathbf{x}\rangle = \mathbf{R}\,|\triangle \mathbf{k}\rangle \ , \qquad (1)$$

where $|\triangle \mathbf{x}\rangle$ is the change of the beam position at the corresponding BPM due to the corrector strength $|\triangle \mathbf{k}\rangle$. If we consider the change of the beam position as the difference between the reference orbit $|\mathbf{x}_r\rangle$ and the current measured orbit $|\mathbf{x}_m\rangle$, the change is

$$|\triangle \mathbf{x}\rangle = |\mathbf{x}_r\rangle - |\mathbf{x}_m\rangle \ . \qquad (2)$$

In order to bring the orbit to the reference one, we need to calculate $|\triangle \mathbf{k}\rangle$ such as

$$|\triangle \mathbf{k}\rangle = \mathbf{R}^{-1}\,|\triangle \mathbf{x}\rangle \ . \qquad (3)$$

2.1 Sigular Value Decomposition (SVD)

In the conventional singular value decomposition (SVD) method used in the global orbit feedback system, one can get $|\triangle \mathbf{k}\rangle$ from eq. (3) for a given set of $|\triangle \mathbf{x}\rangle$ by using SVD algorithm in obtaining $\mathbf{R}^{-1}$. However, some elements of $|\triangle \mathbf{k}\rangle$ obtained in this way may become larger, and the corrected beam orbit is beyond the dynamic aperture. Even, in the worst case, the strength change of the corrector becomes beyond the capacity of the corrector power supply. This is mainly due to the singularity of $\mathbf{R}$, which is originated from the small eigenvalue of the eigen corrector (with corresponding eigen BPM) in the transformed space. This eigen corrector (with corresponding eigen BPM) is not effective in the global orbit correction, and it is called the decoupled channel. When this situation is happened, one can simply remove the decoupled channel from the calculation. In this way, we can avoid the difficulty from the singularity. However, if there are many decoupled channels, the correction efficiency will be reduced significantly.

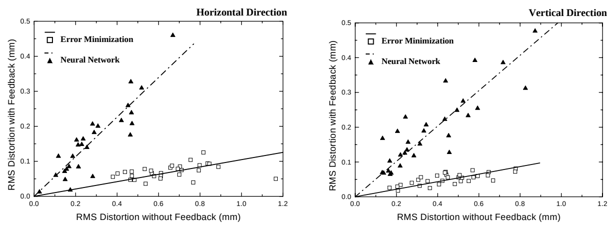
2.2 Error Minimization Method

When the dimension of $\mathbf{R}$ is larger, the ill-posedness [2] of the matrix equation eq. (3) is increased, and $\mathbf{R}$ is more vulnerable to become a singular matrix. A general approach to solve the singular matrix is the regularization method [2] which is depend on the trial-and-error search to find the best result by a control parameter. However, the choice of the control parameter is not systematic and the result is very sensitive to the choice of the parameter.

Our method is to minimize $\|\mathbf{R}\,|\triangle \mathbf{k}\rangle - |\triangle \mathbf{x}\rangle\|$ in the range of corrector power supplies to obtain $|\triangle \mathbf{k}\rangle$. The conjugate gradient method in multi-dimensions [3] is used in the minimization procedure such as

$$|\triangle \mathbf{k}\rangle = \min\left\{|\triangle \mathbf{k}\rangle \ \middle|\ \|\mathbf{R}\,|\triangle \mathbf{k}\rangle - |\triangle \mathbf{x}_0\rangle\|\right\} \ . \qquad (4)$$

Because of the nature in the error minimization method, it takes $4 \sim 8$ times more computing time to find the minimum than the SVD or the regularization method based on our experiences. However, there is a significant effort to find the solution by the trial-and-error search in the regularization method even though single calculation takes less computing time. Similarly, the decoupled channel is not determined systematically in the SVD by single calculation. By counting this extra effort in searching correct solutions, the straightforwardness of the error minimization process, and the faster computing power in recently available computers, an order of magnitude longer computation in the error minimization is still comparable to the SVD or the regularization method.



(a) (b)

Figure 1: RMS Reduction, (a) horizontal direction, error minimization : 0.10465 ± 0.00583, neural networks : 0.59386 ± 0.05804, (b) vertical direction, error minimization : 0.12097 ± 0.01025, neural networks : 0.51641 ± 0.02297

2.3 Neural Network

The neural network is a network of perceptrons with one or more layers. A perceptron has a simple structure that generates an output signal when the sum of input signals reaches the threshold. When perceptrons form a network and there is a suitable synoptic weight between each perceptron, the network generates a characteristic output signal pattern for the specific pattern of input signals. In order to train the neural network, we need a training set which consists of examples to be learned. A common training scenario is the supervised learning that is a training set with most suitable synoptic weights determined by the back propagation algorithm for given input patterns.

For the global feedback system, we can make the training set from the strength changes of correctors and corresponding orbit distortions. Then, the learned neural network uses this input pattern to generate the output pattern that is a set of strength changes for correctors. Thus, the feedback system changes the strength of correctors accordingly, and the inverse orbit distortion generated by the neural network cancels the actual orbit distortion.

3 SIMULATION AND RESULTS

3.1 Error Minimization Method

In order to determine how much the orbit feedback system is effective, we first generate the orbit distortion by changing the strengths of non-feedback correctors randomly within ± 0.1 mrad by MAD. The number of non-feedback correctors is also randomly selected from 4 to 24.

We repeat this process for 30 different sets of orbit distortions in each direction and obtain reductions of orbit distortions after the feedback. Fig. 1 shows the rms orbit distortion before and after the feedback. It shows that the rms orbit distortion after the orbit feedback is reduced significantly than one before the feedback is applied. We can determine the effectiveness of the orbit feedback by defining the reduction rate of the orbit distortion as the ratio of the reduced rms orbit distortion by feedback with the rms orbit distortion before feedback. Actually, the reduction rate is a slope of the linear fitting in Fig. 1. While we are selecting a set of BPMs and correctors used in the feedback system, it is observed that the rms orbit distortion after the feedback is highly depended on the selection of BPMs and correctors, but not on the amount of rms distortion. In order to find the most suitable combination of BPMs and correctors, we repeat this procedure for various combinations of BPMs and correctors as listed in Tables 1 and 2. It shows that a selection of BPMs is very sensitive in the reduction of rms orbit distortions, and the random choice gives better results than any other cases. Especially, the most effective combination is the randomly selected BPMs and the equal number of correctors located in high β_x region. In a good case, we can reduce the orbit distortion by an order of magnitude. Therefore, for the PLS global orbit system, we will use 3 randomly selected BPMs and three correctors (C1, C2, and C3) for the horizontal direction, and 3 randomly selected BPMs and three correctors (C1, C3, and C6) for the vertical direction.

Table 1: RMS reduction done by the error minimization method (horizontal)

BPM Index	Corrector Index	RMS Reduction
Random Choice 2/cell	1, 2 (high β_x)	0.12744
Random Choice 3/cell	1, 2 (high β_x)	0.73252
Random Choice 3/cell	1, 2, 3 (high β_x)	0.10465
Random Choice 4/cell	1, 2, 3 (high β_x)	0.39468
Random Choice 4/cell	1, 2, 3, 6 (high β_x)	0.10408
1, 2, 3, 4	1, 2, 3 (high β_x)	0.32483
1, 2, 3, 4	1,2,3/1,2,6 (high β_x)	0.34521
1, 2, 5, 7 (high β_x)	1, 2, 6 (high β_x)	0.43597
1, 2, 5, 7 (high β_x)	1,2,3/1,2,6 (high β_x)	0.37200
1, 2, 3, 4	1, 3, 5	0.18970
1, 2, 3, 4	2, 4, 6	0.16398

Table 2: RMS reduction done by the error minimization method (vertical)

BPM Index	Corrector Index	RMS Reduction
Random Choice 2/cell	3, 6 (high β_y)	0.12364
Random Choice 3/cell	3, 6 (high β_y)	0.30949
Random Choice 3/cell	3, 6, 1 (high β_y)	0.12097
Random Choice 4/cell	3, 6, 1 (high β_y)	0.43564
Random Choice 4/cell	3, 6, 1, 2 (high β_y)	0.12212
5, 6, 7 (high β_y)	1, 4, 5 (high β_y)	0.15375
5, 6, 7 (high β_y)	1, 4 (high β_y)	0.54967
5, 6 (high β_y)	1, 4 (high β_y)	0.14541
3, 4, 8, 1 (low β_y)	3, 6, 1 (low β_y)	0.15443
3, 4, 8 (low β_y)	3, 6 (low β_y)	0.27259
3, 4 (low β_y)	3, 6 (low β_y)	0.13380

3.2 Neural Network

There are 36 nodes in the input layer, 36 nodes in the hidden layer, and 4 nodes in the output layer for the neural network simulation. It means that there are 36 BPMs to read the orbit change and four correctors to correct this orbit change. These layers are linked with the topology of the forward direction full connection. The identity function is used as the output filter for each node because the PLS lattice used in this MAD simulation is basically linear and the orbit change would be linear accordingly. The neural network topology is generated by Stuttgart Neural Network Simulator (SNNS ver 4.1) and the learning of the neural network is also done by the same simulator [4]. The neural network is learned by the back propagation algorithm for learning patterns which was generated by MAD for the PLS lattice. The iteration used in the learning procedure is included in SNNS.

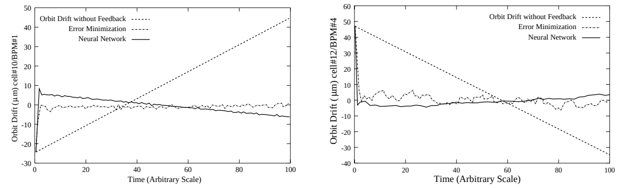
In the next place, we generate the orbit distortion by changing the strengths of non- feedback correctors randomly within ± 0.1 mrad by MAD. The number of non-feedback correctors is again randomly selected from 4 to 24. In order to cancel this orbit distortion, we use the inverse orbit distortion as the input values of the neural network. Then, the learned neural network gives the strength changes for four correctors. In order to determine the rms reduction, we generate 30 different orbit distortions obtained randomly, and apply the neural network technique to correct them. The scattered data plot for rms orbit distortions before and after the feedback is shown in Fig. 1. The reduction rate by the neural network is about 0.594, which is maximum 6 times larger than the one from the error minimization method.

3.3 Orbit Drift

In order to simulate the orbit drift, we select four correctors randomly and change their strengths gradually in time. We choose the magnitude of the drift orbit is within $\pm 40\mu$m, and the corresponding orbit changes obtained by MAD are shown in Fig. 2. In this figure, it is clear that we can move the closed orbit to the center against the orbit drift by the error minimization method, but a little fluctuation is observed. This is less than $\pm$ 5 μm, which is acceptable because it is less than 5% of the PLS beam size ($\sim$ 200 μm). For the correction of the orbit drift done by the neural network, the result is shown in the same figure. The corrections done by the neural network and the error minimization method are quite agreeable. Unlike the error minimization method, there is little fluctuation during the correction of the orbit drift by the neural network. However, small amount of drift in the opposite direction is still remained due to poor learning of the neural network.

4 CONCLUSION

We have simulated the global orbit feedback by using the error minimization method in order to avoid unacceptable



(a) (b)

Figure 2: The orbit drift and its cure simulated by the global orbit feedback. (a) horizontal direction, (b) vertical direction.

correction results raised occasionally in the matrix inversion. The simulation shows that a selection of BPMs is very sensitive in the reduction of rms orbit distortions, and the random choice gives better results than any other cases. Especially, the most effective combination is the randomly selected BPMs and the equal number of correctors located in high β_x region. In a good case, we can reduce the orbit distortion by an order of magnitude. Therefore, in the development of the PLS global orbit system, we will use 3 randomly selected BPMs and three correctors (C1, C2, and C3) for the horizontal direction, and 3 randomly selected BPMs and three correctors (C1, C3, and C6) for the vertical direction.

In order to compare the effectiveness of the neural network method, a neural network is trained by the learning algorithm using the learning data set. For the correction of the orbit drift, the neural network method gives less fluctuated orbits than the error minimization method.

Although the simulation result shows that the neural network method does not give better reduction rates than the error minimization method, the latter method is based on the linear property of the lattice. Since the actual storage ring is no longer linear due to sextupoles and various errors, the actual reduction rate by the error minimization method will be degraded. However, the neural network learned from the real orbit distortion patterns from the storage ring can contain the nonlinear properties, the reduction rate obtained by the neural network will become more realistic. Thus, we will keep the two methods in the realization of the global orbit feedback system in the PLS in near future.

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