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MACHINE LEARNING APPLIED TO PREDICT TRANSVERSE OSCILLATION AT SSRF *

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Abstract

A fast beam size diagnostic system has been developed at SSRF storage ring for turn-by-turn and bunch-by-bunch beam transverse oscillation study. This system is based on visible synchrotron radiation direct imaging system. Currently, this system already has good experimental results. However, this system still has some limitations, the resolution is subject to the point spread function; and the speed of the online data processing is limited by the complex Gaussian fitting algorithm. In order to realize the online fast data processing, we present a technique that applied machine learning tools to predict transverse beam size. Using this technique at SSRF storage ring, we report mean squared errors below 4 µm for prediction of the horizontal beam size.

INTRODUCTION

Research of bunch-by-bunch beam diagnostics at the Beam Instrumentation (BI) group of SSRF (Shanghai Synchrotron Radiation Facility) has been started from the year of 2012 [1]. We also have focusing on the development of a six-dimensional bunch-by-bunch diagnostics system (published on this conference).

With the bunch-by-bunch diagnostics tool, further transverse and longitudinal instability information can be observed. Additionally, it is an excellent tool for machine impendence and wake-field investigations. Moreover, every bunch is the basic unit of the beam physics research, and the motion information of every bunch will be largely approximate to its natural properties.

The six-dimensional bunch-by-bunch diagnostics system consists of the beam position parameters (two dimensions), beam transverse size (two dimensions), beam longitudinal parameters (two dimensions). With this bunch-by-bunch diagnostics system, it is able to build a fast abnormal intelligent trigger system. The layout of the whole system is shown as Fig. 1: The bunch-by-bunch transeverse position was implemented with a resolution of 10 µm and was based on the bunch-by-bunch signal processor and delta over sum algorithm [4, 5]. A two-frequency system was employed for the bunch-by-bunch beam length measurement with large dynamic range of 30 pC–6 nC, and a resolution of less than 0.5 ps calibrated by the Streak Camera [6, 7]. For the bunch longitudinal phase measurement, we used the rise edge detection method to detect the button BPM signal, which could reach the resolution of approximately 1 ps [8]. The bunch-by-bunch beam size system is based on SR (syncrotron radition) light with a PMT (photomultiplier tubes) detector and Gaussian fitting algorithm [3].

Motivation

Previous section shows the whole six-dimension bunch-by-bunch diagnostics system and the fast intelligent trigger system. Fast trigger system relies on the online data processing.

In this paper, we will focus on the transverse oscillations. The transverse oscillations and transverse emittance enlargement will lead to machine instabilities. The precise bunch-by-bunch transverse position and size measurement is critical in machine abnormality studies and improvements.

A bunch-by-bunch beam size measurement system has been developed at SSRF. This system is capable of measuring bunches within a separation of 2 ns [2, 3]. However, this system still has some limitations, the speed of online data processing is limited by its complex algorithm. Fortunately, simple bunch-by-bunch diagnostics such as electron bunch monitors (beam position, beam current) can in principle work at the repetition rate. In order to estblish a fast abnormal intelligent trigger system, it is necessary to obtain the bunch-by-bunch data online.

Machine learning methods have been widely used in various fields. In this paper, the machine learning technique was applied to observe transverse oscillation. We prefer to use simple bunch-by-bunch diagnostics monitors to predict the result of complex bunch-by-bunch beam size monitors.

We have developed a machine learning tool to predict beam transverse size using beam position and charge as input. Using this technique at SSRF storage ring, we report mean squared errors below 4 µm for prediction of the horizontal beam size.

CORRELATION BETWEEN DIFFERENT PARAMETERS

Beam charge, positon, and size are the main parameters which can be used to characterise the transverse oscillation of the bunch. All of these parameters are related to the transverse oscillation. In order to realize the technique that using beam position and charge as input to predict beam size, correlation analysis between those parameters is indeed.

Correlation analysis between those bunch parameters has been started at SSRF.

In steady state of the storage ring, the transverse oscillation of the bunch is not obvious. Fortunately, the injection events can introduce obvious oscillation. Hence, we investigated the relationship between beam intensity and bunch

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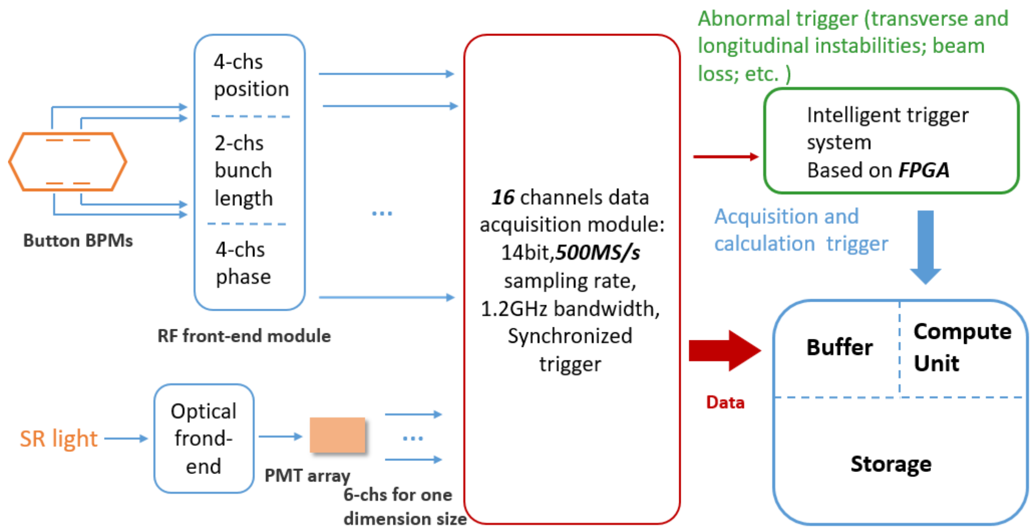

Figure 1: System layout of the six-dimension bunch-by-bunch beam diagnostic system and fast abnormal intelligent trigger system at SSRF.

size, and the relationship between bunch position and bunch size before and after injection events.

The following two figures show the relationship between the beam charge and the size, and between the position and the beam horizontal size [3].

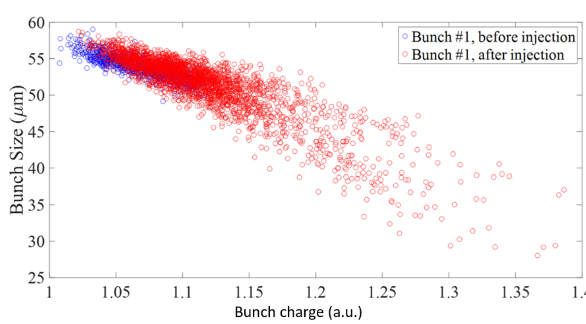

Figure 2: Correlation results between bunch size and bunch charge.

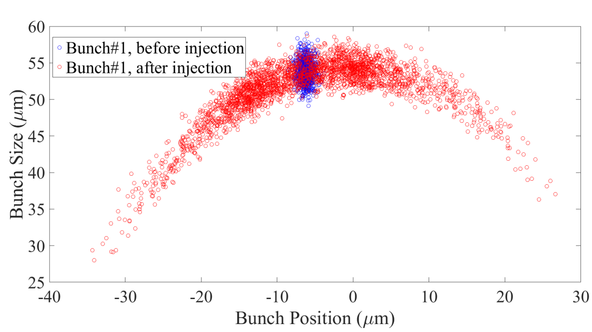

Figure 3: Correlation results between bunch size and center position.

The correlation results show that it is possible to develop a machine learning tool to predict beam transverse size using beam position and charge as input. In the next sections, the machine learning model and the result of the prediction will be presented.

MODEL TRAINNING

The proposed technique based on machine learning for the prediction of transverse beam size is summarized in Fig. 4:

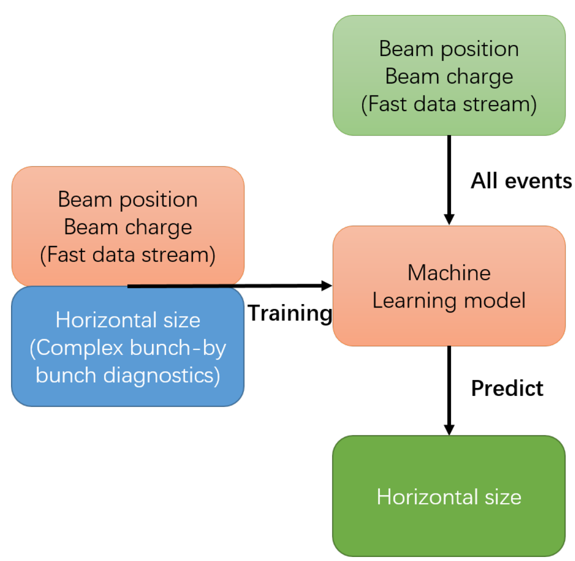

Figure 4: Schematic of the technique based on machine learning to predict transverse beam size.

In this application, the prediction relies on a fast simple bunch-by-bunch data (beam position and charge) for all events, and the offline beam size data obtained from complex bunch-by-bunch beam size monitor for a small fraction of

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the events. The set of events containing correlated information from all device can be splited into three parts: training, validation and test sets.

Machine learning can be divided into supervised and unsupervised learning. Our application is a typical supervised learning, beam size data is the label set. NN (Feedforward neural network) is used as the traning algorithm. Schematic of the designed NN is shown as Fig. 5.

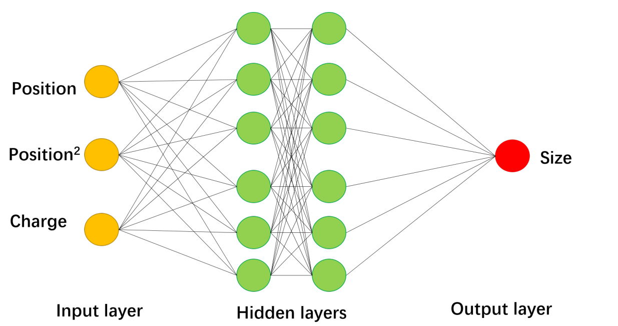

Figure 5: Schematic of the Neural network.

This is a 4 layers NN, in the input layer, we set three features, in the hidden layers, each layer has 6 neurons, we choose 'tansig' as the transfer function; the predicted beam size value can be obtained from the output layer; Levenberg-Marquardt is used as the training algorithm.

For the input layer, we choose the set of injection event. Figures 2 and 3 show the correlation results between horizontal bunch size and beam charge and beam position during the injection event. Hence, for the features selection, we choose position, position * position and Charge value. We prepared data of 500 bunches/turn * 2000 turn as the data set. In this data set, data of 300 bunches/turn * 2000 turn was set as training set; data of 100 bunches/turn * 2000 turn was set as validation set; the last 100 bunches/turn * 2000 turn was set as test set.

The training set is used to train the machine learning model to learn how to predict beam size normally obtained with PMT detetors, based on input variables from simple diagnostics. The validation set is used to optimize the hyperparameters. Finally,the test set is used to test the prediction accuracy of the model for the chosen set of hyperparameters. After this, the model can be applied to predict the beam size with the input variables.

RESULTS AND DISCUSSION

The previous section describes the model building of neural networks and the data set. The NNs were trained until convergence using the Levenberg-Marquardt algorithm. After the training, we get the machine learning model; We applied our technique to predict the test set. Data set of 100 bunches/turn * 2000 turn was set as test set. Figure 6 shows the results of the beam size prediction with the NN learning model.

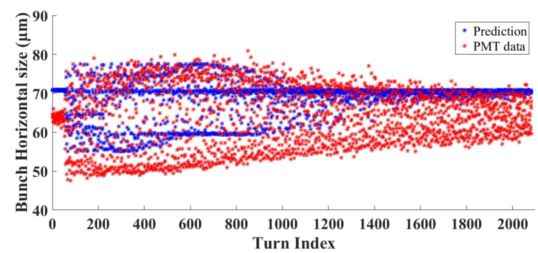

Figure 6: Results of the beam size prediction with the NN learning model.

This figure shows a typical bunch size state of a injection event, here is the change state of the beam horizontal size in 2000 turns.

Finally, the accuracy of each model was quoted as the mean squared error obtained on the test set. In the case of the beam size prediction, we define our accuracy by calculating the agreement between the predicted size and the size measured by the bunch-by-bunch beam size monitor. The results show that all this NN model are able to predict the beam size of the test set with a mean squared error of near 3.8 μm when compared to the actual measured values.

CONCLUSION

Monitors sunch as beam position monitors can be called as a simple bunch-by-bunch diagnostics system. Bunch transverse size is also a critical parameter in the research of transverse oscillation. However, the bunch-by-bunch beam size monitor is a complex tool, is limited by its algorithm. In order to estblish a bunch-by-bunch abnormal intelligent trigger system, We have presented a technique based on machine learning algorithms that can be used to predict transverse oscillation has been developed at SSRF.

Machine learning tool (4 layers neural network) was used to predict beam transverse size using beam position and charge as input, each hidden layer has 6 neurons.

With this technique to observe the transverse oscillation at SSRF storage ring, we report mean squared errors below 4 μm for prediction of the horizontal beam size.

In the furture, an online training network and more machine learning tools will be used in beam diagnostics system at SSRF.

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