DEVELOPMENT OF A BUNCH-BY-BUNCH BPM MEASUREMENT SYSTEM AT SSRF BASED ON MACHINE LEARNING

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Abstract

Real-time bunch-by-bunch monitoring of transverse position and longitudinal phase has become increasingly important for the stable operation of storage ring light sources and for accelerator physics studies. This paper presents a real-time three-dimensional bunch-by-bunch position measurement system based on machine learning. The system eliminates the need for sampling delay adjustment and avoids complex front-end circuitry by directly digitizing BPM electrode signals with high-speed ADCs at a sampling rate of five times the storage ring RF frequency. By deploying neural network models within the FPGA, the system simultaneously achieves real-time measurement of the transverse position and longitudinal phase with low latency. Beam experiments were conducted at Shanghai Synchrotron Radiation Facility (SSRF) to validate the system's phase measurement capability. The results demonstrate a bunch-by-bunch phase resolution of 0.4ps while maintaining a measurement latency within 1µs.

INTRODUCTION

The SSRF is a third-generation medium-energy synchrotron radiation light source. It operates with a beam energy of 3.5 GeV, a storage ring circumference of 432 meters, a harmonic number of 720, and an RF frequency of 499.654 MHz. To improve the operational stability of the facility, implement bunch-by-bunch beam feedback, high-precision online real-time measurements of the storage ring's bunch-by-bunch transverse position and longitudinal phase are required.

Current mainstream online real-time measurement systems are primarily based on digital boards. Data acquired by ADCs, with sampling clocks synchronized to the accelerator machine clock, is directly transmitted to the FPGA to calculate the transverse position. In this scheme, the ADC sampling rate is typically identical to the RF frequency of the electron storage ring. By precisely adjusting the sampling clock delay, the ADC sampling points are aligned with the peak moments of the beam signal. The single-point sample value is then used to represent the signal amplitude[1], which is processed via a difference-over-sum calculation to derive the beam transverse position. Current bunch-by-bunch transverse feedback systems, such as the iGp-12 and Libera Bunch-by-Bunch, all adopt this scheme [2]. The issue with this scheme lies in the need for precise adjustment of the sampling delay, which hinders its application in large-scale engineering projects. Furthermore, beam longitudinal oscillations and clock jitter can cause the sampling points to deviate from the peak, thereby introducing measurement errors.

This paper proposes a bunch-by-bunch transverse position and longitudinal phase measurement system based on machine learning. The system performs RF direct sampling of BPM electrode signals via a high-performance ADC. A fully connected neural network (FCNN) is trained for each BPM electrode channel and the four-electrode sum signal, respectively. The weights and biases are then deployed on the Programmable Logic (PL) side of the processor FPGA.

The input layer consists of N consecutive sampling points belonging to the same bunch. The network undergoes offline training using a large dataset of real beam signals to learn the complex mapping from a sequence of sampling points at arbitrary phases to the true signal peaks and zero-crossings, thereby accurately reconstructing the signal amplitude and zero-crossing time. The zero-crossing points of the four-electrode sum signal serve directly as the longitudinal phase, while the transverse position is obtained by performing a difference-over-sum calculation on the amplitudes of each BPM electrode channel. The phase measurement function has been tested at SSRF. Experimental results demonstrate that the system achieves a bunch-by-bunch phase resolution of 0.4 ps.

THEORETICAL BASIS

When a bunch passes through a BPM, signals correlated with the bunch parameters are induced on the button electrodes. The signal on the BPM electrode is given by:

$$V(t)=\frac{ZSQ(t-t_0)}{\sqrt{2\pi}L\beta c\sigma^3}\exp\left[-\frac{(t-t_0)^2}{2\sigma^2}\right]F(\delta,\theta) \tag{1}$$

Where S is the area of the button electrode, L is the circumference of the vacuum pipe at the BPM, βc is the velocity of the beam, σ is the bunch length, t_0 is the longitudinal phase, Q is the bunch charge, and F is the transverse position factor. Equation (2) represents the sum signal of the four BPM electrodes, where the zero-crossing time is the longitudinal phase.

$$V_S=\frac{4ZSQ(t-t_0)}{\sqrt{2\pi}L\beta c\sigma^3}\exp\left[-\frac{(t-t_0)^2}{2\sigma^2}\right] \tag{2}$$

And the transverse position is obtained by performing a difference-over-sum calculation on the amplitudes of the four electrode signals:

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$$X = K_X\left[\left(V_A + V_D\right) - \left(V_B + V_C\right)\right]/V_S$$
$$Y = K_Y\left[\left(V_A + V_B\right) - \left(V_C + V_D\right)\right]/V_S \quad (3)$$

Where K_X and K_Y are the horizontal and vertical calibration coefficients of the BPM, respectively.

HARDWARE OF THE BUNCH-BY-BUNCH MEASUREMENT SYSTEM

Figure 1 shows the hardware block diagram of the bunch-by-bunch position and phase measurement system. The core component of the system is a beam signal processor based on the RF direct sampling. photograph of the processor is shown in Fig. 2. The processor consists of an ADC daughterboard and an FPGA motherboard. The daughterboard comprises a clock system and four ADC channels, each with a maximum sampling rate of 2.6 Gsps. The sampling clock of the ADC is derived by frequency multiplication from the accelerator machine clock.

The full oscillation information is contained within a bandwidth of ±1/2 RF frequency centered at the storage ring RF frequency. Taking into account both the maximum ADC sampling rate and the RF frequency, a low-pass filter with a cutoff frequency of 780 MHz was selected. The ADC sampling rate of the system is set to 5 times the storage ring RF frequency.

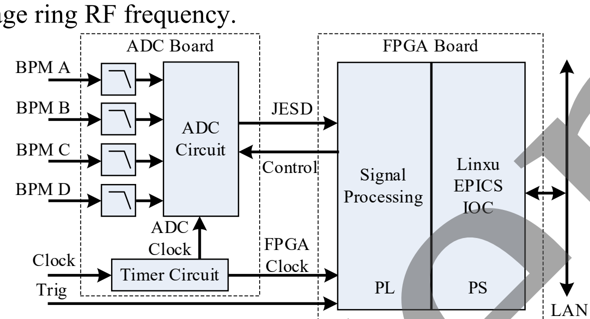

Figure 1: Block diagram of the hardware platform for the bunch-by-bunch measurement system.

Figure 2: Photograph of the RF direct sampling bunch-by-bunch measurement processor.

BUNCH-BY-BUNCH POSITION AND PHASE MEASUREMENT ALGORITHM

The data processing flow of the system algorithm is illustrated in Fig. 3. On one hand, the sampling data from the four electrodes (A, B, C, and D) of the same bunch are fed into a Fully Connected Neural Network (FCNN) to predict the peak amplitude of each electrode signal. Subsequently, based on these peak amplitudes, the transverse position of the bunch is calculated using the difference-over-sum algorithm. On the other hand, the sampling data from the four electrodes are summed to obtain the sum signal, which is then fed into another FCNN to estimate the true zero-crossing point of the sum signal, thereby obtaining the longitudinal phase of the bunch.

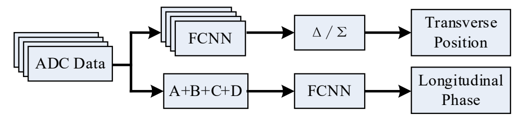

Figure 3: System Algorithm Flowchart.

The block diagram of the FCNN is shown in Fig. 4. The network architecture consists of two hidden layers with 10 and 5 neurons, respectively. This design balances model expressiveness with computational efficiency, making it well-suited for the small-scale regression tasks and FPGA deployment involved in this study.

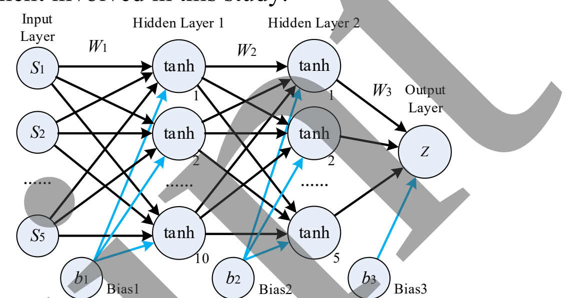

Figure 4: Block diagram of the Fully Connected Neural Network (FCNN) architecture.

The algebraic expression for the forward propagation of the FCNN is given by:

$$\mathbf{s}^{(3)} = \tanh\left[\mathbf{W}^{(2)}\tanh\left(\mathbf{W}^{(1)}\mathbf{s}^{(1)} + \mathbf{B}^{(1)}\right) + \mathbf{B}^{(2)}\right] \quad (4)$$

$$z = \mathbf{W}^{(3)}\mathbf{s}^{(3)} + b^{(3)} \quad (5)$$

Where **V** is the column vector of sampling data after normalization preprocessin. $\mathbf{W}^{(1)}$, $\mathbf{W}^{(2)}$, $\mathbf{W}^{(3)}$ are the weight matrices, while $\mathbf{B}^{(1)}$, $\mathbf{B}^{(2)}$, $b^{(3)}$ are the bias parameters.

To acquire a large volume of real sample data, we utilized an oscilloscope with a sampling rate of 10 Gsps to continuously capture multi-turn data[3]. Since the RF frequency of the storage ring is not an integer multiple of the oscilloscope's sampling rate, the sampling instants of each turn on the signal under test shift relative to the previous turn. By sorting these sampling points in ascending order of phase, it is possible to reconstruct waveform data with an equivalent sampling rate of 1000 GHz.

Furthermore, the BPM four-electrode signals and sum signals for each bunch were extracted. The waveforms of each bunch were then randomly shifted along the time axis. In this way, a large number of bunch signals with random phases were obtained. By selecting sampling points at intervals of the processor ADC's sampling period, a large sample dataset was obtained.

We obtained a dataset of 339,626 samples from data collected between July 2025 and October 2025. These samples were split for training and validation with an 80% training ratio. To ensure that the five sampling points in the sampling sequence fall within the signal range of one bunch, the phase range of the ADC sampling window should be the sampling period (400 ps). Taking the bunch center as the origin, to ensure the output stability of the FCNN at critical sampling phases, we set the random shifting range of the signal along the time axis to ±250 ps when acquiring the sample dataset.

The performance of the FCNN for predicting bunch-by-bunch phase on the validation set is shown in Fig. 5. Within the range of ±250 ps, the mean phase prediction error is 0.5127 ps, and R^2 reaches 0.9999.

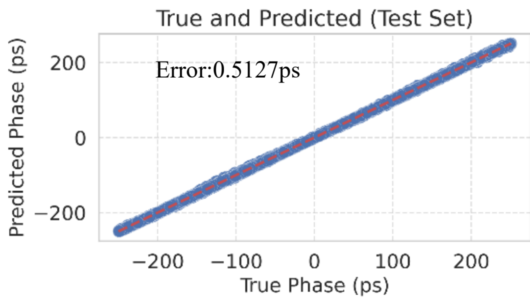

Figure 5: Prediction error distribution for Phase.

Figure 6 show the performance of the amplitude prediction FCNN (taking Channel A as an example). When the sampling phase varies within the range of ±250 ps, the relative deviations for channels A, B, C, and D are 0.45%, 0.38%, 0.44%, and 0.54%, respectively. And the R^2 reaches 0.9996.

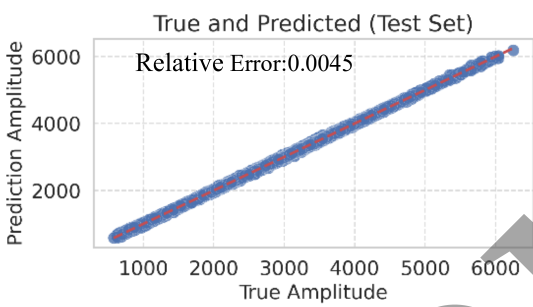

Figure 6: Prediction error distribution for Channel A.

BEAM EXPERIMENTS

Currently, the phase measurement FCNN proposed in this paper has been deployed on the FPGA of the beam signal processor, and beam experiments have been conducted at SSRF. The measurement latency is within 1 µs, which is less than the revolution period of SSRF storage ring (1.44 µs). As shown in Fig. 7 and Fig. 8, the turn-by-turn phase oscillation of a single bunch and its normalized spectrum are presented.

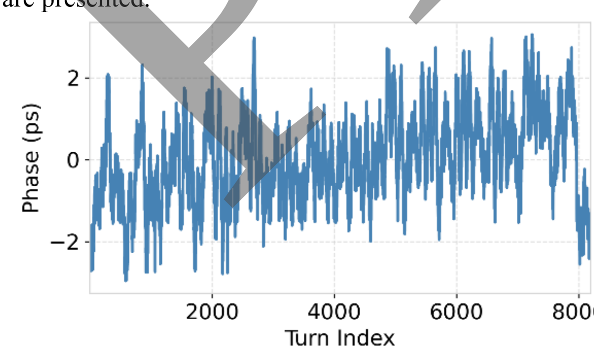

Figure 7: Turn-by-turn phase variation of a single bunch.

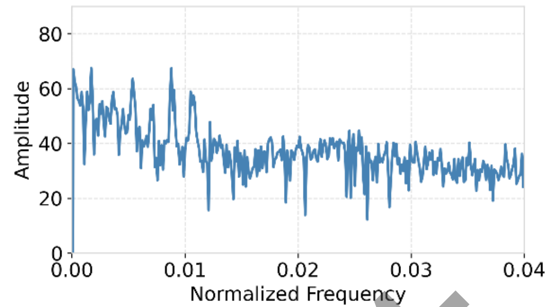

Figure 8: Normalized spectrum of single-bunch turn-by-turn phase oscillation.

The measurement resolution of the system is evaluated using Principal Component Analysis[4].The resulting dependence of the bunch-by-bunch phase resolution on bunch charge is illustrated in Fig. 9. The bunch-by-bunch phase resolution is better than 0.4 ps.

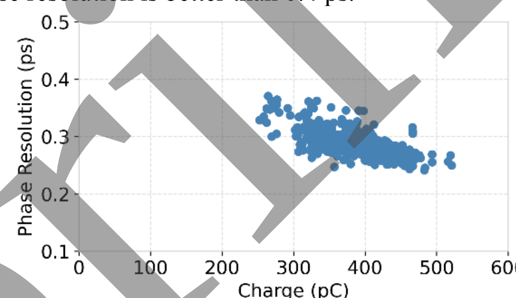

Figure 9: Relationship between bunch-by-bunch phase resolution and bunch charge.

CONCLUSION

This paper presents an online, real-time measurement system for bunch-by-bunch transverse position and longitudinal phase based on machine learning. Beam experiments at the SSRF demonstrate that the system achieves a bunch-by-bunch phase resolution better than 0.4 ps. Future work will focus on completing beam experiments for the transverse position algorithm, aiming to achieve simultaneous measurement of transverse position and longitudinal phase on one processor.

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