Adaptive Interception and Calibration Method for Wall Current Signals during the HIAF Beam Combining Process

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Abstract

In the study of beam merging at HIAF-BRing, effectively obtaining one-dimensional longitudinal profiles is the foundation for analyzing beam evolution. However, the RF frequency sweeping during the merging process leads to dynamic changes in bunch length and revolution frequency, making it difficult for traditional fixed-window slicing to ensure the uniqueness of the physical period within a single frame. Meanwhile, an unknown time offset exists between the acquisition mechanism of the wall current monitor data and the trigger mechanism of the control system, which easily leads to waveform truncation. To construct a standardized dataset, this paper proposes an adaptive slicing and calibration method for detection signals. Addressing the problem of asynchronous timeline alignment, this paper introduces a temporal calibration algorithm based on macro-AC amplitude curves and the maximization of coherence between adjacent turns. This algorithm objectively extracts the absolute system time offset through global optimization. After calibrating the asynchronous timeline based on this offset, the algorithm dynamically adjusts the interception window width turn-by-turn according to the instantaneous revolution frequency, achieving proper alignment of sliced waveforms across various physical stages. Macro-charge integration tests demonstrate that this method effectively mitigates edge truncation issues and preserves the integrity of the physical period well. It achieves a reliable conversion from continuous waveforms to standardized one-dimensional tensors, providing a solid data foundation for subsequent beam dynamics analysis and the training of related deep learning models.

Figure 1

Figure 1: Figure 1

Full Text

Preamble

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1 引言

During the operation of high-intensity heavy-ion accelerators, reliable longitudinal phase space diagnostics are essential for evaluating beam merging efficiency and regulating beam dynamics evolution. The Booster Ring (BRing) of the High Intensity heavy-ion Accelerator Facility (HIAF), a major national scientific infrastructure project, employs a unique beam merging scheme that imposes stringent requirements on the extraction and fidelity of longitudinal signals. During the operational cycle of HIAF-BRing, the longitudinal evolution of the beam follows a specific physical sequence: it begins with an initial coasting beam phase; subsequently, on the extraction energy plateau, the beam undergoes complex direct bunch merging (specifically, "four-to-two" and "two-to-one" operations) through adiabatic voltage control to complete the merging process; finally, once the beam satisfies the extraction conditions, it is kicked out of the ring.

The Wall Current Monitor (WCM) is a critical device for capturing the one-dimensional longitudinal line density of the beam. However, the preservation of raw waveform data in current accelerator operations typically relies on experimental personnel manually triggering and capturing signals via oscilloscopes. In traditional beam physics analysis, manually selecting and extracting a few characteristic cycles is sufficient to meet preliminary diagnostic requirements. However, with the introduction of deep learning technologies into the accelerator field, data-driven models require tens of thousands of standardized tensor data points, each containing a single physical revolution period, as input. During actual merging operations, the control system operates in a dynamic frequency-sweeping state, causing the physical revolution period of the beam to continuously shorten in the time domain.

When faced with macroscopically non-stationary signals containing tens of millions of sampling points (as shown in

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1 所示)，传统的固定窗宽切片方法存在明显局限性。由

As the beam revolution frequency dynamically increases, a fixed-length time window results in a severe mismatch with the actual physical cycles. Within the same interception window width, the initial stage may contain only a partial revolution waveform, while the later acceleration stage may encompass multiple cycles. This data, containing an indeterminate number of physical cycles within a single frame, introduces phase aliasing and is difficult to use directly as a standard input for deep learning models. Furthermore, because the data recording starting point is manually triggered, its timeline remains asynchronous with the theoretical frequency sweep curve of the control system.

If this unknown systematic deviation cannot be reasonably calibrated, automated large-scale homologous slicing becomes difficult to achieve. To address this bottleneck hindering data preprocessing, this paper proposes an automated signal adaptive slicing method.

This method first objectively extracts the systematic timing deviation based on local signal features and a phase drift minimization algorithm. Subsequently, by combining the mapped instantaneous frequency to dynamically adjust the window width on a turn-by-turn basis, a data stream is constructed from the original non-stationary signals into large-scale standardized fixed-length tensors. (2026, Nuclear Physics Review: Adaptive Interception and Calibration Method for Wall Current Signals during Beam Merging; Institute of Modern Physics, Chinese Academy of Sciences, Lanzhou, Gansu; University of Chinese Academy of Sciences, Beijing 100049)

摘要

In the study of beam merging for HIAF-BRing, the effective acquisition of one-dimensional longitudinal profiles is fundamental to analyzing beam evolution. However, the RF frequency sweeping during the merging process causes dynamic changes in both bunch length and revolution frequency, making it difficult for traditional fixed-window slicing methods to guarantee a unique physical period within a single frame. Furthermore, an unknown time offset exists between the data acquisition mechanism of the wall current monitor and the trigger mechanism of the control system, which often leads to waveform truncation. To construct a standardized dataset, this paper proposes an adaptive slicing and calibration method for detection signals. To address the issue of asynchronous timeline alignment, we introduce a temporal calibration algorithm based on the macroscopic AC amplitude curve and the maximization of coherence between adjacent turns. This algorithm objectively extracts the absolute system time offset through global optimization.

After calibrating the asynchronous timeline based on this offset, the algorithm dynamically adjusts the extraction window width turn-by-turn according to the instantaneous revolution frequency, achieving proper alignment of the sliced waveforms across all physical stages. Macroscopic charge integration tests demonstrate that this method effectively mitigates edge truncation issues and preserves the integrity of the physical periods. This approach enables the reliable conversion of continuous waveforms into standardized one-dimensional tensors, providing a solid data foundation for subsequent beam dynamics

analysis and the training of related deep learning models.

关键词

Adaptive synchronization; Dynamic slicing; Wall current monitor; Beam combining; CLC: O571.53; Document code: 10.11804/NuclPhysRev.31.01.01

Nuclear Physics Review

2 WCM

In the practical beam combining operations of the signal adaptive slicing algorithm, converting one-dimensional detection signals into standard tensors compatible with deep learning models requires overcoming two primary physical obstacles. First, due to nonlinear longitudinal dynamical evolution, macroscopic signals exhibit high-frequency distortions, which can cause direct alignment processes to become trapped in local extrema. Second, the manual triggering mechanisms used for long-sequence recording introduce unknown systematic time biases. To address these challenges, this paper designs a data-driven adaptive slicing algorithm. The core processing flow is divided into three stages: benchmark extraction, time-difference optimization, and dynamic slicing. The complete adaptive slicing and normalization process is as follows:

2.1 初始数值计算：时序对齐基准窗提取

Directly performing time-offset optimization on the global signal is susceptible to interference from waveform distortion. Practical observations indicate that during the late stages of the beam combination evolution, the presence of RF phase differences between the participating bunches (for instance, when phases are not yet aligned) leads to significant deformation in the one-dimensional macroscopic waveform. This deformation increases the discrepancy between waveforms of adjacent revolutions. Consequently, the first step of the algorithm involves pre-selecting a relatively clean and stable segment of the waveform as an alignment benchmark, based on the macroscopic evolution trend of the signal.

To quantify the macroscopic amplitude variations of the signal, the algorithm utilizes a microscopic time window of $\Delta t = 0.002$ to calculate the local AC standard deviation, thereby constructing a macroscopic AC amplitude curve. Let the sampling rate be *sample*, such that a single microscopic time window contains N sampling points. The curve value for the i-th time window (corresponding to time t_i) is defined as:

$\sum$ =1 (, −) 2 (1)

( ) =

the i-th voltage sample value within a given time window, and $\bar{V}$ represents the arithmetic mean of the voltage. Based on this curve sequence, the calculation of the time t_{max} corresponding to the peak point satisfies:

Figure 1

Figure 2: Figure 1

Figure 1

Figure 3: Figure 1

peak = arg max ( ) (2)

Based on the calculations, the peak of the curve for the original test batch data is shown in

. When determining the starting point of the reference window, it is critical not to select a time interval that is too early. During the initial phase of the first capture stage (approximately $0.050 \sim 0.070$), the beam consists primarily of a drifting beam where the bunch has not yet fully formed. Performing waveform matching at this stage is prone to calculation errors. Consequently, the algorithm searches from the beginning to identify the position where the curve value first reaches its maximum, which is then designated as the starting point, *start*.

start = min { ( ) 0.15 (peak)} (3)

The threshold indicates that the beam has already formed a relatively stable bunch structure. In the raw signal, the specific value calculated for this starting point is 0.298 s, at which the maximum signal value was extracted.

Once the starting point is determined, a fixed length is intercepted backward to serve as the reference window. The selection of the starting point, *start*, must satisfy the following conditions:

mod < distortion − start (4)

The window length must encompass several complete longitudinal synchrotron oscillation periods to ensure that internal bunch phase jitter is effectively averaged out during correlation calculations. Conversely, the window must not be excessively long, as it must avoid the signal distortion regions that occur at later stages. Taking these factors into account, this study adopts a baseline timing alignment window of $L = 0.080$.

2.2 绝对时间偏差寻优

After obtaining the benchmark window, the second step of the algorithm is to resolve the absolute time offset between the discrete-time sampling sequence and the control system theory.

illustrates the panoramic view of the macro-continuous signal of the beam' s longitudinal evolution. The vertical solid lines in the figure represent reference nodes dividing different physical evolution stages. This signal provides

Figure 2

Figure 4: Figure 2

an authentic record of the beam' s complete physical lifecycle: it sequentially undergoes the initial drift beam injection and RF adiabatic capture phase, the stable acceleration phase, and subsequently, multi-bunch direct merging under variable harmonic control on the extraction energy platform (specifically, the longitudinal topological evolution of "four-to-two"and "two-to-one"merging). Finally, the beam completes fast extraction, after which the detector records only the post-extraction background noise. During the merging phase, because the RF phases of adjacent bunches are not yet fully aligned, their one-dimensional macroscopic projections evolve dynamically, causing the detected signal to exhibit significant non-stationary characteristics.

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shows the workflow for adaptive signal slicing and normalization: (a) the original long-sequence non-stationary signal from the detector controlled by frequency sweeping; (b) the interception of single-turn physical window widths calculated based on the instantaneous revolution frequency; (c) the standard one-dimensional network input tensor after phase alignment and amplitude normalization.

[FIGURE:3] displays the signal time-alignment benchmark window. The red dots in the figure represent the absolute energy extrema during the merging process, while the blue horizontal dashed line indicates the amplitude threshold for the establishment of longitudinal coherence. The green highlighted area represents the objective physical benchmark window ($\text{Window}_{\text{ref}}$) automatically intercepted by the algorithm. This window avoids the initial drift beam and the later non-linear stages to ensure the accuracy of the time deviation (offset) calculation. In practical operation, the data acquisition terminals and the underlying control systems of large-scale accelerators often belong to different hardware architectures; the recording of offline data relies on independent macro-trigger events and clock bases. This physical isolation of reference benchmarks inevitably leads to an objective asynchronous state between the sampling time axis and the theoretical frequency sweep curve.

To resolve this asynchronous mapping problem, the algorithm exploits the underlying physical consistency of the synchrotron: when the introduced test deviation (offset) matches the actual physical deviation, the adjacent physical cycle waveforms segmented by the instantaneous revolution frequency derived from this mapping will exhibit significant topological similarity. This temporal mapping relationship can be expressed as:

rf = osc + offset (5)

The program queries the theoretical sweep frequency curve through this mapping relationship to obtain the corresponding instantaneous cyclotron frequency. Based on this, it dynamically calculates the number of sampling points per turn corresponding to the physical waveform of a single revolution.

$$= 1 \quad \mathrm{rev} \ (\ \mathrm{rf} \ ) \times \quad \mathrm{sample} \quad (6)$$

$$= \sum \quad =1 \ (\quad , \ \bar{} \quad)(\quad +1, \ \bar{} \quad +1 \ )$$

$$\surd \sum \quad =1 \ (\quad , \ \bar{} \quad) \ 2 \sum \quad =1 \ (\quad +1, \ \bar{} \quad +1 \ ) \ 2 \ (7)$$

The arithmetic mean of the cycle waveforms is calculated. Subsequently, a macroscopic objective function, denoted as $offset$, is constructed and defined as the arithmetic mean of the coherence coefficients between adjacent cycles:

$$(\quad \mathrm{offset} \ ) = 1 \ \ -1$$

$$\sum \ =1 \quad (8)$$

The extraction of the absolute time offset is transformed into a maximization problem for the correlation objective function within the global search domain:

$$* \ \mathrm{offset} = \arg\max \quad \mathrm{offset} \ (\quad \mathrm{offset} \ ) \ (9)$$

Through a traversal test with a fixed step size, calculations demonstrate that the objective function possesses an objective optimal solution. This optimization mechanism transforms the asynchronous timeline alignment problem into a data-driven process for maximizing physical coherence. Ultimately, the absolute time bias for this batch of data is calculated as:

2.3 基于瞬时频率的动态切片与归一化

After the algorithm calculates the absolute time deviation (offset), a physical correspondence is established between the experimental time axis and the theoretical sweep frequency curve. The third step of the algorithm involves performing dynamic turn-by-turn slicing and standardized reconstruction of the macroscopic continuous waveforms.

As the beam combining process progresses, the instantaneous revolution frequency of the beam increases, leading to a continuous reduction in the physical duration of a single-turn waveform. The algorithm reads the frequency data for each period via linear interpolation and dynamically updates the single-turn sampling interval. This ensures that each data frame contains exactly one physical revolution period, thereby mitigating the feature aliasing caused by fixed-window slicing.

To establish a standard tensor that meets the input requirements of the deep learning model, the algorithm performs feature normalization on the extracted single-turn slices. Regarding the amplitude dimension:

Nuclear Physics Review. Initial four-bunch stage; intermediate stage of "four-to-two" evolution; intermediate stage of "two-to-one" evolution; final stable single-bunch stage. Single-turn slices of key physical nodes during beam combining are extracted. The figure illustrates the topological evolution of the beam' s longitudinal phase space, starting from the four-bunch oscillation, passing through "four-to-two" and "two-to-one" operations, and concluding with the extraction of a single bunch. The waveforms at each stage remain centered and aligned within the normalized phase window.

In the amplitude dimension, signal intensity is mapped to the range [0, 1] through min-max scaling to eliminate underlying baseline drift:

norm = − min max − min + (10)

represents the raw voltage sample values within a single-turn slice, while and denote the minimum and maximum voltage values within that specific slice, respectively. A small constant, , is introduced to prevent division-by-zero errors. Regarding the phase dimension, considering the dynamic differences in sampling across different frequencies, the algorithm employs an interpolation method to unify all slices onto a normalized phase grid ranging from 0 to 100. Consequently, the underlying detection signals are automatically transformed into time-series tensors characterized by uniform dimensions and well-defined physical boundaries.

3.1 时间偏差寻优结果与物理演化验证

By employing the adjacent-turn autocorrelation optimization algorithm proposed in this paper, dynamic slicing was performed based on the absolute time deviation offset without the requirement of manual prior intervals. The waveforms at each stage achieved excellent centered alignment within the normalized phase window. To verify the validity of these calculated values and their adaptability to long-sequence slicing, this study performed turn-by-turn dynamic slicing and normalized reconstruction on the complete signal based on the deviation values and theoretical curves. Furthermore, the macroscopic physical evolution trajectories of the waveforms at key nodes were examined.

During the actual beam merging operation of the HIAF-BRing, the beam follows a specific topological evolution law in the longitudinal phase space: it sequentially undergoes "four-bunch oscillation," "four-to-two merging," and "two-to-one merging" until a high-intensity "single bunch" is formed for acceleration and extraction. To intuitively evaluate the fidelity of the slicing, representative single-turn normalized slices were extracted at each of these four key physical stages, as shown in [FIGURE:N]. As seen from the extracted characteristic waveforms, the dynamic slicing performed based on the absolute time deviation aligns with the physical expectations of the accelerator RF control. Throughout the span of the beam merging evolution, waveforms across different frequency bands maintained high alignment within the normalized phase coordinates. Even during the "four-to-two" and "two-to-one" intermediate transition states, where deformation is most severe, the macroscopic envelopes remained within a single extraction window. No significant waveform truncation or phase shifts occurred due to the dynamic increase in revolution frequency.

These extraction results, which align with real physical expectations, objectively verify the effectiveness of the time deviation extraction algorithm based on AC amplitude curves. This mechanism successfully transforms non-stationary detector electrical signals into phase-aligned standard one-dimensional tensors. Consequently, it provides a dataset with more complete physical features for subsequent deep learning-based dynamics models.

3.2 基于宏观信号积分的切片完整性验证

To evaluate the beam tracking capability of the slicing algorithm, this paper performs area integration on the raw waveforms captured for each turn. The results are shown in [FIGURE:N]. The hardware primarily measures bunched beams and exhibits a weak response to uniformly distributed drifting beams. Consequently, during the initial "adiabatic capture" phase, the effective signal captured strengthens as the RF voltage gradually gathers the continuous beam into bunches, leading to the observed increase in the integrated area shown in the figure. Upon entering the stable acceleration and subsequent variable harmonic bunch merging stages ("four-into-two" and "two-into-one"), the bunches undergo relative phase shifts under RF control.

Qiao Xiangwen et al.: Adaptive Interception and Calibration Method for Wall Current Signals During Beam Merging. [FIGURE:N] illustrates the evolution of the integrated area of the single-turn waveforms. The figure intuitively demonstrates the process as the beam sequentially undergoes initial adiabatic capture (rising period), stable acceleration and variable harmonic merging (stable period), and fast extraction (precipitous decline). The stable characteristics observed during the middle stage indicate that the slicing window effectively encapsulates the beam bunches.

If the time offset calculation were incorrect during these shifts, the interception window would become misaligned with the actual bunch, causing waveform truncation. This would, in turn, lead to a decrease or oscillation in the integrated area. However, the figure shows that the integrated area during this stage presents a relatively stable horizontal band. This demonstrates that the time offset calculated by the proposed algorithm, combined with the dynamically adjusted window width, allows the interception window to effectively track the main body of the bunch and reduces signal loss.

Finally, at the end of the extraction flattop, the beam is kicked out of the ring, the detector signal returns to zero, and the integrated area experiences a cliff-like drop. This macro-evolutionary curve aligns with the actual physical operation sequence of the machine, further verifying the reliability of the slicing algorithm presented in this paper.

3.3 基于已知延迟注入的双向追踪鲁棒性验证

To further verify the tracking stability of the adaptive extraction algorithm on an asynchronous timeline, this study designed a test based on known delay injection. During the actual acquisition process, non-ideal offsets occur in the oscilloscope's trigger timing. If the trigger occurs early, the front-end drift beam data segment recorded by the detector will be correspondingly extended; if the trigger lags, the front end of the signal will be truncated, causing a time shift of the waveform on the absolute timeline.

To address early trigger conditions (positive delay), pure drift beam sequences with lengths of 0.020 s, 0.050 s, 0.080 s, 0.100 s, and 0.250 s were artificially prepended to the signal start without altering the original physical evolution laws. For late trigger conditions (negative delay), front-end physical truncation of 0.020 s and 0.050 s was performed directly on the waveforms. While maintaining a constant algorithm evaluation benchmark, these sets of data were re-input into the algorithm for calculation. The test results, as shown in [TABLE:N], demonstrate that the linkage mechanism based on macro-AC amplitude curve extraction and adjacent-turn coherence calculation exhibits excellent adaptability. Across the different time-shift conditions, the coherence starting point $start$ redefined by the algorithm and the final calculated absolute time deviation $offset$ both underwent corresponding rigid time translations. In the 0.250 s extension test, the algorithm calculated a negative deviation value of -0.06891 s; similarly, in the truncation tests, the algorithm accurately reflected the injected delay, the relocated starting point $start$, the calculated absolute time deviation $offset$, and the relative translation error.

-0.050 0.024 0.23109 $< 10 -5$

-0.020 0.054 0.20109 $< 10 -5$

0.000 (Original Signal) 0.074 0.18109 - 0.020 0.094 0.16109 $< 10^{-5}$

0.050 0.124 0.13109 $< 10 -5$

0.080 0.154 0.10109 $< 10 -5$

0.100 0.174 0.08109 $< 10 -5$

0.250 0.324 -0.06891 $< 10 -5$

The temporal bias was identified and corrected. The relative translation error for each control group was maintained within the fine-search step size (Δt). These results demonstrate that the algorithm' s decision-making process is primarily driven by the internal micro-physical characteristics of the signal. By reducing dependence on a single absolute time coordinate, the proposed method exhibits robust tracking capabilities for offline data across various trigger states.

4 结论

To address the non-stationary signals encountered during the beam merging process in the HIAF-BRing, this study proposes an adaptive slicing and calibration method. By introducing a macro-AC amplitude curve extraction technique combined with an adjacent-turn autocorrelation maximization algorithm, temporal deviations are objectively resolved.

Integrating a dynamic window width adjustment strategy, the method achieves the automated conversion of raw data into standardized tensors. The physical integrity of the slicing process was further verified through charge integration analysis. This approach effectively mitigates the issues of temporal asynchrony caused by manual triggering and phase aliasing resulting from fixed-window slicing. Consequently, it provides a reliable data preprocessing solution for subsequent longitudinal beam dynamics research and related deep learning models, such as β-CVAE.

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Nuclear Physics Review

CAI F C, YANG J C, XIA J W, et al. Phys Rev Accel Beams, 2020, 23: 064402.

Abstract

This paper presents a comprehensive review and analysis of recent advancements in accelerator physics, specifically focusing on the developments reported in *Physical Review Accelerators and Beams*. The study investigates the dynamics of particle beams, optimization techniques for heavy-ion accelerators, and the implementation of advanced control systems. By synthesizing experimental data and theoretical models, the authors provide insights into the enhancement of beam intensity and stability, which are critical for next-generation nuclear physics research facilities.

Figure 1

Figure 5: Figure 1

Introduction

The evolution of modern nuclear physics is intrinsically linked to the progress of particle accelerator technology. As experimental requirements demand higher energies and greater beam intensities, the challenges associated with beam dynamics and hardware precision become increasingly complex. The High-Intensity heavy-ion Accelerator Facility (HIAF) and similar large-scale scientific infrastructures represent the frontier of this field. This review examines the methodologies employed to overcome technical limitations in beam cooling, injection, and storage ring physics.

Beam Dynamics and Optimization

A primary focus of recent research involves the precise characterization of beam behavior under high-intensity conditions. The interaction between particles, known as space charge effects, significantly influences the emittance and stability of the beam. To mitigate these effects, various numerical simulation tools and machine learning algorithms have been integrated into the design phase.

For a particle beam with a distribution function $f(\mathbf{r}, \mathbf{p}, t)$, the evolution is governed by the Vlasov equation:

$$\frac{\partial f}{\partial t} + \mathbf{v} \cdot \nabla_{\mathbf{r}} f + \mathbf{F} \cdot \nabla_{\mathbf{p}} f = 0$$

where $\mathbf{F}$ represents the total force, including external magnetic fields and internal self-fields. Recent studies [**?**] have demonstrated that optimizing the lattice structure of the storage ring can effectively suppress resonances induced by these forces.

Advanced Control Systems and Diagnostics

The reliability of an accelerator facility depends heavily on its control system and diagnostic instrumentation. Real-time monitoring of beam parameters such as position, intensity, and profile is essential for maintaining optimal performance. Digital signal processing and high-speed data acquisition systems have enabled the implementation of sophisticated feedback loops.

As shown in [

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Adaptive Extraction and Calibration Method for Wall Current Monitor Signals During Beam Merging at HIAF

Xiangwen Qiao, Jiancheng Yang, Jie Liu, Guangyu Zhu, Guimei Ma, Yunpeng Zhu, Zhongtian

Abstract

The High Intensity heavy ion Accelerator Facility (HIAF) requires precise monitoring of beam parameters during the complex beam merging process. The Wall Current Monitor (WCM) serves as a critical diagnostic tool for capturing high-frequency longitudinal beam distributions. However, during the merging phase, the rapid evolution of the beam longitudinal profile and the presence of baseline shifts pose significant challenges for accurate signal extraction and calibration. This paper proposes an adaptive extraction and calibration method for WCM signals. By implementing a dynamic windowing algorithm based on the RF phase and a baseline restoration technique utilizing statistical noise analysis, the method achieves high-precision capture of the beam evolution. Experimental results demonstrate that this approach effectively suppresses noise interference and provides reliable data for the optimization of beam merging efficiency at HIAF.

1. Introduction

The High Intensity heavy ion Accelerator Facility (HIAF) is a next-generation nuclear physics research facility designed to provide high-intensity, high-energy ion beams. One of the core technical challenges in achieving high-intensity beams is the longitudinal beam merging process in the Booster Ring (BRing). During this process, multiple beam bunches are merged into a single bunch to increase the particle density. To monitor this dynamic process, the Wall Current Monitor (WCM) is employed to measure the longitudinal distribution of the beam with high temporal resolution.

The WCM signal is characterized by high-frequency components and is often susceptible to electromagnetic interference and baseline drift. In the context of beam merging, the bunch length and shape change rapidly, making fixed-window extraction methods inadequate. Furthermore, the integration of the WCM signal to obtain the total charge requires a stable and accurate baseline. Traditional manual calibration or fixed-offset subtraction cannot meet the requirements for real-time, high-precision diagnostics. Therefore, developing an adaptive extraction and calibration method is essential for the successful operation of the HIAF beam merging system.

2. Principles of WCM Signal Acquisition

The Wall Current Monitor detects the image current flowing on the vacuum chamber wall, which is proportional to the beam current. The equivalent circuit of a WCM can be modeled as a parallel *RLC* circuit, where the response is optimized for high-frequency performance. The voltage signal $V(t)$ measured

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Abstract

In the study of beam merging at HIAF-BRing, effectively acquiring the one-dimensional longitudinal profile is fundamental for analyzing beam evolution. However, the radio frequency sweep during the merging process causes dynamic changes in bunch length and revolution frequency, making it difficult for traditional fixed-width slicing to en- sure the uniqueness of the physical period within a single frame. Meanwhile, an unknown time offset exists between the data acquisition mechanism of the wall current monitor and the trigger mechanism of the control system, which easily leads to waveform truncation. To construct a standardized dataset, this paper proposes an adaptive slicing and cali- bration method for detection signals. To address the asynchronous time axis alignment, a timing calibration algorithm based on the macroscopic AC amplitude curve and the maximization of adjacent-turn auto-correlation is introduced.

This algorithm objectively extracts the absolute system time offset through global optimization. After calibrating the asynchronous time axis based on this offset, the algorithm dynamically adjusts the slicing window width turn-by-turn according to the instantaneous revolution frequency, achieving reasonable alignment of the sliced waveforms across various physical stages. Macroscopic charge integration tests indicate that this method effectively mitigates edge trun- cation, preserves the integrity of the physical period well, and realizes the reliable conversion of continuous waveforms into standardized one-dimensional

Figure 4

Figure 6: Figure 4

tensors, providing a solid data foundation for subsequent beam dynamics analysis and the training of related deep learning models.

Key words: adaptive synchronization; dynamic slicing; wall current monitor; beam merging; HIAF

Figures

Source: ChinaXiv —Machine translation. Verify with original.