

Dual-sensor correlation for wideband HFCT partial discharge detection and interference suppression in transformers

Guanghu Xu ^{*,1,2,a}, Zhongqiang Zhan ^{1,2,b}, Dandong He ^{1,2,c}, Qingchuan Zhang ^{1,2,d}, Gang Chen ^{1,2,e}

¹Xinjiang Key Laboratory of Extreme Environment Operation and Testing Technology for Power Transmission & Transformation Equipment, Urumqi, China

²State Grid Xinjiang Electric Power Company Electric Power Research Institute, Urumqi, China

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Abstract

On-site partial discharge (PD) detection of power transformers is challenged by strong electromagnetic interferences, including converter pulsation, corona, and power-side harmonics, whose spectra overlap with PD signals. A dual-channel synchronous detection system based on self-developed wideband high-frequency current transformer (HFCT) sensors was developed. The HFCT had an operating band of 3–50 MHz and an average transfer impedance of 16 mV/mA, whereas the signal-conditioning system covered 150 kHz–60 MHz. A 14-bit acquisition unit sampled both channels at 250 MSps using a common clock, corresponding to a sampling interval of 4 ns. Satellite timing synchronized distributed acquisition units with an accuracy better than 100 ns. A dual-sensor correlation discrimination method was proposed using time-of-arrival difference, polarity sign, and amplitude transfer ratio as weighted decision parameters in the propagation-path domain. Experiments on a 220 kV/2 MVA single-phase transformer simulation platform using a dataset of 2,800 frames, comprising 2,400 defect-interference combination frames, 240 background-noise frames, and 160 calibration-signal frames, achieved 91.3% recognition accuracy, 14.2 dB SNR improvement, 37.8 ms processing time per 4,096-sample event window, and a 2.4% detection blind zone. The event-level evaluation included 800 PD events and 1,600 interference events extracted from the defect-interference combination frames. Compared with wavelet thresholding, EEMD, and adaptive SVD, the proposed method improved accuracy by 3.7–8.6 percentage points, with recalculated electrical-localization errors ranging from 0.21 to 0.40 m, while the minimum identifiable apparent charge for air-gap discharge was approximately 5.8 pC. The method provides an effective solution for reliable on-site PD detection under complex electromagnetic environments.

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1. Introduction

Ultra-high voltage (UHV) and extra-high voltage (EHV) transformers are indispensable components in contemporary electrical power systems, acting as vital pieces of equipment used for bulk power transmission over long distances and energy interconnections across regions. As compiled in [1] from CIGRE reports on UHVDC transmission-system outages, roughly 58.8% of outages are due to transformers, and almost 50% of transformer-related outages are attributed to insulation failure. It is generally acknowledged that partial discharge (PD) is the most prominent sign of insulation degradation, and early PD detection is essential for avoiding insulation failure [1].

*Corresponding author: guanghuXu123@hotmail.com

^aorcid.org/0009-0002-7761-7984; ^borcid.org/0009-0009-1758-4915; ^corcid.org/0009-0004-3042-6106;

^dorcid.org/0009-0000-8701-8673; ^eorcid.org/0009-0000-4207-0670

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However, there are always three key technical challenges for on-site PD measurement. One challenge is that the substation's electromagnetic environment is extremely complicated, featuring harmonic, converter-caused pulse disturbance, and white noise. In one reported example, the background noise was so serious at the Qiantangjiang Converter Station that the existing PD measuring equipment could barely sense a square-wave pulse signal calibrated with an injection charge of 20,000 pC [2]. This detection difficulty was primarily associated with the spectral overlap between strong converter-generated low-frequency interference and the limited operating bandwidth of the conventional measurement chain used at the site, which attenuated the high-frequency diagnostic components of the PD pulses. The second limitation is that the traditional pulsed current techniques, based on IEC 60270 and GB/T 7354, have limited bandwidth of less than 1 MHz; therefore, higher frequency information contained in the discharge pulse currents will be filtered out, and the external interference will inevitably overlap the PD signals spectrally [3]. The third limitation is that the 12-pulse thyristor interference has a periodicity of 1.67 ms (periodic one-twelfth of the power frequency cycle) with predominant energy up to 400 kHz, which overlaps the frequency range of PD signals [4].

Recent advances in PD interference suppression have led to the adoption of several signal-processing methods. Some works have utilized wavelet thresholding methods using db5 or sym8 mother wavelets alongside soft or hard thresholding rules [5]. Other researchers have used empirical mode decomposition (EMD) and its variations (EEMD and CEEMDAN) to partition the signals based on their instantaneous frequencies [6, 7]. The singular value decomposition technique, which includes adaptive singular value decomposition and short-time singular value decomposition, makes use of the Hankel matrix rank properties to extract discharge modes [8]. Another promising approach is variational mode decomposition coupled with the white noise test [9, 10]. Hybrid systems, including VMD-wavenet thresholding [11, 12], parameter selection based on dispersion entropy [13], optimized thresholding algorithms for stator winding detection [14], and VMD-SVD combination [15, 16], have significantly enhanced denoising capability. But all such schemes for time frequency analysis for single channel face similar drawbacks that while combating with the problem of pulsations interference, they inevitably reduce the high-frequency PD components, they depend too much on the process of tuning and have very expensive computational requirements [17, 18].

Considering the limitations above, this paper does not employ the time-frequency analysis approach used by conventional single-channel methods but opts for a new measurement scheme using two sensors on two separate grounding lines to create a coordinated measurement channel. Correlation information including arrival time difference, polarity and amplitude ratio is acquired in order to distinguish between external noise and internal discharge. This method uses a self-developed wideband high-frequency current transformer (HFCT) sensor operating from 3 to 50 MHz, together with a signal-conditioning system covering 150 kHz–60 MHz, to retain the waveform characteristics of nanosecond-scale discharge pulses for propagation-path correlation analysis. The rest of this paper is arranged as follows. The next section presents details of the wideband HFCT detection system, dual-sensor deployment strategy, three-parameter correlation criteria and the test plan comprising four defect cases and three interfering signals. Time-frequency characteristics of common interferences, discrimination capabilities of the dual-sensor technique, fault diagnosis and location outcomes, and comparative analysis among three state-of-the-art single-channel approaches are described in Section 3. Section 4 includes discussion on the physical basis for the new criteria, benefits of using wideband HFCT compared to traditional pulse current techniques, literature review, and current shortcomings. Section 5 is the conclusion.

2 Materials and Methods

2.1 Wideband HFCT Sensing System and Detection Platform

This platform is focused on a single-phase 220kV transformer physical simulator which is designed for partial discharge studies. It has a power rating of 2MVA, frequency of 50 Hz and rated voltages on high and low voltage sides of 230/√3kV and 10.5kV respectively. Its impedance is 16.5% and the type of cooling used is ONAN. The connection symbol of this device is IiO. It can withstand a test

voltage of 395 kV under power frequency and 750 kV during switching impulse conditions; its no-load and load losses are equal to 6 kW and 16 kW, correspondingly. In total, thirteen PD defect models, labelled D1–D13 in Figure 1(a), were installed in the transformer tank. Eight models were positioned within the winding region and energized by an external high-voltage source, whereas five models were installed in the oil-tank region and energized from the transformer windings. The experiments reported in this study used D1 and D13 for tip discharge, D2 and D5 for air-gap discharge, D7 and D10 for surface discharge, and D9 and D12 for floating discharge, as summarized in Table 1. Each defect model comes with a stepwise press down system that offers 0–40 mm gap between needle and plate.

The sensor uses a nanocrystalline toroidal core with an initial relative permeability of approximately 3.0×10^4 and a maximum relative permeability of approximately 4.0×10^4 . The geometry parameters of the core are $R_1 = 60$ mm, $R_2 = 80$ mm, and $d = 15$ mm. The core is wound with 24 turns of enameled copper wire having a diameter of 0.6 mm, divided symmetrically between the two sides to reduce susceptibility to external electromagnetic stray fields [19]. The use of an aluminum alloy shielding box that has a 2 mm radial slot interrupts the circulating eddy-current path in the aluminum-alloy shielding case without sacrificing the high-frequency performance. The frequency range is 3 MHz – 50 MHz, while the average transfer impedance comes out to be 16 mV/mA, which is much higher than the reference value of 5 mV/mA [20]. In all laboratory tests the grounding conductor was fixed on the axis of the HFCT aperture, and k_0 was calibrated in this fixed geometry.

The detection host utilizes a multi-core 64-bit heterogeneous processor clocked at 1.6 GHz, having 2 GB DDR4 RAM and 16 GB eMMC internal storage space. The signal-conditioning system had an electronic bandwidth of 150 kHz–60 MHz and an input-referred noise level below 0.5 mV. The 150 kHz lower limit characterizes the signal-conditioning electronics rather than the HFCT; because the HFCT response decreases rapidly below 3 MHz, the effective operating band of the complete measurement chain was determined by the HFCT and was therefore 3–50 MHz the sampling rate for the analog-to-digital converter is 250 MSps, while the two channels within one acquisition unit shared a common crystal oscillator, corresponding to a sampling interval of 4 ns. The schematic of the simulation environment along with the structure of the HFCT sensor is shown in Figure 1.

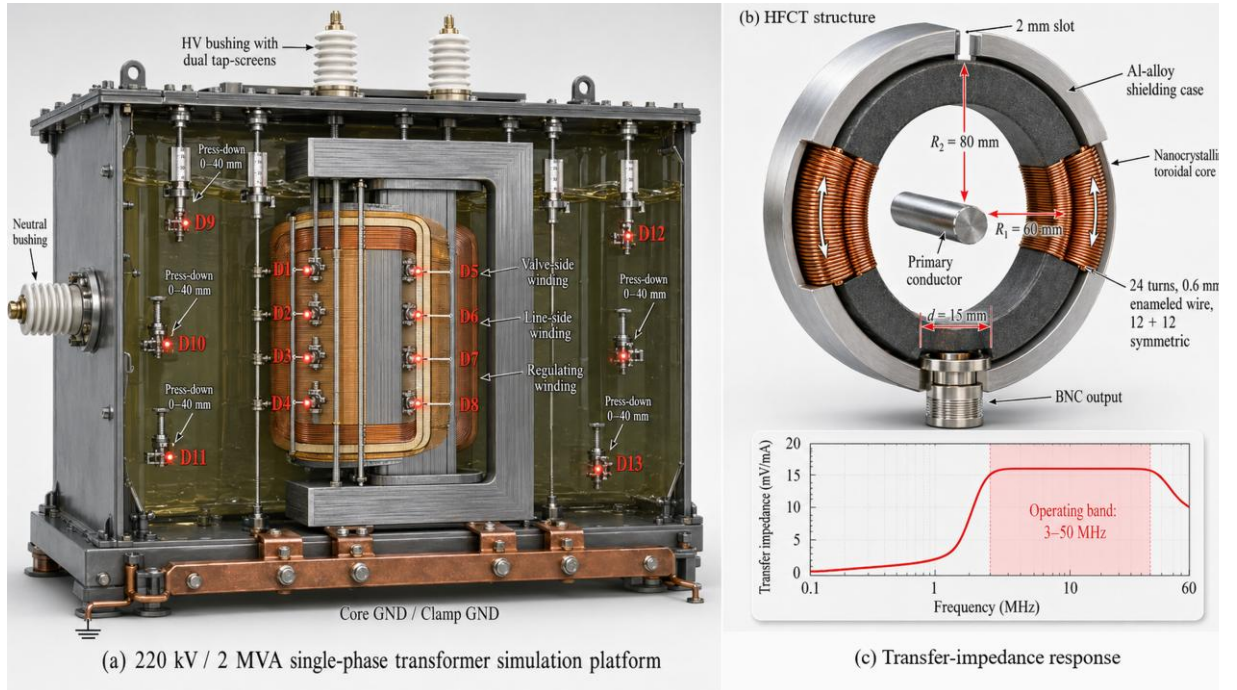


Fig. 1. Experimental platform and HFCT design: (a) schematic configuration of the transformer test platform; (b) three-dimensional structure of the self-developed HFCT; and (c) measured transfer-impedance response of the HFCT

2.2 Dual-HFCT Deployment Strategy and Synchronous Acquisition Scheme

Considering the various situations for detecting the source on-site, three configurations for using two sensor pairs have been made, each designed to discriminate a specific task. In all three configurations evaluated in this study, the two HFCT channels were connected to the same local acquisition unit and shared a common crystal oscillator. Configuration A uses a combination of the HV bushing tap screen and neutral bushing tap screen and is mainly used for identifying discharge sources within the winding propagation route. The combination causes an internal discharge that travels through the distributed characteristics of the winding, resulting in stable time of arrival difference and amplitude transfer ratio at the two measurement points. In configuration B, the core grounding wire is matched with the clamp grounding wire, thus helping determine the common mode interference from the grounding current path. The external disturbances reaching the circuit through the common mode path reach the grounding points close together, with equal polarity, thus giving us a distinctive pattern for rejection. Configuration C comprises a bushing tap-screen coupled with the power supply grounding point, which is used specifically for detecting and discriminating the source side disturbances, like harmonics produced by the test loop and pulses coming from series resonant power supplies. Here, the source disturbance reaches the power supply grounding point prior to the bushing tap-screen.

The dual-channel time base employs only one common crystal oscillator per detection system, thereby ensuring that the inter-channel error remains limited to the acquisition resolution itself. Satellite-based timing was reserved for synchronization between physically distributed acquisition units and was not used to calculate the 25–70 ns inter-channel arrival-time differences reported in this study. All TDoA results presented in Sections 3.2 and 3.3 were therefore calculated from the two locally synchronized channels of a single acquisition unit. The processing steps performed on the raw data are given below: Each HFCT channel is connected to the programmable gain amplifier via a 15 m long shielded coaxial cable. This is followed by band pass filtering, followed by sampling using the 14-bit ADC card, and buffering in FPGA, and finally, transferring to the host computer where it is parsed. The trigger logic employed consists of an amplitude-based trigger coupled with pre/post trigger sampling windows.

2.3 Correlation Criterion Based on Time-of-Arrival, Polarity, and Amplitude Transfer Ratio

The discriminant analysis model uses three correlated parameters obtained from the simultaneous dual-channel recordings.

The signed time difference of arrival was defined as $\Delta t = t_{\text{neutral}} - t_{\text{HV}}$, with the HV-bushing HFCT assigned as Channel 1 and the neutral-point HFCT assigned as Channel 2 throughout all experiments. Under this fixed channel assignment, internal PD signals propagated toward the HV-bushing and neutral-point measurement locations with a positive signed delay of 25–70 ns, whereas source-side interference could produce a negative delay because of its opposite propagation direction. The effective propagation velocity along the oil-paper-insulated winding was calibrated by injecting reference pulses at five known winding positions, with 20 repeated injections at each position. The calibrated effective propagation velocity was $(1.58 \pm 0.05) \times 10^8$ m/s and was used in all subsequent electrical-distance calculations instead of the propagation velocity in bare copper. The electrical-path difference was calculated as $\Delta l = v_{\text{eff}} \Delta t$, and the discharge position measured from the HV-bushing end was estimated as $x = (L + v_{\text{eff}} \Delta t)/2$, where L denotes the calibrated winding-path length. Field measurements support this range, including 58 ns at Suidong converter transformer, 56–64 ns at Qiantangjiang converter transformer, 34 ns at Durong high voltage shunt reactor, and 25–51 ns at a 500kV main transformer in southwest China. External common mode interference on the other hand affects both the channels almost simultaneously with Δt less than 10 ns or even reverse in direction, whereas disturbance on the source side leads to Δt more than 100 ns or may propagate in the reverse direction, such as the –45 ns delay measured at a bushing of the 1,000 kV Ganjiang Substation. Calculation of Δt can be enhanced using generalized cross correlation method that enhances the correlation peak[21].

The polarity-sign principle is based on the physical observation that the current direction at the head and tail terminals of the winding differs; hence, the internal signal exhibits different polarity at the bushing screen and the neutral point, while any external noise enters both paths with identical polarity. The polarity consistency factor is calculated by the equation $P = \text{sign}(A_1) \cdot \text{sign}(A_2)$; for $P = -1$, it is concluded that the internal discharge exists, while $P = +1$ means external interference presence.

The amplitude transfer ratio, expressed as $k = A_1/A_2$, is normalized through a test pulse injection of 2000 pC square wave, with its reference value being k_0 . The test pulse for the Durong shunt reactor showed that $k_0 = 16$ [22]. For internal discharges, the variance between k and k_0 is expected to fall within $\pm 15\%$; for the same test carried out at the Durong shunt reactor under operating voltage, k is known to have been 14.98, with a variance of 6.4%, clearly indicating the presence of HV bushings. However, external interferences have no set path of propagation, hence the scattering of k values.

The three parameters are combined into a weighted decision function:

$$F = w_1 \cdot I(\Delta t \in [25, 70] \text{ ns}) + w_2 \cdot I(P = -1) + w_3 \cdot I\left(\frac{|k - k_0|}{k_0} < 0.15\right) \quad (1)$$

Here, $I(\cdot)$ denotes the indicator function, which equals 1 when the condition in parentheses is satisfied and 0 otherwise. The weights w_1 , w_2 and w_3 take the values 0.4, 0.3 and 0.3 and correspond to the time-difference-of-arrival, polarity-sign and amplitude-transfer-ratio criteria respectively, and a value of $F \geq 0.6$ identifies an internal discharge. The TDoA criterion was assigned the largest weight because it showed the clearest separation between internal-PD and interference events in the training data. The three weights were selected by a grid search with a step size of 0.05 under the constraint that their sum equaled 1, using balanced accuracy on the training subset as the optimization criterion. The decision threshold of 0.6 was subsequently selected on the validation subset from the receiver operating characteristic curve and was kept fixed during testing. Weighted aggregation was used instead of a strict logical product so that an occasional deviation in one parameter did not invalidate the overall decision.

2.4 Experimental Design and Defect-Interference Combination Scheme

There are four discharge defect configurations that are typical for this platform. Air-gap discharge configuration is provided by the use of an epoxy resin block having an enclosed air gap inside. Surface discharge configuration is obtained using a needle-to-plate electrode assembly immersed in oil-filled paperboard. Floating discharge configuration is obtained by providing a shielding ring with poor contact with the winding. Tip discharge is achieved by placing a metallic thin tip on the terminal ends of the high-voltage winding. The chosen defects represent common mechanisms for insulation degradation in practical transformers, and their waveforms have the same propagation patterns observed in actual transformer windings[23].

Three types of interference are used to create the conditions for the electromagnetic environment at the installation site. The 12-pulse interference is simulated by a signal generator using a periodicity of 1.67 ms, an edge steepness of 3.9 μs , and a pulse duration of 80 μs to simulate valve commutation in a converter station. The corona interference is created by a supplementary rod-plate electrode pair in the test circuit and is referenced at the phase angles of 90° and 270°. The power-side harmonic interference is created by a phase-shifting transformer adding the 3rd, 5th, and 7th harmonics to the supply voltage.

The voltage levels below the measured discharge inception voltage were intentionally included as negative-control conditions for evaluating interference responses in the absence of detectable PD activity. However, the binary event labels were assigned from the recorded pulse characteristics rather than from the applied-voltage level alone because PD inception is stochastic near the threshold. In all eight levels, twenty-five cycles are collected for the power frequency. Therefore, 2,400 defect-interference combination frames were obtained from the matrix of four defect types, three interference types, eight voltage levels, and 25 power-frequency cycles. An additional 400

reference frames, consisting of 240 background-noise frames and 160 calibration-signal frames with a 2,000-pC injected pulse, were collected.

Table 1. Experimental design matrix for defect–interference combinations and voltage levels

Defect type	Defect model	Inception voltage ($\times U_0$)	Interference type	Samples per voltage level	Voltage levels ($\times U_0$)	Total samples
Air-gap discharge	Epoxy embedded bubble (D2, D5)	0.5–0.6	12-pulse	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Air-gap discharge	Epoxy embedded bubble (D2, D5)	0.5–0.6	Corona	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Air-gap discharge	Epoxy embedded bubble (D2, D5)	0.5–0.6	Power harmonic	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Surface discharge	Needle-plate on oil-paper (D7, D10)	0.6–0.7	12-pulse	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Surface discharge	Needle-plate on oil-paper (D7, D10)	0.6–0.7	Corona	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Surface discharge	Needle-plate on oil-paper (D7, D10)	0.6–0.7	Power harmonic	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Floating discharge	Loose shielding ring (D9, D12)	0.4–0.5	12-pulse	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Floating discharge	Loose shielding ring (D9, D12)	0.4–0.5	Corona	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Floating discharge	Loose shielding ring (D9, D12)	0.4–0.5	Power harmonic	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Tip discharge	Metal protrusion (D1, D13)	0.4–0.5	12-pulse	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Tip discharge	Metal protrusion (D1, D13)	0.4–0.5	Corona	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Tip discharge	Metal protrusion (D1, D13)	0.4–0.5	Power harmonic	25	0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1	200
Background noise	–	–	–	–	–	240
Calibration signal	2,000 pC pulse injection	–	–	–	–	160
Total						2800

Note: U_0 denotes the rated phase voltage. Each defect–interference combination comprised 25 power-frequency frames at each of eight voltage levels. The 2,400 matrix entries represent complete combination frames rather than mutually exclusive PD-only or interference-only samples. The additional 400 reference frames comprised 240 background-noise frames and 160 calibration-signal frames. Tests were conducted from April to October 2025 at 18–28 °C and 40–75% relative humidity.

The 2,400 observations in the experimental matrix denote complete defect–interference combination frames, whereas the 800 PD and 1,600 interference observations used for binary

classification denote annotated transient events extracted from these frames. Event labels were assigned using the defect energization state, phase-resolved discharge pattern, dual-channel propagation direction, and reference-channel waveform. The process of data collection was conducted during the months of April to October 2025, involving spring, summer, and autumn seasons. The laboratory temperature ranged from 18 °C to 28 °C and relative humidity from 40% to 75%. This helped in testing the performance of the detection system in fluctuating environments. The complete experimental matrix is summarized in Table 1.

3. Results

3.1 Time-Frequency Characteristics of Typical Interference Signals

The repetition period of the 12-pulse disturbance is 1.67 ± 0.03 ms, which is equal to one-twelfth of the power frequency period. In one 20 ms power frequency cycle, there are two types of pulses, including 3 high pulses and 9 low pulses, with the amplitude ratio of two amplitude types being 1.4–1.6. The average rising edge of the pulses is $3.92 \mu\text{s}$, with a deviation value of $0.18 \mu\text{s}$, and the average width of the pulses is $79.6 \mu\text{s}$. The energy spectrum indicates that all energies are lower than 400 kHz with 98.7%, and the center frequency is around 100 kHz. The phase locking property of corona disturbance is quite evident since 61% of the pulses appear at 90° while 35% of the pulses occur at 270° . There is considerable phase constancy from one cycle to another. Each pulse has an average rise time of 276 ns with a standard deviation of 32 ns with an oscillating tail lasting between 300–500 ns. The spectral range is wider as compared to the 12-pulse disturbance, with energy ranging from 50 kHz to 500 kHz.

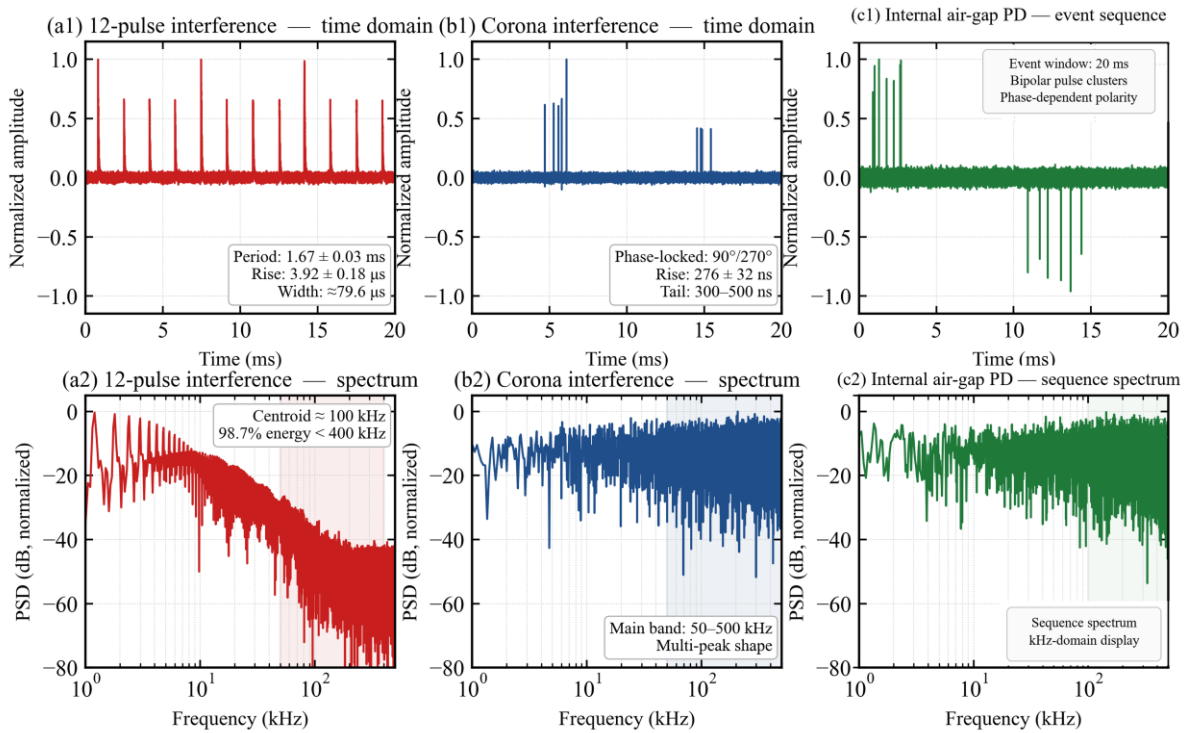


Fig. 2. Time- and frequency-domain characteristics of two typical interferences and an internal air-gap PD signal. (a1, a2) 12-pulse interference. (b1, b2) corona interference. (c1, c2) internal air-gap PD, shown as a phase-resolved event sequence over one power-frequency cycle and its corresponding sequence spectrum

The disturbance generated by the power side results in a consistent time delay of about 42 ns, where the power source grounding is ahead of the bushing tap screen. Same polarity events for both channels total 89%, while the amplitude transfer ratio k differs significantly from the baseline k_0 corresponding to internal discharges. The level of the background white noise is 1.78 mV, and its standard deviation is 0.21 mV. The frequency spectrum of the white noise is almost constant in the region of interest, with variations of less than 3 dB in the frequency range of 3 to 50 MHz. The

time- and frequency-domain characteristics of the 12-pulse interference, corona interference, and internal air-gap PD signal are illustrated in Figure 2 and provide the empirical basis for calibrating the correlation criteria described in Section 2.3. The power-side harmonic interference was evaluated using the dual-channel propagation parameters reported in Section 3.2 rather than included in the time-frequency comparison in Figure 2.

3.2 Effectiveness of the Dual-Sensor Correlation Discrimination

The arrival time difference Δt is the best indicator of distinguishing internal discharges from external noise. Among the 800 annotated internal-PD events, the measured values of Δt for air gap, surface, floating, and tip discharges are 41.3 ± 8.6 ns, 52.8 ± 11.2 ns, 35.7 ± 9.4 ns, and 28.4 ± 6.9 ns, respectively, all within the range of 25 to 70 ns set out in Section 2.3. For the 1,600 annotated interference events, their respective distributions are 6.2 ± 2.1 ns for the 12-pulse disturbance, 4.8 ± 1.7 ns for corona, and -42.5 ± 5.3 ns for the harmonics on the power side, in which the minus sign indicates reverse direction. The distribution of none of the interferences lies within the range of the internal discharge pulse train.

The polarity sign criterion yields stable results, but with less purity than the other criteria. Of the internal discharge cases, 87.4% display the anticipated opposite polarity reaction ($P = -1$), whereas 91.2% of the interfering cases display same polarity ($P = +1$). Misclassifications fall into two categories: far internal discharges traveling a great distance where the polarity change is attenuated, and highly oscillatory disturbances where polarity is unstable at the moment of sampling.

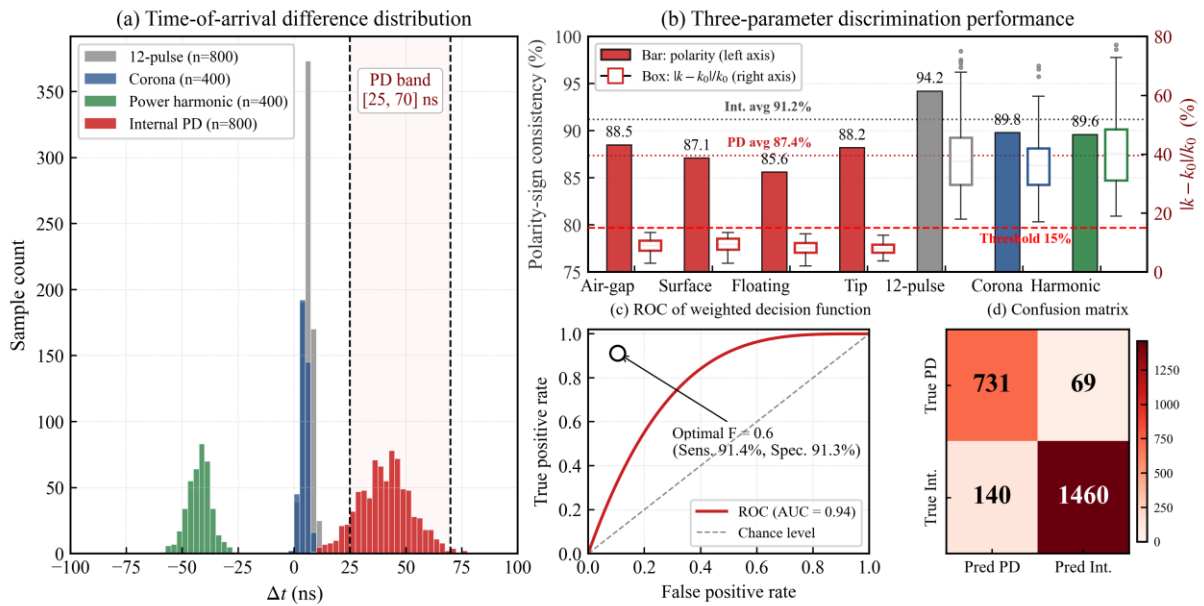


Fig. 3. Discrimination performance of the dual-sensor correlation method: (a) time-difference-of-arrival distributions; (b) polarity-sign consistency and amplitude-transfer-ratio deviation; (c) receiver operating characteristic curve of the weighted decision function; and (d) confusion matrix. The sample counts denote annotated transient events extracted from the defect-interference combination frames

A high amplitude transfer ratio k results in an extremely large contrast in dispersion. For the internal discharge data, there is a deviation from k_0 of $\pm 8.7\%$, with a maximum value of $\pm 13.4\%$, which does not exceed $\pm 15\%$. For the interference case, due to lack of any well-defined propagation path, there is a deviation of $\pm 37.6\%$. The recognition accuracy obtained when these three features are combined using the weighted decision function is 91.3% among the 2,400 annotated transient events. These events were extracted from the defect-interference combination frames and were labelled according to their recorded pulse and propagation characteristics rather than the applied-voltage level alone. On an interference-by-interference basis, the rejection rates are 94.8% for the 12-pulse interference, 89.6% for corona, and 93.1% for power-side harmonics. The major sources

of errors are floating discharges with low amplitude less than $0.6U_0$ classified wrongly as interference (5.2%), and distant corona classified wrongly as discharge (3.5%). A total of 8.7% of the data belong to the range where classification ambiguity occurs, specifically when $F = 0.6$. No combination frame was excluded solely because its applied voltage was above or below the nominal discharge inception range. The complete distribution of the three correlation factors and classification efficiency is presented in Figure 3. The 2,400 entries in Figure 3 represent annotated transient events extracted from the defect-interference combination frames rather than 2,400 mutually exclusive acquisition frames, comprising 800 internal-PD events and 1,600 interference events.

3.3 Detection and Localization Results for Four Defect Types

The air-gap spark resulted in a steady initiation voltage of $0.6 U_0$, and the signal stayed constant after a voltage application of $1.0 U_0$. The monopole showed a rise time of 16-20 ns characterized by a single-peak conical waveform without any sign of oscillation at the tail. For a voltage of $1.0 U_0$, the apparent charge obtained from the high-voltage bushing tap screen was around 185 pC while just 12 pC at the neutral position with $k = 15.4$. The electrical source location error using the time difference was ± 0.29 m.

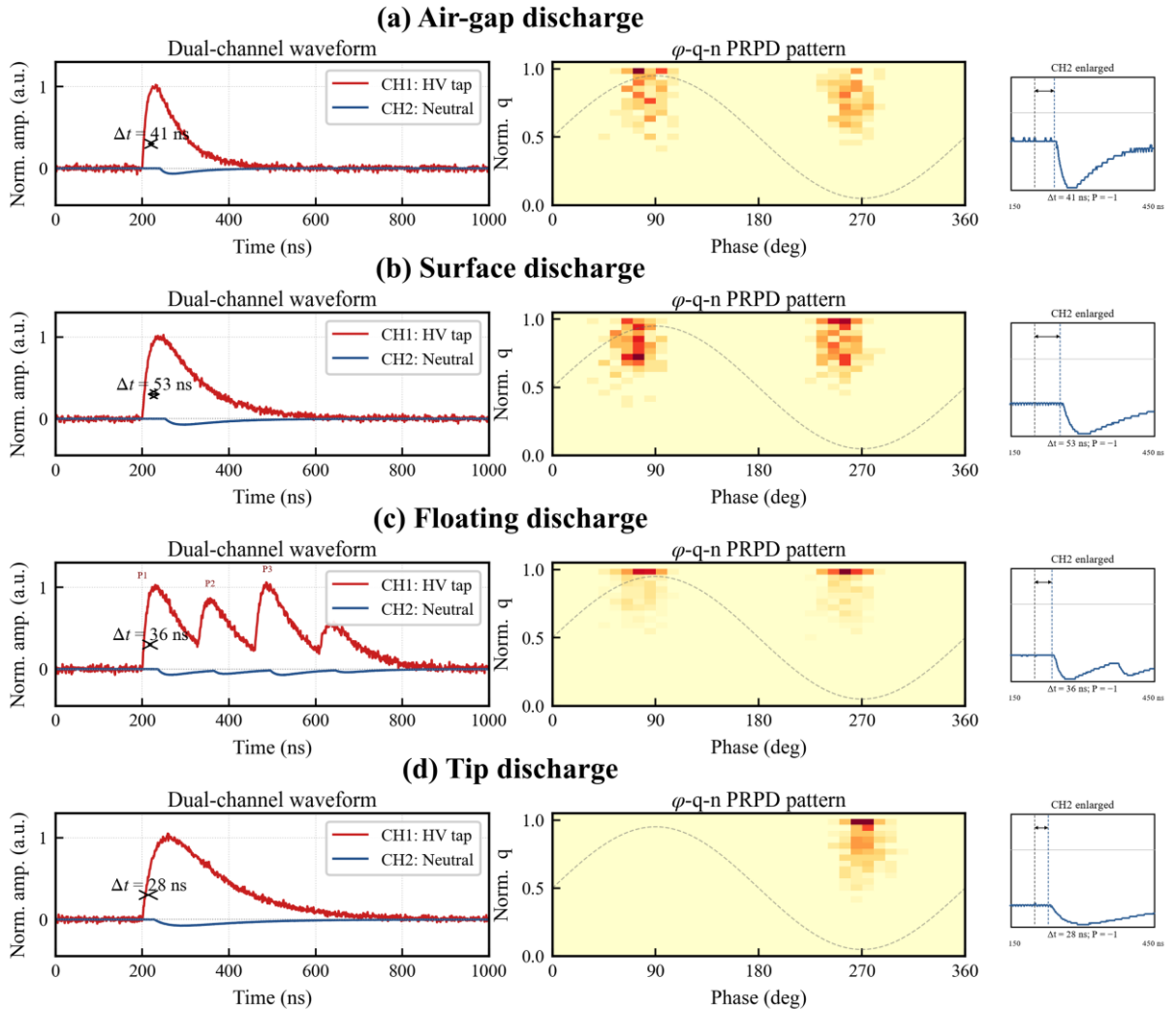


Fig. 4. Dual-channel waveforms and ϕ -q-n PRPD patterns of four PD defect types: (a) air-gap discharge; (b) surface discharge; (c) floating discharge; and (d) tip discharge. The CH2 insets use an independent vertical display scale to visualize the attenuated neutral-point pulses, their arrival times, and negative first-peak polarities. All TDoA, polarity, and amplitude-transfer-ratio values were calculated from the original unnormalized dual-channel recordings. P1-P3 denote successive pulses in the floating-discharge waveform

The surface discharge had an inception voltage of $0.7U_0$ and produced apparent charge of close to 320 pC at HV bushing tap-screen at $1.0U_0$. The transfer ratio $k = 14.7$ differed from the reference calibration value of $k_0 = 16$ by 8.1%, which lies safely within the $\pm 15\%$ limit of variation. The average rise time was 24 ns and pulse duration approximately 240 ns. The discharge locations were consistently placed in the first and third quadrants of PRPD distribution with great symmetry, with localization error of ± 0.40 m. Floating discharge showed initiation voltage of $0.5 U_0$ and had extremely symmetric behavior (skewness less than 0.08) within the first and third quadrants. Time to peak was in the range of 18-22 ns; also, pulse amplitudes were high and distributed from 500 to 1500 pC at the bushing tap screen. There was an evident inter-electrode fingerprint: the polarity at the high-voltage bushing tap screen was inverted relative to that of the core-clamp ground paths. The localization accuracy was within ± 0.35 m.

Table 2. Detection and localization results for four typical PD defect types under the dual HFCT system (statistics from 8 voltage levels, 200 annotated PD events per defect type)

Defect type	Inception voltage (U_i , $\times U_0$)	Pulse rises time (ns)	Pulse width (ns)	Apparent charge at $1.0 U_0$ at HV bushing tap (pC)	Transfer ratio k (HV/neutral)	Phase concentration	Electrical localization error (m)
Air-gap	0.6 ± 0.04	18.3 ± 2.6	152 ± 38	185 ± 41	15.4 ± 1.9 (Mean deviation from k_0 : 3.8%)	1st & 3rd quadrants	± 0.29
Surface	0.7 ± 0.05	23.7 ± 3.2	238 ± 47	318 ± 62	14.7 ± 1.6 (Mean deviation from k_0 : 8.1%)	1st & 3rd quadrants	± 0.40
Floating	0.5 ± 0.06	19.8 ± 2.9	175 ± 52	982 ± 287	13.9 ± 2.4 (Mean deviation from k_0 : 13.1%)	1st & 3rd, symmetric	± 0.35
Tip	0.5 ± 0.04	44.2 ± 5.1	326 ± 41	426 ± 74	14.2 ± 1.8 (Mean deviation from k_0 : 11.3%)	$\approx 270^\circ$	± 0.21

Note: Electrical-localization errors were calculated from Δt using the calibrated effective winding propagation velocity of $(1.58 \pm 0.05) \times 10^8$ m/s. The voltage-to-charge calibration factor was 1.46 pC/mV; therefore, the 1.78 mV background corresponded to approximately 2.6 pC. The minimum identifiable apparent charge of approximately 5.8 pC applies to the air-gap discharge configuration. The comparatively wide standard deviation of the floating-discharge apparent charge follows from the intermittent charge accumulation on the isolated shielding ring, whose discharge magnitude is governed by the instantaneous floating potential at breakdown rather than by a fixed electrode geometry.

The discharge at the tip had a threshold voltage of $0.5U_0$ and showed a steady signal with a peak voltage of $1.0U_0$, where the rise time was 40 – 50 ns while the pulse width was 300 – 350 ns, similar to the 30ns / 345ns value observed in a Ganjiang bushing case and the 17ns / 540ns value in a Qiantangjiang converter transformer case. The phase angle value continued to stay in the vicinity of 270° , and the localization accuracy was kept within ± 0.21 m. The voltage-to-charge conversion factor was established using the 2,000-pC reference-pulse calibration and was 1.46 pC/mV for the acquisition channel used in this test. Accordingly, the measured background level of 1.78 mV corresponded to an apparent-charge-equivalent level of approximately 2.6 pC. With a background noise level of 2.6 pC, the minimum apparent charge that can be recognized for air gap discharge was about 5.8 pC, equivalent to a SNR threshold of around 6.9 dB. The waveforms and PRPD features of the four defect types are illustrated in Figure 4, and the statistics of these defects are provided in Table 2. The waveform traces in Figure 4 were normalized only for visualization, whereas the polarity, TDoA, and amplitude transfer ratio were calculated from the unnormalized dual-channel recordings. The CH2 arrival time and first-peak polarity were determined within the cross-correlation-derived local pulse window rather than from the complete millisecond-scale record, thereby reducing the influence of the background noise on the attenuated neutral-point signal. Several pulses may occur within one event window, as in the floating-discharge trace where three successive pulses are labelled P1 to P3. The correlation parameters were calculated from the

first pulse crossing the trigger threshold, since the later pulses originate from the same defect and traverse the same propagation path.

3.4 Comparison with Wavelet Thresholding, EEMD, and Adaptive SVD

A controlled comparison was carried out on a 600-sample subset corrupted by the 12-pulse disturbance, with all four algorithms running on the same dataset and the same hardware platform. All four algorithms operate on 4,096-sample event windows, each spanning $16.384 \mu\text{s}$ at 250 MSPs, and no down sampling is applied within a window, so the original 4 ns sampling interval is retained. A power-frequency record is partitioned into consecutive windows of this length, each processed independently and then reassembled for display and spectral estimation. The 2.4 ms segment in Figure 5 comprises 146 such windows, which is why its spectra resolve components below the 61 kHz bin width of a single window.

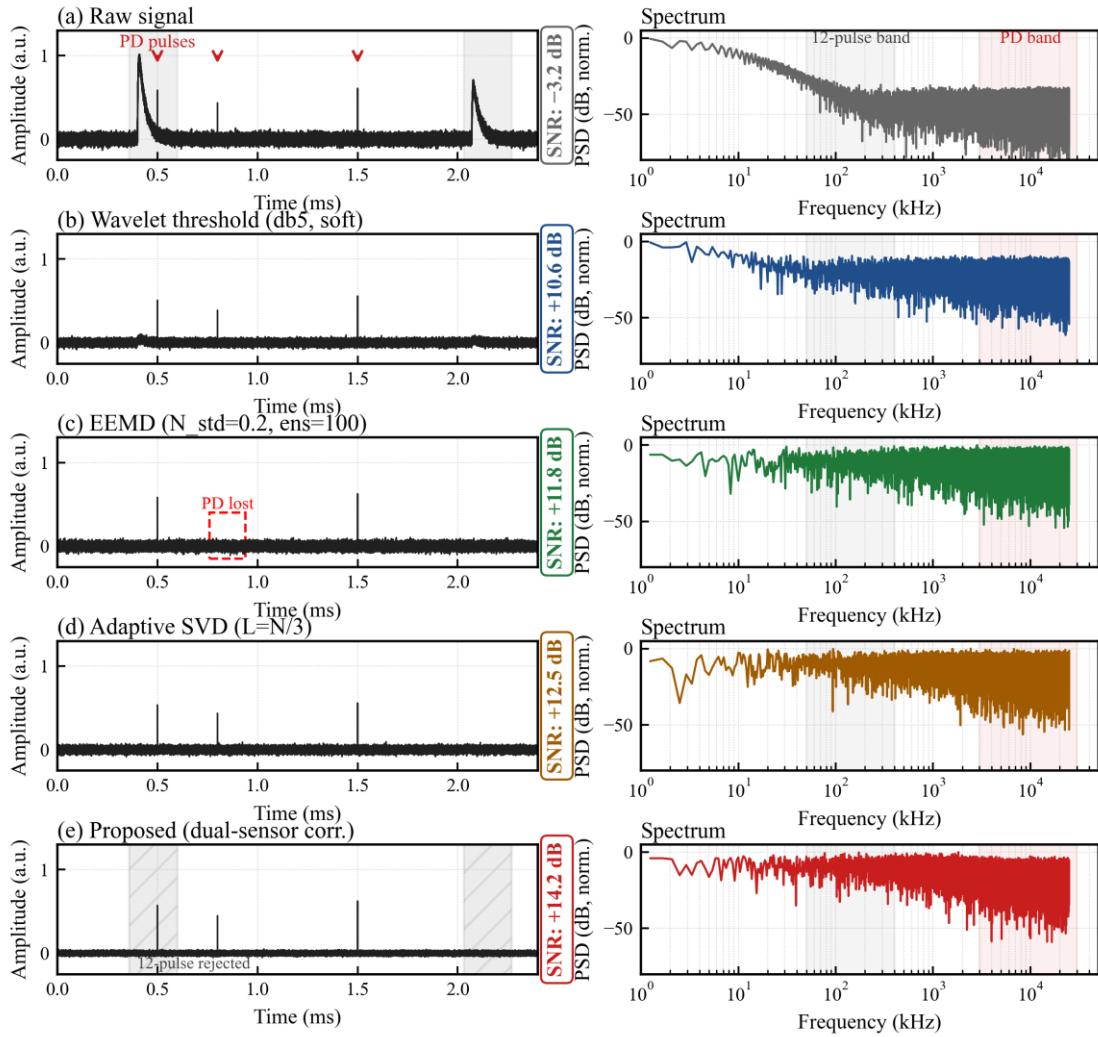


Fig. 5. Comparison of four interference-suppression methods for a PD signal corrupted by 12-pulse interference. Panels corresponding to the proposed method show the output of propagation-path-domain temporal gating; rejected windows are set to zero, and the spectrum is calculated from the retained pulse windows

For the suggested dual-sensor correlation-based technique, improvements in SNR, processing time per event window, blind-zone percentage, and recognition rate were 14.2 dB, 37.8 ms (20 ms in the FPGA side and 17.8 ms in the host side), 2.4%, and 91.3%, respectively. In turn, for the wavelet thresholding procedure applied with db5 wavelets, six levels of decomposition, and soft thresholding parameter $\lambda = \sqrt{2 \log N}$, improvements in SNR, computation time, blind-zone percentage, and accuracy were 10.6 dB, 82.4 ms, 4.1%, and 82.7%, respectively, although waveform distortion could be observed at the frequencies where both 12-pulse interference (lower than 400

kHz) and PD pulses overlap. EEMD using Nstd = 0.2 with an ensemble size of 100 had an SNR enhancement of 11.8 dB with 418 ms per event window, where the blind zone was 3.6% and accuracy was 85.1%. Mode mixing in the low-frequency IMFs caused some low-amplitude PD pulses to be filtered out unintentionally. Adaptive SVD using Hankel matrix length $L = N/3$ and retaining 1/100 singular values resulted in an SNR enhancement of 12.5 dB with processing time 258 ms and a blind zone of 3.2%, and accuracy of 87.6%. Computational complexity increased significantly with signal length. The reported 37.8 ms is a latency per event window rather than a continuous-throughput figure. The pipelined FPGA stage keeps pace with the uninterrupted 250 MSps stream and passes only triggered windows to the host stage, so the host stage runs on sparse events rather than on the full data rate.

Overall, the proposed algorithm is better than the others based on three criteria: the proposed FPGA-assisted implementation showed a shorter measured latency than the CPU-only EEMD and SVD implementations evaluated using the same event-window length; its detection blind zone is 2.4%, which is less than the 3.2% to 4.1% span of the other algorithms; and its recognition rate is higher by 3.7 to 8.6 percentage points compared to their single-channel counterparts. The SNR improvement of the proposed method is close to that of SVD and slightly better than wavelet thresholding and EEMD. Unlike wavelet, EEMD, and SVD filtering, the proposed method applies propagation-path-domain temporal gating: windows that fail the dual-sensor correlation criteria are suppressed, whereas accepted pulse windows retain their original waveform samples. Consequently, the near-zero regions in Figure 5(e) represent closed interference windows rather than frequency-domain attenuation, and the displayed spectrum was calculated from the retained pulse windows. The reported 14.2 dB SNR improvement therefore quantifies the combined effect of event discrimination and temporal gating and should not be interpreted as the passband gain of a conventional spectral filter. The detailed comparison is presented in Figure 5, with the overall performance summarized in Table 3 and the robustness evaluation under varying SNR conditions reported in Table 4.

Table 3. Performance comparison among four denoising algorithms on 600 event windows containing 12-pulse interference

Algorithm	SNR improvement (dB)	Processing time per 4,096-sample event window (ms)	Detection blind zone (%)	Recognition accuracy (%)	Waveform distortion (NCC)	Parameter dependence
Wavelet threshold (db5, 6 layers, soft threshold)	10.6 ± 0.8	82.4 ± 5.2	4.1	82.7	0.873	High (basis, level, threshold)
EEMD (Nstd = 0.2, ensemble = 100)	11.8 ± 0.9	418.3 ± 21.7	3.6	85.1	0.891	Medium (noise std, ensemble)
Adaptive SVD (Hankel $L = N/3$)	12.5 ± 0.7	258.6 ± 14.3	3.2	87.6	0.908	Medium (window length)
Dual-sensor correlation (proposed)	14.2 ± 0.6	37.8 ± 3.1	2.4	91.3	0.946	Low (one-time calibration)

Note: NCC: normalized correlation coefficient between denoised and reference PD waveforms. Processing times are measured on Intel Core i7-12700H, 16 GB RAM, MATLAB R2023a. The proposed method includes a 20 ms FPGA pre-processing stage, whereas the other three methods run entirely on the CPU in MATLAB. For adaptive SVD, $N = 4,096$ and $L = N/3$ was rounded to 1,365, producing a $1,365 \times 2,732$ Hankel matrix.

Table 4. Robustness evaluation under varying SNR conditions and interference combinations

Test condition	Input SNR (dB)	Output SNR – Wavelet	Output SNR – EEMD	Output SNR – SVD	Output SNR – Proposed
12-pulse only (low intensity)	5	14.8 ± 0.62	16.1 ± 0.58	16.9 ± 0.55	18.4 ± 0.48
12-pulse only (high intensity)	-3	6.5 ± 0.81	7.9 ± 0.76	8.7 ± 0.70	10.6 ± 0.61
Corona only	2	11.2 ± 0.68	12.5 ± 0.64	13.1 ± 0.60	15.0 ± 0.52
Power harmonic only	0	9.8 ± 0.73	10.9 ± 0.69	11.8 ± 0.65	13.7 ± 0.56
Mixed (12-pulse + corona)	-5	4.2 ± 0.90	5.6 ± 0.84	6.3 ± 0.78	8.9 ± 0.69
Mixed (all three types)	-8	1.8 ± 1.02	2.7 ± 0.96	3.5 ± 0.89	6.1 ± 0.78

Note: Values are reported as mean ± SD over 100 repeated trials for each interference and input-SNR condition. The input SNR in Table 4 is defined over the whole event window with respect to the full interference energy, most of which lies below the 3 MHz HFCT passband. The amplitude trigger operates on the band-limited content of the HV-bushing channel (CH1), where the PD pulse retains the larger amplitude, with the threshold set at 3.5 times the running RMS of the pre-trigger interval. A window triggered by interference is not discarded but passed to the correlation criteria, where the near-zero Δt and identical polarity of interference lead to its rejection, so false triggers increase the host-stage load rather than the error rate. Windows in which no CH1 crossing occurs constitute the blind zone reported in Table 3.

4. Discussion

4.1 Physical Basis of the Dual-Sensor Correlation Criterion

The rationale behind the reliability of the dual-sensor technique lies in the fundamental distinction between the signal transmission routes for interference and partial discharge signals. External interferences such as 12-pulse converter pulsation, corona, and power-side harmonics are fed into the detection system via common mode coupling or through the source circuit. The arrival time difference between the two ground HFCTs is close to zero, and their polarities are also identical. Their transfer ratio is not constant because there is no fixed physical benchmark[24].

On the other hand, internal partial discharges travel through the distributed parameter network inside the winding of the transformer. With the fixed HFCT channel assignment used in this study, the different electrical distances from the discharge source to the tap-screen and neutral-point sensors resulted in a stable positive signed time difference of 25–70 ns. By contrast, interference propagating in the opposite direction produced a negative time difference; therefore, an interference event with $\Delta t = -45$ ns did not satisfy the signed decision criterion $\Delta t \in [25, 70]$ ns. There is always a reverse current at the head and tail of the winding, resulting in the stability of polarity change. The amplitude ratio, determined by the distributed parameter values of the capacitance and inductance in the winding, is also stable for each specific defect position.

This classification on the level of paths is independent of the frequency domain decomposition method used; thus, the criteria are robust against the selection of wavelet bases, decomposition levels, and thresholding functions, and hence do not suffer from the parameter dependence limitation of traditional techniques [25]. Practical examples from the converter transformer at Suidong and the HVSR at Durong, where the discharge locations have been estimated precisely within ±1 m by time difference and transfer ratio only, provide additional evidence for the practicality of the proposed methodology.

4.2 Advantages of Wideband HFCT Detection over the Conventional Pulse Current Method

However, the traditional pulsed current technique, as defined by IEC 60270, has its limitation on the bandwidth of the measurement system below 1 MHz, which means that only the low-frequency component of the pulse signal can be retained. When dealing with the Qiantangjiang converter transformer, the traditional PD meter could not recognize the presence of a 500-pC calibration square wave; the test charge was increased to 20,000 pC to detect the presence of the pulse, while

the background noise stood at 15,992 pC. A sensitivity limit of this type makes engineering tests pointless [26].

The wideband frequency range of the 3 MHz to 50 MHz HFCT ensures that the nanosecond rising edges of the pulse are preserved, making steepness discrimination possible because normal PD pulses have rising edges of 16 to 30 ns, while external interference lasts 200 to 4000 ns. In addition, the relatively large transfer impedance of 16 mV/mA significantly helps in detecting the small amplitude signals because the same primary signal results in a higher secondary amplitude in the conditioning stage. Furthermore, the accurate modeling of the wave propagation in the winding also supports the behavior of the high-frequency equivalent model of transformer windings [27]. At the very same location on the Qiantangjiang test line, after eliminating the 12-pulse interference using the wideband system, the background level dropped to 55.9 pC and a doubtful event of 409.4 pC, $0.7 U_0$ with a risetime of 17 ns and pulse width of 540 ns occurred, the origin of which turned out to be a discharge from the grading cap. The narrow-band values were obtained with an IEC 60270 detector calibrated by terminal charge injection, whereas the wideband values were obtained by converting the recorded HFCT peak voltage through the charge-per-millivolt factor from a reference-pulse injection on the same test loop. Both scales are anchored to the same injected reference charge and are therefore comparable in magnitude, although the wideband values retain high-frequency content that the narrow-band chain integrates away.

4.3 Comparison with Recent Studies

Recent research on PD interference suppression has mainly followed three methodological directions. The first trend is based on using the variational mode decomposition method together with white-noise test (VMD-LB) or wavelet thresholding method with PSO optimization (PSO-WTD). It seeks to detect the signals from only one channel via optimal frequency band partitioning [28]. In the second path, deep learning models like DnCNN and autoencoders are used in an end-to-end manner for noise removal or pattern detection, where both the processes of feature extraction and noise suppression are simultaneously learned from labeled data sets [29, 30]. In the third path, the compressed sensing reconstruction method, based on the sparsity property of PD pulses in transform domains, is studied. These techniques have made an improvement to the signal-to-noise ratio on a per channel basis but continue to show observable distortions of signals when there is interference by factors like the 12-pulse disturbance where there is significant overlap between its spectrum and that of the PD frequency band. The deep learning methods, on the other hand, rely heavily on the training set size and uniformity of the scenarios [31].

The dual-sensor correlation scheme developed in this paper relocates the function of interference cancellation from the signal processing space to the path processing space. This is because the physical basis is very simple, and the involved parameters are not many and are all associated with the hardware configuration, requiring only one calibration session to achieve. This technique can even assist the single-channel techniques—firstly using the correlation criteria to cancel the vast part of common-mode interference and then removing the remaining noise by using single-channel filtering techniques.

4.4 Limitations and Future Improvements

There are still some shortcomings in with the proposed technique that need improvement in four aspects. The first one is that there is still a limitation with the ability of separating simultaneous multi-source discharges because it would become confusing if there were two discharge sources with nearly equal time difference arrival values [32]. Second, the thresholds must be recalibrated for transformers with various configurations because differences in winding distributed parameters result in a drifting reference transfer ratio k_0 and Δt range. Third, the transfer impedance falls steeply below 3 MHz, so kilohertz-range converter interference is recorded with strong attenuation rather than at its true magnitude. Rejection of that interference nevertheless relies on the wideband components of its 3.9 μ s commutation edges, which fall inside the 3–50 MHz passband and reach both channels with a near-zero arrival-time difference and identical polarity. Fourth, the transfer impedance of the 24-turn HFCT may vary when the primary conductor is

displaced from the center of the aperture; therefore, a centering fixture and a conductor-offset calibration are required for field installation.

There are three proposed approaches for future research. First, lightweight neural networks are expected to be applied for secondary sample discrimination, when the samples are located within the ambiguous zone, when $F \approx 0.6$, without need to use huge training databases; secondly, pattern recognition templates based on PRPD images could help in this step as well [33]. The ultrasound sensors will also be included to establish an acoustic-electric correlation model with four parameters; for example, a time-of-arrival difference of 433.3 μs was observed between the acoustic and electric channels for a specific source-to-sensor distance of approximately 0.6 m in the Durong shunt reactor system [34]. The cross-transformer adaptive threshold calibration scheme will be designed to reduce the engineering implementation cost and adapt to site conditions [35].

5. Conclusions

In order to solve the problem of distinguishing between strong-field interference factors, such as the 12-pulse converter pulsation, corona, and power-side harmonics, from the real partial discharge phenomena when conducting on-site testing of transformers, a dual-channel synchronous detection apparatus was constructed using a self-developed wideband HFCT operating from 3 to 50 MHz and a signal-conditioning system covering 150 kHz–60 MHz with a transfer impedance of about 16 mV/mA, an analog-to-digital sampling speed of 250 MSps, with local inter-channel timing limited by the 4 ns sampling interval of the common-clock acquisition unit and distributed synchronization accuracy better than 100 ns using satellite timing. Based on the hardware platform, a dual-sensor correlation discrimination technique focused on three factors was presented.

The experiments were conducted on a 220 kV/2 MVA single-phase transformer simulation platform. Four defect types (air-gap, surface, floating, and tip discharge) and three interference types (12-pulse converter noise, corona, and power-side harmonic interference) were evaluated at eight voltage levels from April to October 2025, yielding 2,400 defect–interference combination frames and 400 reference frames, including 240 background-noise frames and 160 calibration-signal frames. The event-level evaluation comprised 2,400 annotated transient events extracted from the combination frames, including 800 internal-PD events and 1,600 interference events. Under the fixed HFCT channel assignment, the internal-PD events exhibited a stable positive signed time difference of 25–70 ns, and the opposite-polarity rate ($P = -1$) for internal-PD events was 87.4%. The mean deviation of the amplitude transfer ratio k from its reference value k_0 was $\pm 8.7\%$. Consequently, the three-parameter weighted decision function achieved a classification accuracy of 91.3% for distinguishing internal PD from external interference, improved the signal-to-noise ratio by 14.2 dB after suppressing the interference, required 37.8 ms per 4,096-sample event window in the evaluated FPGA-assisted implementation, and created a blind zone of 2.4%.

In comparison with three conventional techniques using single-channel data, wavelet thresholding (+10.6 dB / 82.4 ms / 4.1%), empirical mode decomposition (EEMD) (+11.8 dB / 418 ms / 3.6%), and adaptive singular value decomposition (+12.5 dB / 258 ms / 3.2%), the suggested technique presents obvious benefits in terms of processing time and detection dead zone, and enhances the classification accuracy by around 3.7% to 8.6%. Using the calibrated effective winding propagation velocity, the electrical-localization errors ranged from 0.21 to 0.40 m. The minimum identifiable apparent charge of approximately 5.8 pC applied specifically to the air-gap discharge configuration.

The results of this study show that it is indeed feasible to use interference suppression techniques in the propagation path domain as an engineering approach to partial discharge detection in transformers. The next direction to follow in the future research is acoustic-electric correlation and adaptive thresholding.

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