

Article

High-Precision and Long-Distance Detection Technology for Information Data Under Given Mass Based on Fractional-Order Calculus

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Abstract

High-quality information data refers to data meet the quality requirements of operational systems. Among these, the accuracy of information data measurement values serves as a key indicator for evaluating high-quality information data. Information data quality is reflected in two aspects: the measurement accuracy and signal transmission strength. The combined effect of these two issues results in significant measurement errors in the information detected by the information-detection system. Therefore, improving data quality essentially involves reducing the differences between information data to enhance measurement accuracy and increasing signal strength during information data transmission to compensate for energy loss and enhance anti-interference capability during long-distance transmission. In the field of signal detection and transmission, fractional calculus (FC) demonstrates dual advantages in data measurement: it can regulate signal strength across different frequencies and improve the algorithm's generalization ability and data fusion accuracy, thereby significantly enhancing data quality. The spectral characteristics of the fractional differential operator indicate that data quality is closely related to frequency ω and fractional order ν . In this study, the influence mechanism of parameters h and ν on the information data quality of fractional-order differential operators constructs a mathematical model for information data fusion based on fractional-order operators, realizes high-precision detection technology for information data, and constructs a mathematical model for signal strength based on fractional-order differential operators to realize long-distance transmission of information data. By jointly solving these two models, high-precision, long-distance detection of information data under a given quality is achieved. Finally, application examples verify the feasibility of this method. In this case, we successfully met the quality requirement of a standard deviation $S_g = 0.05 \pm 0.05$ for the information data transmitted over a distance of 3 km by the information detection system. The feasibility of the method was verified.

Keywords: established quality objectives; fractional-order differential operators; information data fusion; high-precision data; signal intensity enhancement; long-distance transmission

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1. Introduction

With the rapid advancement of scientific and technological capabilities and industrial production, there is an increasing demand for real-time characteristics and accurate information data. Currently, information network technologies have become increasingly mature, and the issue of real-time data detection has been largely resolved; however, their accuracy remains somewhat insufficient.

Throughout the evolution of information data, it is evident that information data detection technologies have undergone three qualitative leaps based on traditional methods: high-precision detection, high-precision long-distance detection, and high-precision detection technology for information data with specified quality requirements.

In the field of high-precision information data detection, Ning proposed a dual-branch grouped multiscale residual-embedding U-Net with cross-attention fusion (DGMRU_CAF) for hyperspectral image classification. Spatial GMRU compensates for feature information loss caused by spatial characteristics during downsampling, whereas spectral GMRU addresses redundancy issues in the spectral domain [1]. Xu developed a novel deep learning algorithm for object detection and classification, CSW-Yolov7, which achieved an mAP@0.5 score of 93.3% [2]. Li et al. reported a diffraction sensor utilizing a single-pixel terahertz detector to rapidly detect hidden defects/objects in 3D samples, eliminating the need for sample scanning or image acquisition/processing [3]. Yanhong applied fractional calculus theory to the high-precision detection of information data from discrete manufacturing equipment [4–6].

Long-distance high-precision detection technology, built on the foundation of high-precision information data detection, is the predominant technique in current information data monitoring. Over the years of development, the academic community has produced extensive research findings spanning multiple fields such as physical-layer positioning, fiber-optic remote sensing, aerial remote sensing, wireless communications, and industrial monitoring. Li pioneered the development of continuous-variable quantum state manipulation techniques immune to channel fluctuations, enabling long-distance free-space Gaussian-modulated coherent quantum key distribution under asymptotic conditions [7]. Reference [3] constructed an ultrahigh-capacity distance-product single-mode fiber transmission experimental system to simulate transoceanic transmission scenarios. Researchers have developed a lightweight model suitable for the precise positioning of small and medium-sized marine vessels [8]. To enhance the performance of information detection systems, reference [9] developed the ViT-FRCNN model by integrating ViT and convolutional neural networks (CNNs), effectively improving real-time data detection capabilities. Reference [10] applied ViT to the YOLO series object detection tasks, achieving a multi-task detection approach based on pre-trained Transformers. To further optimize system performance, reference [11] proposed a complex mask image modeling (MIM) pre-training method for enhancing ViT's effectiveness in object detection. For improved detection efficiency, reference [12] established an MIMDET-based detection model that generates multi-scale feature maps using single-scale ViT, significantly accelerating data processing speed. Yanhong Zuo applied fractional calculus theory to the acquisition of information data at a depth of 500 m underground and to the detection of ground vehicle positions during operation [13–15].

In engineering practice, it has been observed that different detection subjects have varying requirements for the accuracy of information data. High-quality information data refer to data that meet the predefined accuracy standards of the detection subject. Among these, the accuracy of information data measurement values serves as a key indicator for evaluating high-quality information data. If the accuracy falls below the set threshold of the system, the obtained data are considered invalid; conversely, excessively high accu-

racy may result in poor cost-effectiveness. Consequently, remote information data detection that satisfies specified quality requirements has become a prominent research focus. However, owing to the field's relatively late development, the accumulated research achievements remain limited. Remote information data detection technology under defined quality requirements represents the most advanced level in this domain. Existing research findings are primarily applied in areas such as machine vision, optics, radar and laser technology, and fiber-optic sensors.

Visual Domain: Representative achievements include Wang Jiabao's detection accuracy of 0.001741 and 0.001739 in dynamic root-mean-square (RMS) errors for azimuth/pitch angles within a 6.5 km conical spatial angular range. Wang J. et al. applied dynamic chirped pulse interferometry for rapid absolute distance measurement, achieving system-specified performance targets of "range > 10 km; ranging accuracy $\pm 5 \mu\text{m}$ (5 micrometers)" [16].

Optical Domain: Xu Xinyang proposed a rapid absolute distance-measurement method based on dynamic optical frequency-comb chirped-pulse interferometry. By linearly scanning the repetition frequency, this method determines the dynamic frequency shift from the widest fringe in the chirped spectral interference signal, enabling high-precision distance measurements with a range > 10 km, accuracy $\pm 5 \mu\text{m}$, and non-blurred range extension to the hundred-meter level [17]. Wei developed an innovative real-time long-range infrared small-target detection network using a Reparameterized Efficient Detection Transformer (REDETR-RISTD). This network significantly reduces computational complexity while maintaining detection accuracy, achieving a detection rate of 98.7%, a false alarm rate of 0.02%, and a positioning error < 1.2 pixels in infrared scenarios spanning 3–5 km [18].

In the field of LiDAR, Kulcu and S achieved an $\text{mAP}@0.5 > 95\%$ performance on the challenging real-world DAAN maritime radar dataset by combining block-based training with the SAHI and YOLOv11-OBB methods, outperforming standard full-image detection approaches. In sea surface scenarios at 5–10 km depth, their center localization error was <10 pixels and the distance error was $\pm 3 \text{ m}$ [19]. Hongpeng proposed a drone target detection algorithm based on an improved RT-DETR to address common challenges in lightweight drone image target detection, including low detection accuracy, complex backgrounds, large target size variations, dense target distributions, and high model parameter complexity, thereby meeting the application requirements for small-target detection in drone aerial imagery [20].

In the field of fiber-optic distributed sensing, Feng Yuxiang designed a Raman distributed fiber-optic temperature measurement system that determines the temperature by analyzing the power ratios of Raman Stokes and anti-Stokes scattered light, achieving the research objectives of a temperature measurement deviation of -0.8 of $0.9 \text{ }^{\circ}\text{C}$ and a root mean square error of $0.5 \text{ }^{\circ}\text{C}$ [21]. Liu Kun proposed a high-precision positioning method based on synchronous compressed wavelet transform, and by obtaining a 20 dB bandwidth of the interference signal through power spectrum analysis, the method performs time-frequency analysis on the two interference signals using WSST to adaptively extract effective phase change features, ultimately achieving a vibration signal positioning accuracy of approximately 35.43 m along a 128 km-long sensing fiber [22].

Although the aforementioned research findings have demonstrated excellent application outcomes in processing established quality information data, the following limitations persist in industrial information data detection.

- **Limited application domains:** Most research achievements are confined to specific domains, making it difficult to achieve interoperability among advancements in machine vision, optics, radar/laser technologies, and fiber-optic distributed sensors.
- **Single applicability scope:** The detection targets of information data encompass both tangible objects and intangible substances. However, current research findings are

limited to a single detection target and lack the capability to apply to information data involving both types of objects.

- Inadequate cost-effectiveness: Existing research is primarily based on high-cost instruments and equipment. However, most engineering applications do not require high-quality data, thereby eliminating the need for high-precision instruments.

The history of fractional calculus dates back to the late 17th century, and its development has undergone a long journey, from mathematical conjectures and theoretical foundations to modern applications. In 1695, German mathematician Leibniz and French mathematician l'Hôpital first discussed in their correspondence whether the order of a derivative could be a fraction. When l'Hôpital asked about the meaning of a “semi-derivative” (i.e., with order $1/2$), Leibniz, though unable to provide a clear definition, predicted: “This will ultimately prove to be an extremely useful result.” This correspondence is regarded as the origin of fractional calculus [23]

In our preliminary research, we discovered that fractional differential operators serve a dual purpose: integrating variations among information datasets and enhancing the signal strength. By leveraging these variations, the detection accuracy is improved, and the increased signal strength enhances data robustness against distortion during transmission. More importantly, as a software-based approach, it is highly cost-effective. This method has been applied to high-precision detection of stationary information datasets [4–6] and long-distance high-precision detection [13–15]. We aim to extend these findings to information detection under specified quality requirements, utilizing fractional calculus theory to enable the detection of various information datasets under defined quality standards.

This article contains the following content and will be implemented step by step.

- (1) This paper introduces the fractional calculus theory and analyzes the spectral properties of fractional differential operators.
- (2) Based on the spectral characteristics of fractional-order differential operators, mathematical models for information data fusion and signal strength enhancement are established, respectively, using fractional calculus theory.
- (3) By analyzing the two independent mathematical models above, this study explores a mathematical model for information data processing based on fractional calculus theory under established quality criteria.
- (4) Using application examples to validate the feasibility and innovativeness of the research findings

2. Fractional Calculus Theory

2.1. Definition of Fractional- Order Differential [24]

This theory primarily comprises three categories: Grunwald–Letnikov (G-L), Caputo’s approach, and Riemann–Liouville’s framework [25,26].

2.1.1. R-L Definition of Fractional Differential the Fractional

The Riemann–Liouville (R-L) definition of the fractional-order differential involves first performing a fractional-order integral on the function, followed by an integer-order differential. Consequently, the equation based on this R-L definition of the fractional-order differential is

$${}_a D_t^\nu f(t) = \frac{d^n}{dt^n} [{}_a D_t^{\nu-n} f(t)] = \frac{1}{\Gamma(n-\nu)} \frac{d^n}{dt^n} \int_a^t (t-\tau)^{n-\nu-1} f(\tau) d\tau. \quad (1)$$

In the equation above, $0 \leq n-1 < n$, Γ is the gamma function.

By analyzing (1), we can see that the defining feature of the Riemann–Liouville (R-L) method lies in its ability to obtain the initial value of the Laplace transform simply using

integer-order derivatives. However, its major drawback is the stringent requirement for the function $f(x)$: its integer-order derivatives must be integrable.

2.1.2. Caputo Definition of Fractional Differential the Fractional

The Caputo definition is a fractional-order derivative formulation widely used in physics and engineering, characterized by its ability to employ initial conditions consistent with classical calculus, thereby endowing it with greater physical relevance in practical modeling.

For the function $f(x)$, its Caputo fractional derivative at t_0 is

$${}_a^C D_t^v f(t) = {}_a D_t^{-(n-v)} [D^n f(x)] \quad (2)$$

In the equation above, $0 \leq n - 1 < n$.

As shown in the above formula, the Caputo definition offers the following advantages:

- Clear physical meaning—the initial conditions consist of observable quantities, such as displacement and velocity.
- Facilitates numerical solutions: These can be directly integrated into conventional differential equation solving frameworks.

Therefore, the Caputo fractional differential equation is applicable to systems with nonzero initial values, addressing the modeling challenges associated with the RL definition under such conditions.

2.1.3. G-L Definition of Fractional Differential the Fractional

The G-L definition arises from a direct generalization of integer-order difference formulas and formally resembles the limit definition of classical differentiation.

For any real number v , where the integer part of v is denoted as $[v]$, assuming that the function $f(t)$ has $(n + 1)$ -order continuous derivatives within the interval $[a, t]$, when $v > 0$ and $n \geq [v]$, the fractional v -order derivative is defined as follows:

$${}_a D_t^v f(t) = \lim_{h \rightarrow 0} f_h^{(v)}(t) = \lim_{h \rightarrow 0} h^{-v} \sum_{j=0}^{\left[\frac{t-a}{h}\right]} (-1)^j \binom{v}{j} f(t - jh). \quad (3)$$

In the above equation, $0 \leq n - 1 < n$, $\binom{v}{j}$ is a binomial coefficient, and its formula is

$$\binom{v}{j} = \frac{v(v-1)(v-2)\dots(v-j+1)}{j!} = \left[\begin{matrix} -v \\ j \end{matrix} \right]. \quad (4)$$

In the equation, If $v > 0$, (2) is a fractional differential equation; if $v < 0$, it is a fractional integral equation. Based on the analysis of (2), the G-L fractional differential definition offers the following advantages:

- Memory-dependent: Calculating the fractional derivative at the current instant relies on all historical values from the initial time t_0 to the present moment, thereby enabling the description of system behaviors that exhibit hereditary and memory effects.
- User-friendly numerical implementation: Owing to its discrete summation structure, the G-L definition is highly suitable for numerical calculations and simulations, making it widely adopted in engineering and control systems. Considering these advantages, the G-L definition is extensively applied in areas such as general image edge detection, signal processing, and numerical simulation.

Compared with the other two definitions, the G-L definition offers inherent advantages in numerical computation and discrete systems. This differential -based approach facilitates easier algorithmic implementation, resulting in simpler computations that make it suitable for digital signal processing and real-time control systems. Because

the focus of this study is on detection methods for information data, this study adopts the G-L definition as the mathematical tool for information data analysis.

2.2. Effect of Fractional Differential on Detection Signal

The detection process of information data essentially involves the perception and transmission of detection signals. Consequently, the real-time performance and accuracy of these detection signals serve as critical indicators for assessing data precision. In engineering practice, signals exhibit diverse forms and origins coupled with increasingly complex application scenarios, posing significant challenges for modern signal analysis and processing.

Fractional calculus is a novel mathematical tool that offers innovative approaches and methods for modern signal analysis and processing. Its operations, involving non-integer inverses and integrals, enable more precise characterization of complex signals, facilitating effective signal analysis and processing.

It is assumed that there is a detection signal $S(t)$, where $S(t) \in L^2(\mathbb{R})$, and its Fourier transform is

$$S(\hat{\omega}) = \int_{\mathbb{R}} S(t) e^{-i\omega t} dt. \quad (5)$$

Let $S^v(t)$ be the v -order differential of $S(t)$. According to the properties of the Fourier transform, we know that the v -order differential operator is equal to the multiplicative operator of the v -order differential multiplier function $\hat{d}(\omega) = (i\omega)^v$. Thus, we can obtain the following equation:

$$D^v S(t) \stackrel{FT}{\Leftrightarrow} (\hat{D}S)^v(\omega) = (i\omega)^v S(\hat{\omega}) = |\omega|^v e^{i\theta^v(\omega)} S(\hat{\omega}). \quad (6)$$

From the perspective of signal modulation, the fractional-order differentiation (FOD) of the detection signal is physically equivalent to generalized amplitude and phase modulation. From the perspective of signal processing, performing v -order fractional-order differentiation on the detection signal is equivalent to establishing a linear time-invariant filtering system. Its filtering function is

$$d^v(\hat{\omega}) = [\omega]^v e^{i\theta_v(\omega)}. \quad (7)$$

From (7), we know that after fractional differential processing, the signal has the following characteristics:

Based on the aforementioned filtering function, we can plot the spectral characteristic curves of the fractional-order differential operators in signal processing, as shown in Figure 1. Analysis of these spectral curves reveals the following properties of fractional-order calculus in signal processing:

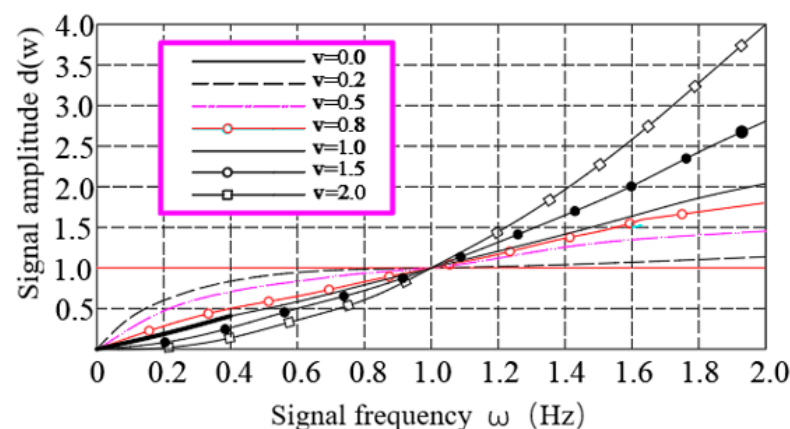


Figure 1. Amplitude–frequency characteristic curves of FOD operator [6].

- Enhance the high-frequency and mid-frequency components while preserving low-frequency details. Fractional differentiation boosts high-frequency components (such as edges and transition points) while non-linearly enhancing the mid-frequency range, with a lesser attenuation effect on low-frequency components compared with integer-order differentiation. This enabled the algorithm to retain background information while capturing subtle changes more sensitively, making it suitable for detecting areas with weak textures or uniform grayscale regions.
- Enhanced Edge Detection Accuracy and Robustness: In image or signal edge detection, fractional-order differential operators significantly improve the detection rate: more real edges are identified; -positioning accuracy: edge locations are more precise; -noise resistance: compared to integer-order methods such as Sobel and Canny, they exhibit superior noise robustness. Experiments demonstrate that the combined use of improved Canny and SIFT operators with fractional-order derivatives achieves a higher matching accuracy in blurry or low-contrast images.
- Enhanced Data Fusion and Detection Performance: In multi-sensor or mobile device detection scenarios (e.g., underground operations and logistics vehicles), fractional-order differential operators enhance multi-source detection data by amplifying the effective signal strength, suppressing interference and errors, and improving the overall detection accuracy and system reliability. For instance, the 0.5-order partial differential equation has proven to be effective for oil temperature detection data fusion.
- Flexible Frequency Response Control: While integer-order derivatives (e.g., first- and second-order derivatives) exhibit strong high-frequency amplification, but tend to amplify noise, fractional-order derivatives allow fine-tuned filtering and enhancement balance by adjusting the order ν ($0 < \nu < 1$). Their amplitude-frequency characteristics demonstrate nonlinear growth in the mid-to-high-frequency range, avoiding the “excessive response” issue associated with integer-order derivatives.

Fractional derivatives inherently possess a “non-local” nature, where the current state depends on all previous states, making them particularly suitable for describing memory effects (e.g., in viscoelastic materials), genetic properties (such as diffusion processes), and complex damping behaviors that lie between solids and fluids. Over years of research, a substantial body of findings has emerged, significantly advancing scientific and technological progress [27,28]. Key research achievements include: Reference [29] successfully applied fractional-order partial derivatives in practical scenarios to develop thickness design techniques for high-temperature protective clothing under specific conditions. Reference [30], through research on the properties of fractional-order differential operators, demonstrated the advantages of fractional calculus in fields such as image processing, step effect suppression, and signal denoising. Building upon fractional-order differentiation, reference [19] effectively utilized fractional-order partial derivatives in fluid mechanics research. During information data acquisition, the measurement environment undergoes random fluctuations, while signal transmission involves complex and dynamic conditions, resulting in significant random errors in measured data. Fractional calculus offers dual benefits: integrating variations among data points and enhancing signal strength, making it particularly suitable for long-distance, high-precision data measurement applications. Therefore, this study applies fractional-order differential operators to achieve high-precision, remote measurement of information data under specified quality requirements.

3. Applications of Fractional-Order Differential Operators in Signal Processing

3.1. Mathematical Model of Fractional-Order Differential Operators in Signal Processing

Assuming that a set of data points f_i ($1 < i < m$) is detected, with the influence factor of each measurement value f_i denoted as $x \in [a, b]$, the function linking the measurement values to their influence factors is defined as $f(x)$, where $x \in [a, b]$. In the expression of the fractional-order calculus under the G-L definition, time t in the signal $f(t)$ is the impact parameter of the signal amplitude, where $t \in [t_1, t_2]$. If $t_i = x_i$ and $[t_1, t_2] \Leftrightarrow [a, b]$ refer to (1), we can obtain the following equation:

$${}_a^G D_t^v f(t) \Leftrightarrow {}_a^G D_x^v f(x) = \lim_{h \rightarrow 0} h^{-v} \sum_{i=0}^{\lfloor \frac{b-a}{h} \rfloor} (-1)^i \binom{v}{i} f(x - ih). \quad (8)$$

where $h \rightarrow 0$, and $h = (b-a)/n$; $n-1 < v < n$, and

$$\binom{v}{i} = \frac{v(v-1)(v-2)\dots(v-i+1)}{i!}. \quad (9)$$

3.2. Analysis of Application Characteristics

As shown in Figure 2, curve (8) presents the characteristic profile of the information data after fusion processing using fractional differential operators. This figure reveals two distinct features in the processing of information data using fractional differential operators.

- Fractional-order differential operators can enhance the accuracy of information. When the fractional order v is appropriately selected, the processed information data exhibit a smoother distribution characteristic curve after integration by the fractional-order differential operator, indicating its strong ability to mitigate errors between data points. Moreover, the integration accuracy improved as the step size h decreased.
- Fractional-order differential operators can amplify data information. Moreover, the amplification coefficient k depends on both the fractional order v and the influencing factor x ; when the fractional order v is fixed, the amplification coefficient k increases with the growth of the influencing factor x . Conversely, when the influencing factor x is fixed, the amplification coefficient k increases with an increase in the fractional order v .

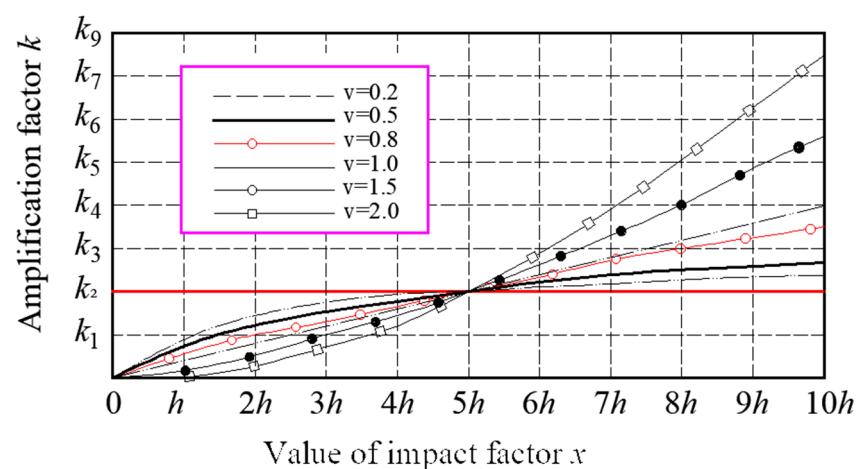


Figure 2. Characteristic curve of information data after fusion by FDO [6].

4. High-Quality Information Data Detection Technology Based on Fractional-Order Differential

4.1. Theoretical Basis

As shown in Figure 1, the fractional differential operator effectively serves a dual purpose of reducing signal volatility across different frequencies while enhancing signal intensity. Figure 2 demonstrates the dual functionality of minimizing variations among information data points and amplifying the measured data values. To better investigate the relationship between the fractional differential operator and both information data precision s and amplification factor k , the selected regions from Figure 2 were analyzed. Within this region, with the fractional differential operator $v=0.5$, and the influence factor x ranging from $[a, b]$, the characteristic curve of the information data function $f(x)$ after a 0.5-fold differential processing is plotted in Figure 3.

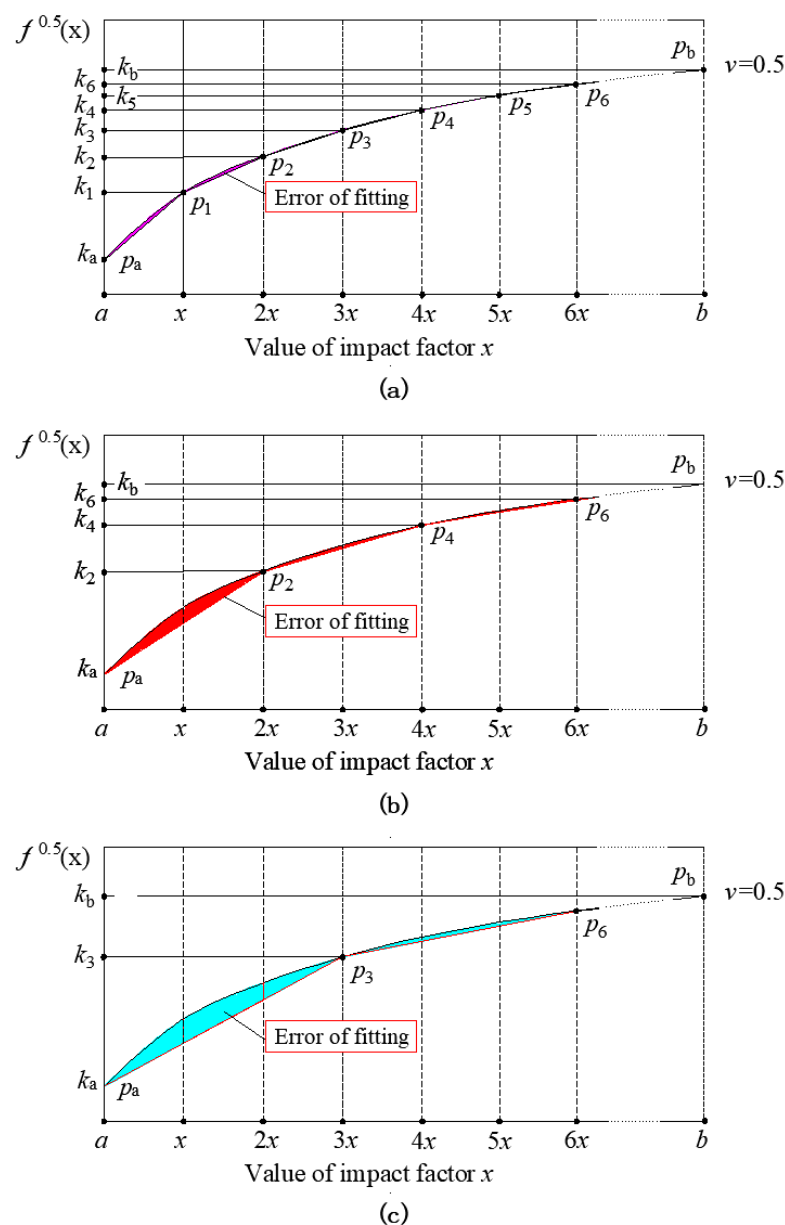


Figure 3. Schematic of the fusion accuracy of the information data function $f^{0.5}(x)$ for different step sizes. (a) $h = x$, (b) $h = 2x$, (c) $h = 3x$.

The analysis in Figure 3 reveals that when the fractional order v and the influence factor x are fixed values, the information data processed through fractional differential operations exhibit the following characteristics:

- The fusion accuracy s of the information data depends on the step size h , while the accuracy s increases progressively with larger h values, and its growth rate gradually decreases as h increases.
- The amplification factor k of the information data is correlated with the value of the fractional-order influence factor x . Moreover, the amplification factor k increases progressively as the influence factor x increases, but its growth rate gradually slows with increasing x .

Since the influence factor x (where $x \in [a, b]$) is related to the step size h , and $x_i = a + i^*h$, the relationship between the information data fusion accuracy s and the magnification coefficient k is as follows: first determine the step size h that satisfies the information data detection accuracy, then calculate the magnification coefficient k using this step size h . Each fusion operation applies the magnification coefficient k to the information data; thus, after n fusions, the total magnification coefficient becomes $K = k^n$.

High-quality information data refer to data that meet the specified information accuracy S_d and magnification factor K_d of the information system. Based on the analysis of the relationship between information data accuracy s and magnification factor k using the fractional differential operator mentioned above, a framework for detecting high-quality information data based on fractional differential methods can be established.

4.2. System Architecture

The high-precision long-range detection process based on the given quality of information data is shown in Figure 4.

Implementation Steps:

- Establish quality standards S_g and K_g ;
- Collect raw data F_i ;
- Analyze data F_i to construct a function $F(x)$ linking information data F_i with the influence factor x ;
- Refer to the quality standards to calculate the data accuracy S and signal strength k that meet these criteria;
- Perform fractional differential processing on the raw data to obtain $F^v(x)$, and determine the optimal step size h_g that satisfies accuracy S ;
- Derive the amplification coefficient k using the fractional differential function $F^v(x)$ and the optimal step size h_g ;
- Combine the required signal strength K_g specified by the quality standards to determine the number of differential processing steps n for the information data;
- Obtain information data that complies with the system-defined quality standards.

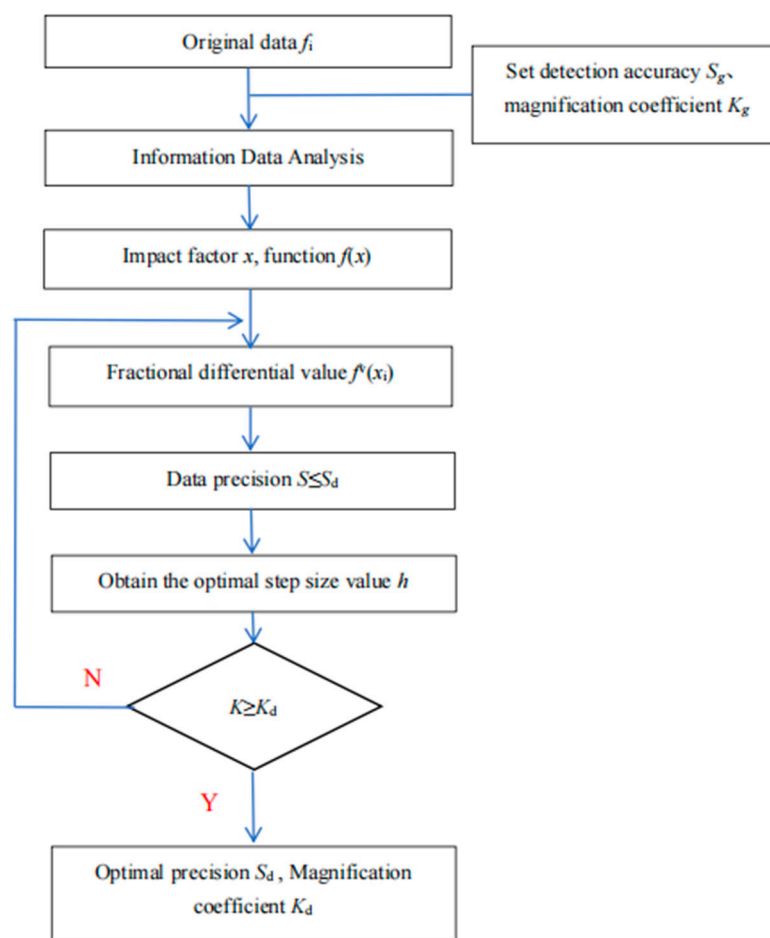


Figure 4. Architecture diagram of a high-quality information data detection system based on fractional-order differential.

5. Mathematical Model

Assuming that the information detection system aims to obtain the numerical value of parameter A in the working system, the distance between the information data acquisition center and the sampling point is L . The quality requirements specified for the detection system are real-time data acquisition, with an information data accuracy of S_g and an amplification factor of k_g .

To enhance the accuracy of the information data, n sensors were employed to obtain the measured values of parameter A . The sensors operate simultaneously and sample m times within the same time interval. The information data collected by the i -th sensor on the j -th occasion are denoted as F_{ij} , with $i \in [1, n]$ and $j \in [1, m]$. Under the given quality conditions, the detection method for information data proceeds sequentially through the following steps.

5.1. The Functional Relationship Between the Information Data F_{ij} and the Impact Factor x

Based on the information dataset F_{ij} , the primary influencing factor x that affects the variability among the data points was identified. Then, the measurement mean of each sensor is defined as its true value, the true value for the i -th sensor is F_i , and the average of all measurements constitutes the true value F .

$$\begin{cases} F_i = \frac{1}{m} \sum_{j=1}^m F_{ij} \\ F = \frac{1}{m * n} \sum_{i=1}^n \sum_{j=1}^m F_{ij} \end{cases} \quad (10)$$

Based on all the sensor measurements F_i and their influencing factor values x_i (where $I \in [1, n]$), a data-fitting function is applied to establish the functional relationship between them:

$$F(x) = a_0 + a_1 * x + a_2 * x^2 + \dots + a_k * x^k. \quad (11)$$

where $x \in [a, b]$, and the fitted information data F_{ij} yields the measurement data $F(x_i)$ for the i -th sensor.

5.2. Numerical Result F_{ij}^v Obtained After Fusing the v -th Derivative of the Information Data F_{ij}

Referring to Figure 2 and Equation (8), select the optimal order v ($0 < v < 1$) and step size h ($h < (b-a)$) for the fractional differential equation. The v -order differential equation of function $F(x)$ can then be obtained as

$${}_a D_x^v F(x) = \lim_{h \rightarrow 0} F_h^v(x) = h^{-v} \sum_{i=0}^n (-1)^i \binom{v}{i} F(x - ih) \quad (12)$$

where

$$\binom{v}{i} = \frac{v(v-1)(v-2)\dots(v-i+1)}{i!}, \text{ and } n = [b - a] / h.$$

By substituting the influence factor x_i of the i -th sensor into (12), we obtain the fused data value resulting from the v -th order differential operator application to the information data $F^v(x_i)$ collected by the i -th sensor, as follows:

$${}_a D_x^v F(x_i) = \lim_{h \rightarrow 0} F_h^v(x_i) = h^{-v} \sum_{i=0}^n (-1)^i \binom{v}{i} F(x_i - ih) \quad (13)$$

where

$$\binom{v}{i} = \frac{v(v-1)(v-2)\dots(v-i+1)}{i!}, \text{ and } n = [b - a] / h.$$

5.3. Information Data Amplification Factor k

As shown in Figures 1 and 2, the signal intensity is enhanced after processing with the fractional-order differential operator, resulting in amplification of the measured information data. Amplification factor k is expressed as follows:

$$k = \frac{F^v(a) + F^v(a+h) + F^v(a+2h) + \dots + F^v(b)}{F(a) + F(a+h) + F(a+2h) + \dots + F(b)} \\ = \sum_{i=0}^n F^v(a+ih) / \sum_{i=0}^n F(a+ih) \quad (14)$$

5.4. The Final Value F_{iz} of the Information Data $F(x_i)$ After Fractional Differential Processing

According to (10) and (13), the information data measured by the i -th sensor can be obtained. After fractional-order differential processing, the final value is

$$F_{iz} = F^v(x_i) / k. \quad (15)$$

5.5. Standard Deviation S Between Information Data

According to the definition of the standard deviation between the information data, it can be concluded that after differential processing by v , the standard deviation between the information data is as follows:

$$S = \left(\frac{\sum_{i=1}^n (F_{iz} - kF)^2}{k^2(n-1)} \right)^v \quad (16)$$

5.6. Step Size h_d for a Given Accuracy S_d

As shown in (16), at this point:

$$S_g = S = \left(\frac{\sum_{i=1}^n (F_{iz} - kF)^2}{k^2(n-1)} \right)^{0.5} \quad (17)$$

Based on the aforementioned derivation steps and relevant and using Simulink software, the step size h_g under the specified accuracy is determined as follows:

$$h_g = \frac{(b-a)}{m*n} \left(\sum_{i=1}^n \sum_{j=1}^m F_{ij} F_{ij} \binom{v}{i}^n \binom{v}{j}^m * F(b-a) - \frac{1}{m} \sum_{i=1}^a F_{ij} \binom{v}{i}^m * F(b-a) - \frac{1}{n} \sum_{j=1}^b F_{ij} \binom{v}{j}^n - (b-a)^{m*n} \right) \quad (18)$$

5.7. Implementation of the Signal Amplification Factor K_g

Referring to Figure 2 and Equation (12), it is evident that when the fractional order v , the value range of the influence factor x , and the step size are determined, the amplification coefficient k of the information data becomes a fixed value. Therefore, by applying (14), the amplification coefficient k_g of the information data after the differential processing of the information function $F(x)$ with respect to v can be obtained as follows:

$$k = \sum_{i=0}^n F^v(a+ih) / \sum_{i=0}^n F(a+ih) \quad (19)$$

In other words, for each v -order differential operation applied to the information function $F(x)$, the amplification factor of the information data is k ; thus, after p differential operations, the overall amplification factor K_g is equal to k^q .

Assuming the wireless signal transmission distance is L , to ensure that the signal amplification factor remains no less than k^q during transmission, the amplification coefficient must satisfy the following formula, which is essential for ensuring reliable information data transmission and optimal system efficiency.

$$\begin{cases} K = k^q \\ k^{q-1} < K_g < K \end{cases} \quad (20)$$

In the formula, parameter q represents the number of differential fusion operations applied to the information data v when the detection system achieves an amplification factor K_g .

6. Example Application

6.1. Experimental Environment

A manufacturing enterprise generates significant noise during production, creating a poor working environment that severely affects the living conditions of nearby residents. Therefore, the information data monitoring system combines on-site data collection with remote transmission to send operational data to the information data management center

located approximately $L = 3$ km from the production site. The system requires the real-time acquisition of reliable data with a standard deviation of $S_g = 0.05 \pm 0.05$.

Based on the experimental conditions and system requirements, an experimental platform capable of achieving high-precision information data acquisition and long-distance transmission was established. First, noise data from the production site were collected using noise sensors (BYZ08) that were randomly deployed across various locations within the operational area. The collected data are then transmitted via a local area network (Switch) to the enterprise's internal data acquisition center, where they are categorized and processed. Finally, the processed data are sent through a wireless network to a data management center located 3 km away. The specific architecture is illustrated in Figure 5.

Due to the large scale of the enterprise, it is impractical to use excessively dispersed measurement points for data acquisition; therefore, a single-point monitoring approach was adopted. This decision took into account multiple factors, including the cost-effectiveness and operational efficiency of the spatial layout of the measurement system. Refer to [31], eight BYZ08 capacitive noise detection sensors were randomly deployed at various locations at the work site. All sensors were operated simultaneously and sampled once every minute for a total of six samples. The raw data collected from the work site were as follows:

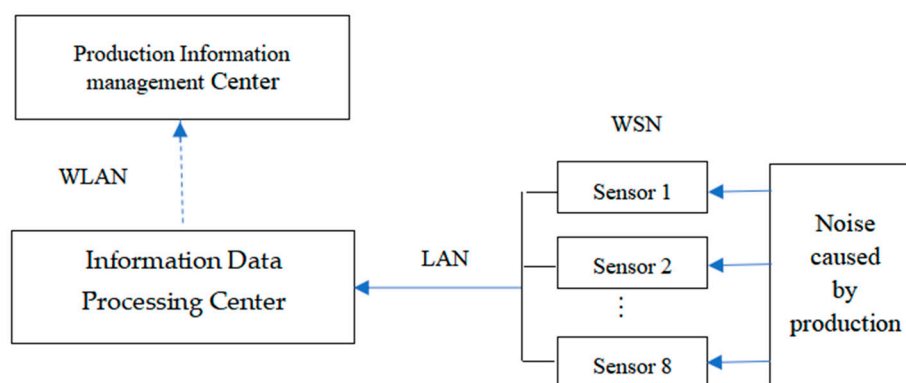


Figure 5. Structure diagram of the gas concentration detection system.

6.2. Pre-Processing of Data

6.2.1. Measurement Value Analysis

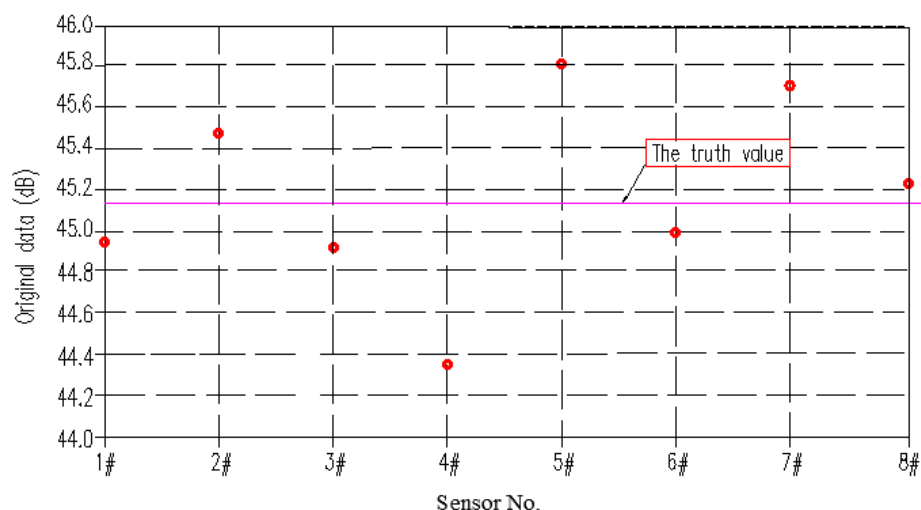
To facilitate the analysis of correlations among information data and the influencing factors of measurement values, we used the average of six measurements from each sensor as its true measurement value, and the average of all measurements as the true measurement value obtained by the information detection system. Based on the experimental data in Table 1, the data analysis results are presented in Table 2, and a distribution plot of the information data measurements is generated, as shown in Figures 3–6. The figure shows that the measurement data from each sensor were dispersed around their respective measurement values, with significant measurement errors.

Table 1. Experimental data table (db).

Sensor No.	1#	2#	3#	4#	5#	6#	7#	8#
1st measured value	45.2	46.3	44.1	43.9	46.5	44.9	46.1	45.8
2st measured value	44.8	45.8	44.6	44.2	46.1	44.5	45.8	44.8
3st measured value	45.9	44.7	44.9	43.8	45.8	45.2	45.3	45.1
4st measured value	44.2	44.9	45.6	45.2	46.2	45.9	45.7	45.8
5st measured value	45.4	45.3	45.2	44.8	45.5	44.8	44.9	45.3
6st measured value	43.8	45.8	44.8	44.2	44.7	44.7	46.4	44.6

Table 2. Summary of experimental data (db).

Sensor No.	1#	2#	3#	4#	5#	6#	7#	8#
Average value $\bar{E}_i$	44.88	45.47	44.87	44.52	45.80	45.00	45.70	45.23
Sensor accuracy S_i	0.78	0.61	0.51	0.49	0.64	0.50	0.54	0.50
True value E	45.18							
Initial data accuracy S	0.447							

**Figure 6.** Distribution diagram of original information data.

6.2.2. Factors Affecting Measurement Results

The measurement errors of the information data are closely related to factors such as the working environment, measurement time, and equipment performance. However, in this experiment, all measuring instruments operated under identical conditions ran simultaneously, and all experimental data were collected at the same time point. Consequently, it can be concluded that the working environment and measurement time have minimal impact on the measured values; thus, the performance of the instruments is the primary factor contributing to variations in the measurement data. Because the standard deviation s serves as an ideal indicator for evaluating instrument performance, it was selected as the influencing factor x for the measurement data in this experiment, and the functional relationship between the standard deviation and measurement data was defined as $E(x)$.

6.2.3. Definite of the Function $E(x)$

The fitting methods for information data primarily include linear regression, polynomial fitting, the least squares method, nonlinear regression, Gaussian distribution fitting, Fourier series fitting, and smoothing fitting. Among these, the least-squares method serves as the foundational approach for both linear and nonlinear fitting, estimating optimal parameters by minimizing the sum of squared errors between observed values and model predictions; thus, it is widely applied in various regression analyses. Accordingly, this experiment employed the least squares method to fit the functional relationship $F(x)$ between the information data influence factor x_i and the measured value E_i . Based on the definition of the least-squares method, the following function can be derived as follows:

$$E(x) = a_0 + a_1x + a_2x^2 + \dots + a_nx^n. \quad (21)$$

According to the application rules of the least-squares method, the parameter n in the functional equation must be less than the sample size i ; therefore, the range for n in

the formula is $0 < n < 8$. In this experiment, the measured true value served as the criterion for evaluating the optimal functional equation, and the equation yielding the smallest error between the fitted measurements and the true values was identified as the optimal functional equation $E(x)$. Using the Polyfit function in Simulink, the total errors for the fitted values at different orders were calculated, with the specific data presented in Table 3. The data in Table 3 show that when $n = 1$, the error between the fitted values and the measured true values is minimized at 0.37. The corresponding functional equation is given in (22).

Table 3. Summary of experimental data (db).

Order n	1	2	3	4	5	6	7
Total error	0.50	2.53	2.67	2.71	2.75	2.82	2.89

$$E(x) = 0.798x + 44.73. \quad (22)$$

6.3. Achieving the Specified Data Precision

6.3.1. Achieving the Accuracy of Information Data

Analysis of Formula (4) and Figure 1 reveals that when the fractional order satisfies $0 < v < 1$, the fractional-order differential operator exhibits distinct amplitude-frequency characteristics. In the high-frequency domain of signals, fractional-order differential operators enhance the accuracy of information data representation; however, as signal frequency increases, the improvement in detection accuracy achieved by different fractional orders becomes nearly identical. For computational convenience, we set the fractional order to $v = 0.5$.

According to (7), we can obtain the formula for the standard deviation of the data.

$$S = \left(\frac{\sum_{i=0}^{\lfloor b-a \rfloor / h} \left(E^{0.5}(x + ih) - \bar{E}^{0.5}(x) \right)^2}{nK} \right)^{0.5}, \quad (23)$$

where

$$E^{0.5}(x + ih) = \lim_{h \rightarrow 0} E_h^{0.5}(x + ih) = h^{-0.5} \sum_{i=0}^{\lfloor b-a \rfloor / h} (-1)^i \binom{0.5}{i} E(x - ih). \quad (24)$$

Combined with (17), the data shown in the table were processed by the 0.5-order differential operator, and the result was:

$$E^{0.5}(x_i) = h^{-0.5} \left(E(x_i) - 0.5E(x_i - h) - \frac{0.5(1-0.5)}{2!} E(x_i - 2h) - \dots \right. \\ \left. - \frac{\Gamma(1-0.5)}{n! \Gamma(n+1-0.5)} E(x_i - nh) \right), \quad (25)$$

where $b = 0.78$; $a = 0.50$; $n = \lceil (0.78 - 0.50)/0.008 \rceil = 35$.

6.3.2. Calculation of the Step Size h Based on the Iterative Method

To improve the efficiency of the system, a step-by-step method was used to adjust the step value h to achieve a continuous improvement in the accuracy of the system data and select the best step value in terms of data accuracy and efficiency. Using the Simulink mathematical simulation software, substituting the information data accuracy $S_g = 0.05$ into Formula (18) yields that when $h = 0.0078$, the accuracy of the information data after fractional-order differentiation meets the system's specified requirements.

As mentioned above, when the h -value decreases below a certain threshold, its impact on information data accuracy diminishes significantly while simultaneously leading

to a sharp decline in processing efficiency. Therefore, considering both information data accuracy and processing efficiency, the processing model for the detection data was selected with steps of $h_g = 0.008$ and order $v = 0.5$. Through the following derivation process, we can verify the accuracy of the calculated step size value h and explore the feasibility of applying the research findings presented herein to information data detection under specified quality requirements. According to (11) and (24), we obtain the following:

$$E_{0.01}^{0.5}(x) = 10 \sum_{i=0}^{19} (-1)^i \binom{0.5}{i} E_{0.01}(x - 0.19). \quad (26)$$

According to the data shown in Table 2 and (25), the experimental data shown in Table 4 were obtained for fractional order $v = 0.5$, and step size $h_g = 0.008$.

Table 4. Experimental data summary table when $h = 0.008$ (db).

Sensor No.	1#	2#	3#	4#	5#	6#	7#	8#
Average value $\bar{E}_i$	44.88	45.47	44.87	44.52	45.80	45.00	45.70	45.23
Sensor accuracy S_i	0.78	0.61	0.51	0.49	0.64	0.50	0.54	0.50
True value E	45.18							
Value after fusion $E_{0.008}^{0.5}$	54.95	55.05	55.11	55.09	55.04	55.13	55.1	55.12
Post-fusion mean $\bar{E}_{0.008}$	55.07							
Amplification factor k	1.22							

The effectiveness of fractional-order differential operators in merging information data must be evaluated under identical conditions. Therefore, dividing the data in Table 4 by the amplification factor k yields the results presented in Table 5.

Table 5. Experimental data summary table when $h = 0.008$ (db).

Sensor No.	1#	2#	3#	4#	5#	6#	7#	8#
Average value $\bar{E}_i$	44.88	45.47	44.87	44.52	45.80	45.00	45.70	45.23
Sensor accuracy S_i	0.78	0.61	0.51	0.49	0.64	0.50	0.54	0.50
Fusion final value E_{iz}	45.04	45.12	45.17	45.16	45.11	45.19	45.16	45.18
Original Precision S	0.445							
Final Precision S_z	0.049							

Based on the data presented in Table 5, a distribution plot of the original information data processed by fractional-order differentiation ($v = 0.5$, $h = 0.008$) is generated according to the data shown in Table 1, as illustrated in Figure 7. As can be observed from Figure 7, the processed data values are randomly distributed around the mean value, with relatively small differences among the data points. Combining Figures 6 and 7, a comparative plot of the information data before and after processing via fractional-order differentiation ($v = 0.5$, $h = 0.008$) is plotted, as shown in Figure 8. From Figure 8, it is evident that after applying the fractional-order differentiation ($v = 0.5$, $h = 0.008$) to the information data, the accuracy among the data points is significantly improved.

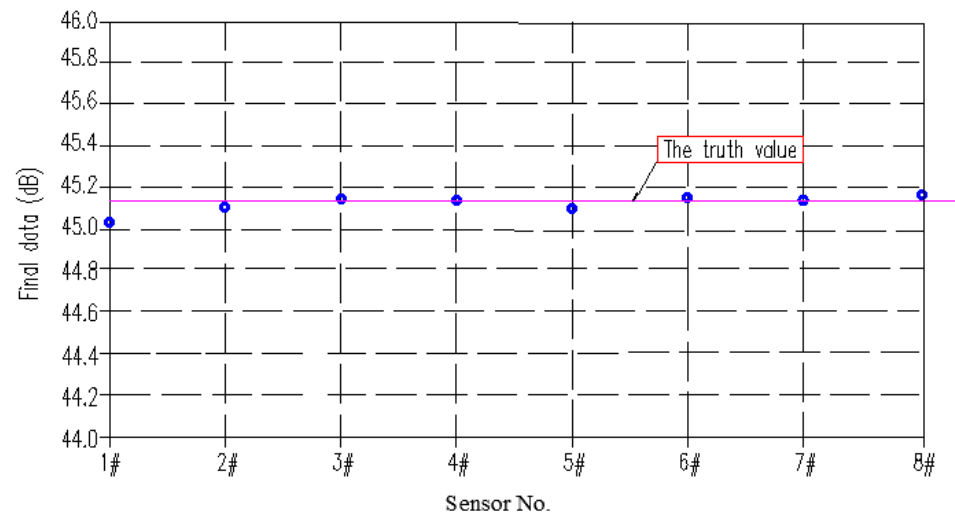


Figure 7. Final value distribution after fractional differential fusion processing of information data.

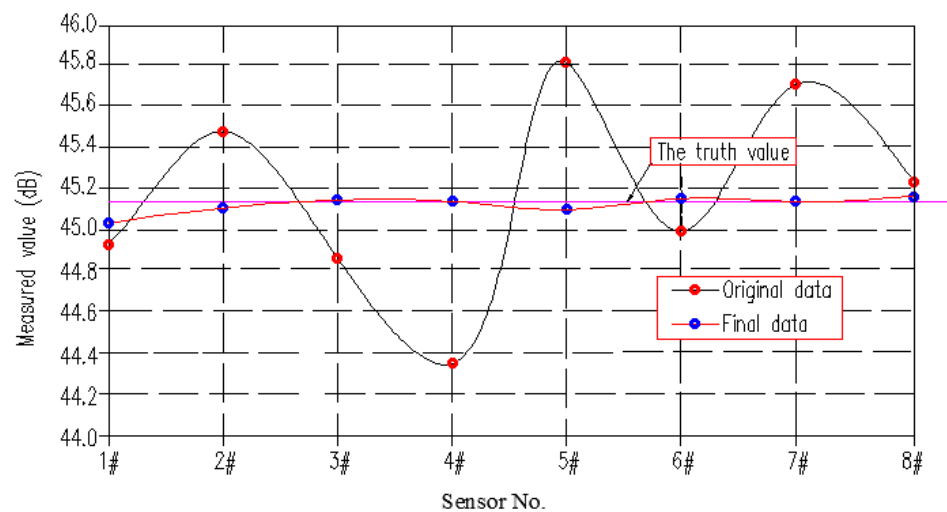


Figure 8. Distribution curve of information data: fractional differential fusion processing before and after.

6.4. Get the Specified Signal Strength

Through field experiments and theoretical analysis, it is evident that when the amplification factor K_g for production-site information data exceeds 105 times,

The collected data can be reliably transmitted to a trusted data management center located 3 km away.

Based on the above research findings, we can conclude that if q is defined as the order of fractional differential processing applied to the signal, and according to the signal intensity requirements specified by the detection system, the following equation must be satisfied.

$$\begin{cases} K = 1.22^q \\ 1.22^{q-1} < K_g < K \end{cases} \quad (27)$$

By solving for q in (27), we can see that under the above detection conditions, when the FOD operator steps $h_g = 0.008$, the number of FOD processing cycles $q = 24$. Substituting into (27), we obtain

$$\begin{cases} K = 1.22^{24} = 118.2 \\ 96.9 < 105 < 118.2 \end{cases} \quad (28)$$

As shown in (28), after processing the information data with a 24-step differential operator characterized by a step size $h_g = 0.008$ and a fractional order $v = 0.5$, the transmitted signal overcomes any distortion during transmission, ensuring the reliable delivery of the detection data to the information data management center located 3 km away.

6.5. Experimental Results and Their Analysis

Based on the aforementioned research findings, information data tables were compiled before and after fractional differential processing, as shown in Table 6. The data demonstrate that, when applying the research results to the case study, the original noise detection data from the enterprise production process (as presented in Table 1) exhibited a final standard deviation of 0.049 after processing with a fractional differential operator ($v = 0.5$, step size $h_g = 0.008$), representing a 9.1-fold improvement in accuracy that fully meets the detection system's precision requirement of $S_g = 0.5 \pm 0.05$. The information data transmission signal, after undergoing 24 applications of this fractional differential operator, saw its intensity amplified nearly 118-fold, satisfying the system's requirement for real-time, reliable transmission to the information data management center located 3 km away. When signals are transmitted via radar, the methods described in reference [19] result in significant energy loss, leading to average information data values that are substantially lower than the actual values, with a data accuracy coefficient of $S_g = 0.73$; whereas when using the method described in reference [22], although the energy loss during fiber optic transmission is minimal, certain measurement errors still persist, yielding a data accuracy coefficient of $S_g = 0.61$. Therefore, in this experiment, all methods described in the aforementioned references fall short compared to the method proposed in this paper.

Table 6. Summary of final processing results of experimental data (db).

Sensor No.	1#	2#	3#	4#	5#	6#	7#	8#
Average value E_i	44.88	45.47	44.87	44.52	45.80	45.00	45.70	45.23
Sensor accuracy S_i	0.78	0.61	0.51	0.49	0.64	0.50	0.54	0.50
Fusion final value E_{iz}	45.04	45.12	45.17	45.16	45.11	45.19	45.16	45.18
Original Precision S	0.445							
	Standard deviation after treatment S4							
	0.0019							
Fixed precision S_g	0.05±0.05							
Final Precision S_z	0.049							
Given amplification factor K_g	>105							
Final amplification factor K_z	118.2							

7. Conclusions

An analysis of the evolution of information detection technologies and the current information quality requirements in industrial applications reveals that data detection technologies that meet specified quality standards have become the pinnacle and ultimate goal of detection technology development. Driven by industrial advancement requirements, data detection under defined quality criteria has emerged as a focal research area. In recent years, numerous innovative scientific achievements have been successfully achieved in various fields. However, analysis of existing research indicates that most studies suffer from limitations, such as suboptimal cost-effectiveness, restricted application scope, and limited applicability. Fractional-order differential operators possess dual characteristics: integrating data errors while enhancing signal strength and improving both data accuracy and transmission range—features that enable high-precision long-distance

detection, as validated in prior studies. To advance detection technologies for diverse information datasets under specified quality standards, this study conducted deeper research on fractional calculus applications in information detection based on prior studies. This research identifies critical aspects of information data detection.

- The numerical values of order v and step size h of fractional-order differential operators directly influence the detection accuracy of the information data. When the order v is fixed, the detection accuracy improves as h decreases, but the improvement diminishes with decreasing h , enabling high-precision information data detection technology.
- Order v of the fractional differential operator and the value of the influencing factor x determine the signal strength during information data transmission. When the order v is a fixed value, and the signal amplification coefficient decreases progressively as x increases, long-distance information transmission is enabled.
- High-quality information data refer to data whose accuracy and signal strength meet the system requirements. This can be achieved by integrating two techniques, the high-precision and long-range capabilities of fractional-order differential operators, to develop information data detection technologies under specified quality criteria.
- The essence of the research findings lies in applying the “Software Law” to develop high-quality detection technologies for various parameter information datasets, thereby offering advantages such as excellent cost-effectiveness and broad applicability across diverse fields and user scenarios.
- Theoretically, ultra-high-quality information detection technology can be achieved by adjusting the fractional order v of the fractional-order differential operator, step size h , and iteration coefficient q .

Therefore, the research findings are of great significance for enhancing information quality and data-detection technologies and advancing industrial development.

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