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YOLOv11 Optimized Weighted Cross-Correlation High-Temperature Ultrasonic Temperature Measurement Method

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Abstract: Traditional cross-correlation algorithms are prone to time-of-flight (TOF) calculation errors under conditions of strong noise interference and complex temperature gradients, resulting in a decline in the accuracy of ultrasonic temperature measurement. To this end, this paper proposes an ultrasonic temperature measurement method that combines YOLOv11 target detection with energy-type weighted cross-correlation algorithm. The YOLOv11 model is utilized to conduct target detection and key area positioning on the ultrasonic signal waveform diagram, automatically identifying characteristic waveforms such as node waves and end face waves, and achieving adaptive extraction of the effective signal interval. Further introduce the energy-based weighted cross-correlation algorithm. Based on the signal energy distribution, the cross-correlation results are weighted and processed to enhance the main wave response and suppress noise interference. Experiments show that the YOLOv11 model has high detection accuracy (Precision = 0.987, Recall = 0.958, mAP@50 = 0.988); The proposed method maintains the stability of time delay estimation under strong noise and high temperature (> 1200°C), with the average time delay error reduced by approximately 35% to 50% compared to traditional algorithms. This verifies its high robustness and temperature measurement accuracy in complex environments, and it has a promising engineering application prospect.

Keywords: Ultrasonic temperature measurement; YOLOv11; Weighted cross-correlation; Strong noise environment; Flight time

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1. Introduction

Against the backdrop of the increasing demand for measurement in complex electromagnetic environments, ultrasonic temperature measurement, as an emerging acoustic temperature measurement technology, has gradually been widely applied in industries and other fields, thanks to its advantages such as resistance to electromagnetic interference [1–4]. Compared with traditional contact temperature measurement methods such as mercury thermometers, thermocouples and thermal resistors, its non-contact and anti-interference characteristics are remarkable [5–9]. The basic principle is to measure the flight time (TOF) of ultrasonic waves in the medium and calculate the temperature in combination with the function relationship between sound velocity and temperature. However, in practical applications, the precise measurement of TOF faces multiple challenges, such as factors such as background noise interference, medium temperature gradient effect, and waveform distortion all significantly increase the difficulty of TOF extraction [10].

Existing studies have proposed a variety of solutions to the above problems. For instance, traditional methods (such as maximum eigenvalue detection based on time-domain features, waveform feature separation, etc.) have enhanced the sensitivity of TOF measurement and the efficiency of feature extraction in low-noise environments, but they lack robustness under strong noise or complex waveform interference [11]. Barshan designed the sliding window method to measure the flight time of ultrasonic waves. This method involves setting a rectangular window to slide along the time axis to search for ultrasonic echo signals, and determining the moment of the echo signal by calculating the variance size [12]. Jackson *et al.* utilized the cross-correlation method to process discrete data. The product of the sample points that achieved the maximum value in the cross-correlation function and the sampling period was used as the measurement method for ultrasonic flight time [13].

Based on the above research, this paper proposes a TOF calculation method that combines YOLOv11 object detection and weighted cross-correlation algorithm. YOLOv11 is a high-performance object detection model that can accurately identify key areas in ultrasonic signal waveforms while maintaining computational efficiency. This method first uses YOLOv11 to locate the key waveform regions, then calculates the TOF through the weighted cross-correlation algorithm, and ultimately achieves the measurement of medium temperature. Compared with traditional methods, this technology has stronger anti-noise ability and higher measurement accuracy in complex interference environments such as strong noise and large temperature gradients, and can maintain stable time delay estimation and temperature measurement performance.

2. Theory and problems

2.1. Theory of ultrasonic temperature measurement

The principle of ultrasonic pulse temperature measurement is shown in **Figure 1**. When ultrasonic waves propagate in a solid waveguide rod and encounter areas where the acoustic impedance does not match, part of the ultrasonic waves will be reflected, forming two characteristic reflected waves: one generated at the groove position on the waveguide rod, which is called the node wave; Another one is generated at the end of the waveguide rod and is called the end wave. When the ultrasonic wave reaches the groove again, a secondary echo will be generated. By measuring the flight time Δt (i.e., ultrasonic time delay) from the first reflected wave (node wave) to the second reflected wave (end wave), and knowing the length ΔL of the waveguide rod between the groove and the end, the sound wave propagation speed v can be calculated according to Equation (1).

$$v = \frac{2\Delta L}{\Delta t} \tag{1}$$

The propagation speed v of ultrasonic waves has a defined functional relationship with temperature, as expressed in Equation (2).

$$v(T) = \sqrt{\frac{E(T)}{\rho(T)}} \tag{2}$$

The propagation speed v of ultrasonic waves is strongly influenced by the material's Young's modulus E and density ρ. Under high-temperature conditions, both E and ρ vary with temperature, resulting in corresponding changes in v. Leveraging this relationship, the temperature within the material can be determined by measuring the ultrasonic propagation speed. Consequently, accurate identification of the node wave and end wave, along with precise measurement of their flight time , Δt is essential for implementing the ultrasonic pulse temperature measurement method.

Figure 1. Principle of ultrasonic temperature measurement.

2.2. Problem description

This study establishes an ultrasonic temperature measurement system based on the experimental setup illustrated in **Figure 2**. The flight time of ultrasonic waves is obtained using a cross-correlation algorithm, and the corresponding sound velocity is calculated according to Equation (1). During the experiment, a muffle furnace capable of reaching 1800 °C was employed for heating and cooling calibration, and time-delay data were recorded at 100 °C intervals.

However, background noise and specific interference components, such as lateral vibration waves induced by thermal stress (**Figure 3**), are unavoidable in high-temperature environments. These disturbances distort the characteristic waveforms of ultrasonic signals, making accurate identification of key waveform features difficult. Imprecise localization of characteristic waves ultimately results in time-delay estimation errors in the cross-correlation algorithm. Traditional approaches, such as the maximum eigenvalue method or waveform feature separation, struggle to maintain stability and accuracy under strong noise, high temperatures, or large temperature gradients, particularly when temperature varies rapidly.

Therefore, to reliably extract ultrasonic flight time under severe noise interference, the cross-correlation algorithm must be optimized to improve its anti-interference robustness and feature-recognition accuracy in environments characterized by strong noise and significant thermal gradients.

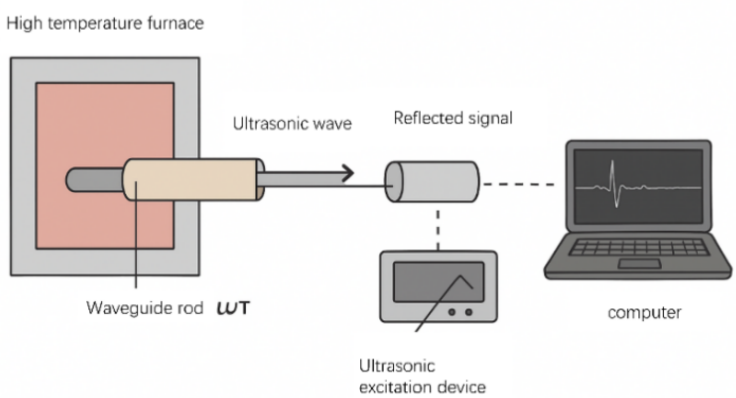

Figure 2. Ultrasonic temperature measurement system.

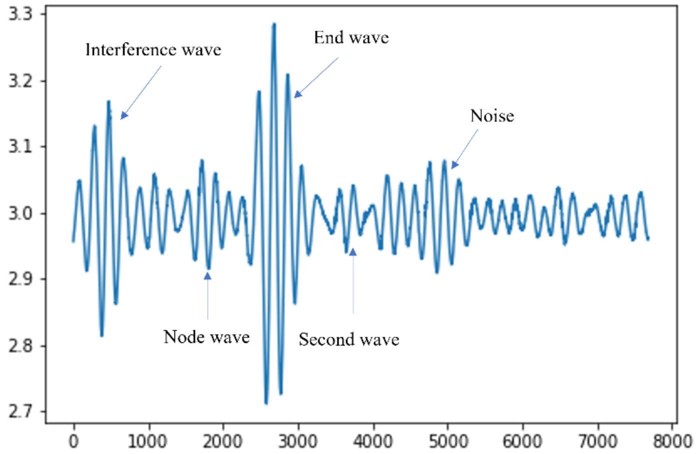

Figure 3. Waveform diagram in a complex environment.

3. Research methods

3.1. Yolo model

In recent years, the rapid development of deep learning has led to widespread adoption of object detection algorithms, particularly the YOLO family, for feature localization due to their excellent real-time performance and high detection accuracy [14,15]. The latest model, YOLOv11, introduces several key architectural enhancements, including the C3K2 module, the C2PSA (Parallel Spatial Attention) mechanism, and an improved SPPF (Fast Spatial Pyramid Pooling) structure (**Figure 4**). These improvements substantially strengthen feature extraction capability and computational efficiency. Compared with its predecessors, YOLOv11 provides more effective multi-scale feature fusion and significantly better performance in small-target detection. Additionally, it supports multi-task learning, enabling high-precision localization across a wide range of applications, including object detection, instance segmentation, keypoint localization, and rotated-object recognition.

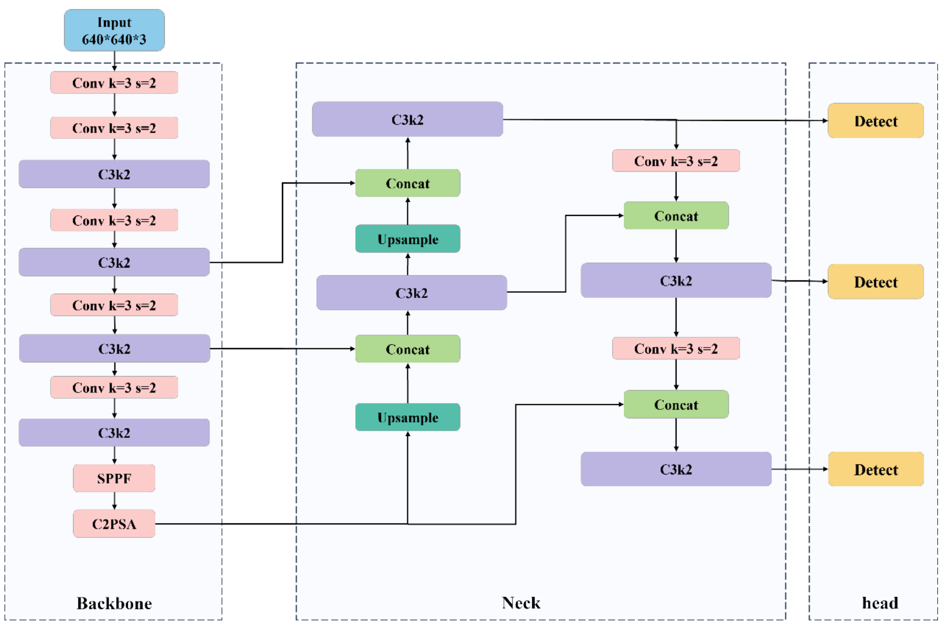

Figure 4. Network structure of yolov11.

In this study, YOLOv11 was employed to identify key characteristic regions in ultrasonic signal waveforms, such as node waves, end-face waves, and secondary echoes. Its target detection function can locate these feature areas and automatically extract the effective time interval between the node wave and the end-face wave. Meanwhile, the keypoint detection branch can precisely mark the starting point and peak position of the characteristic wave, providing an accurate reference for subsequent flight time calculations. Additionally, the extended instance segmentation and rotated-target detection functions can further identify high-energy noise regions and tilted interference waveforms in complex signals. Through this multi-functional collaborative mechanism, the system can stably extract key feature regions under conditions of strong noise or large temperature gradients, providing reliable input for delay calculations in subsequent cross-correlation algorithms.

3.2. Optimization of the cross-correlation algorithm

In ultrasonic temperature measurement systems, the precise calculation of flight time directly affects the accuracy of sound velocity determination, which in turn impacts the accuracy of temperature measurement. The traditional cross-correlation algorithm calculates the time delay by evaluating the correlation between two signal segments, and its mathematical expression is:

$$R_{xy}(\tau) = \int x(t)y(t+\tau)dt \tag{3}$$

While the traditional cross-correlation algorithm achieves high accuracy under ideal conditions, practical temperature measurement experiments often face challenges. Signals can be affected by high-temperature noise, transverse wave interference in the waveguide rod, and waveform distortions caused by thermal stress. These factors may produce multiple peaks or obscure peaks in the cross-correlation function, making it difficult to accurately determine the arrival time of characteristic waves. To improve the algorithm's robustness in complex interference environments, this study proposes an enhanced weighted cross-correlation method. By introducing a weighting function and assigning differentiated weights to various time segments, this method amplifies the response of the main characteristic interval while suppressing noise interference. Its computational formula is expressed as:

$$R_{xy}^{\omega}(\tau) = \int \omega(t)x(t)y(t+\tau)dt \tag{4}$$

In this context, *x(t)* represents the node wave echo signal, and *y(t)* represents the end wave echo signal. The delay time $\tau_{\Delta T}$ corresponding to the sample point τ, where the cross-correlation function attains its maximum, is defined as the ultrasonic flight time. Here, ΔT denotes the sampling period.

The weight function is designed based on the signal's energy distribution. The core idea is to assign differentiated weights according to the local energy of the signal, so that segments with high energy and prominent main wave characteristics contribute more significantly to the correlation calculation. The energy-based weights can be expressed as:

$$\omega(t) = \frac{x^2(t)+y^2(t)}{2\max\left(x^2(t),y^2(t)\right)+\varepsilon} \tag{5}$$

Here, ε is a small constant introduced to prevent division by zero. This weight function adaptively adjusts the contribution of each segment based on the signal strength, emphasizing regions with high main-wave energy while suppressing low-energy noise. As a result, the main peak in the cross-correlation function is enhanced, false peak interference is reduced, and the accuracy of time-delay estimation is significantly improved.

4. Results and discussion

4.1. Characteristic wave recognition

4.1.1. Experimental environment

The model in this study was implemented using the PyTorch framework. The experimental setup and configuration details are summarized in **Table 1**.

Table 1. Experimental environment configuration table

Name	Version
CPU	Intel(R) Xeon(R) E5-2680 v4 @ 2.40GHz
GPU	RTX 3090 24GB
Programming language	Python3.10
Operating system	Ubuntu 22.04
Deep learning framework	PyTorch2.2.2+Cuda12.1

4.1.2. Evaluation criteria

To comprehensively evaluate the performance of the YOLOv11 model for ultrasonic waveform feature recognition, a series of evaluation metrics were employed in this study, including Precision (P), Recall (R), Mean Average Precision (mAP), and multi-threshold mean Average Precision (mAP_{50-95}). These metrics serve as the primary indicators for assessing the model's detection accuracy. The calculation formulas are as follows:

$$precision = \frac{TP}{TP+FP} \tag{6}$$

$$recall = \frac{TP}{TP+FN} \tag{7}$$

$$AP = \frac{\sum precision}{N} \tag{8}$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N} \tag{9}$$

$$mAP_{50-95} = \frac{1}{10}\sum_{t=0.50}^{0.95} mAP_t \tag{10}$$

4.1.3. Analysis of test results

In the experiments conducted in this study, the YOLOv11 model achieved performance metrics on the validation set of P = 0.987, R = 0.958, mAP_{50} = 0.988, and mAP_{50-95} = 0.776. These results demonstrate that the model possesses high accuracy and robustness in ultrasonic waveform feature recognition, providing a reliable foundation for subsequent TOF extraction and temperature inversion. The detailed test results are presented in **Figure 5**.

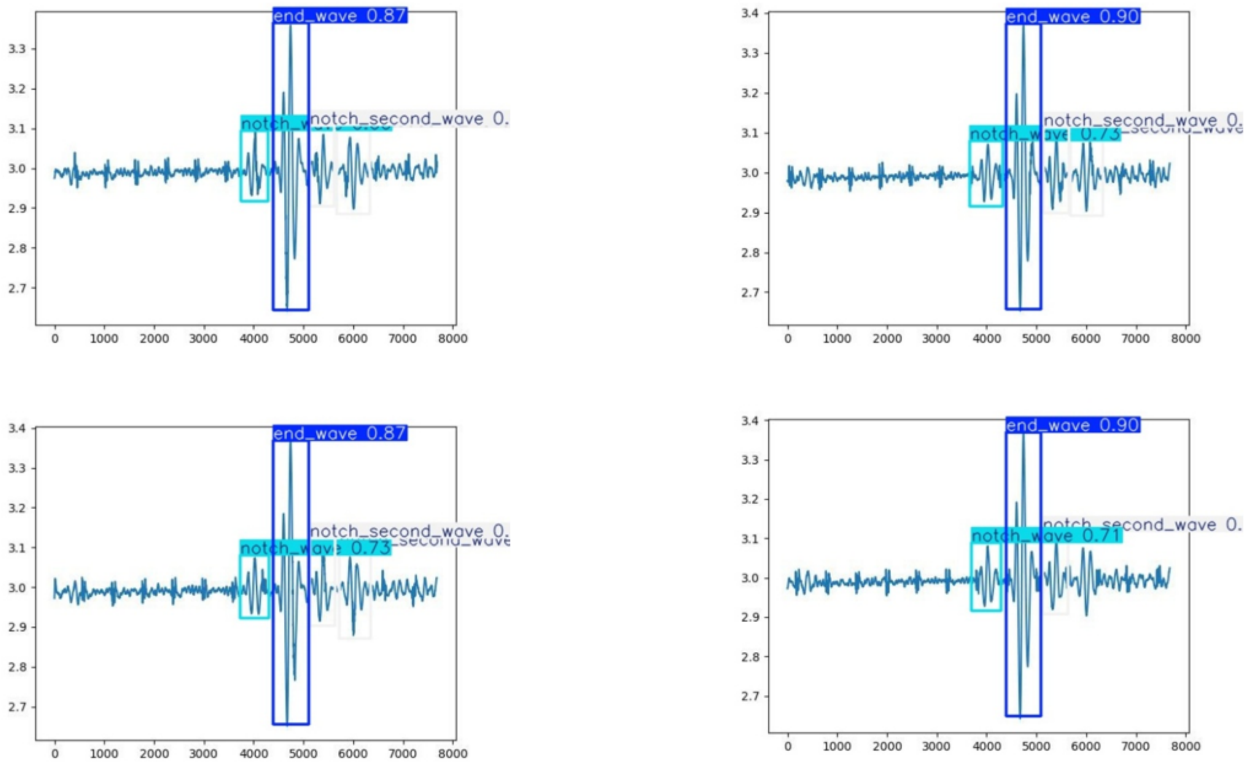

Figure 5. Detection results.

The YOLOv11 model outputs target parameters including position [x, y, ω, h], confidence score (conf), and category probability (class). The position parameters [x, y, ω, h] represent the center coordinates (x, y) and the width and height (ω, h) of the target region in the waveform diagram, enabling precise mapping of the target area to the corresponding interval on the time axis and accurate localization of characteristic waves. The confidence score (conf) indicates the likelihood of the target's presence within the detection box, while the category probability (class) identifies the specific type of waveform feature, such as node waves, end-face waves, or secondary echoes.

In this study, the position information from YOLOv11 is used to automatically define the effective analysis window for the cross-correlation algorithm. The detected waveform feature regions are mapped to their corresponding time-axis intervals, which serve as the analysis window for the cross-correlation calculation. Within this window, the energy-weighted cross-correlation algorithm is applied to calculate the ultrasonic flight time, effectively reducing the impact of noise and interference and improving both the accuracy and robustness of the time-delay measurement.

4.2. Calculation of ultrasonic flight time

To verify the accuracy and effectiveness of the TOF calculation method based on the combination of YOLOv11 and the weighted cross-correlation algorithm proposed in this study, a set of ultrasonic temperature measurement experimental data ranging from room temperature to 1600 °C was used as test samples. In the experiment, both the traditional cross-correlation algorithm and the YOLOv11-optimized weighted cross-correlation algorithm were applied to calculate the time delay and predict the temperature on the same dataset. This allowed a direct comparison of the time-delay extraction and temperature measurement performance of the two methods across the full temperature range.

To quantitatively analyze the differences between the algorithms, the results obtained using the optimized cross-correlation algorithm were taken as the reference benchmark, while the results from the traditional cross-correlation algorithm were treated as the comparison values. The deviation of the traditional algorithm was evaluated by calculating the relative error between the two methods, using the following formula:

$$\delta = \frac{|T_m - T_c|}{T_c} \times 100\% \tag{11}$$

Among them, Tm represents the temperature value calculated by the traditional cross-correlation algorithm, T_c is the calculation result of the YOLOv11 optimized cross-correlation algorithm, and δ indicates the relative error percentage.

As shown in **Table 2** and **Figure 6**, when the temperature exceeds 1200 °C, the traditional cross-correlation algorithm is significantly affected by thermal noise and waveform distortion in the high-temperature environment, leading to large fluctuations in the delay calculation results. In contrast, the optimized method proposed in this study maintains stable delay calculations under the same conditions, with output results varying more smoothly and continuously with temperature. This demonstrates that YOLOv11 effectively mitigates the influence of interfering waves on the cross-correlation calculation by automatically identifying characteristic waves and restricting the effective sampling interval. As a result, the accuracy of time-delay estimation is enhanced, leading to improved overall temperature measurement performance.

Table 2. Comparison of experimental data

Temperature (°C)	Cross-correlation (us)	Weighted cross-correlation (us)	Error rate
20	16.475	16.475	0.000%
300	17.050	17.025	0.147%
400	17.225	17.200	0.145%
500	17.425	17.425	0.000%
600	17.625	17.650	0.142%
700	17.850	17.825	0.140%
800	18.100	18.075	0.138%
900	18.450	18.450	0.000%
1000	19.225	19.225	0.000%
1100	20.550	20.525	0.122%
1200	20.925	20.900	0.120%
1300	21.825	21.900	0.342%
1400	22.375	22.450	0.334%
1500	23.025	23.075	0.217%
1600	ERROR	23.650	EMPTY

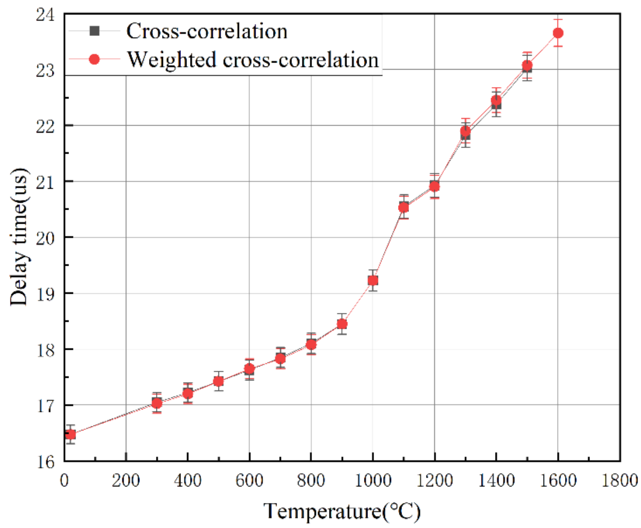

Figure 6. Data comparison.

5. Conclusion

This paper addresses the limitations of traditional cross-correlation algorithms, which are prone to flight time calculation errors in strong noise environments, by proposing an ultrasonic temperature measurement method that combines YOLOv11 feature recognition with an energy-weighted cross-correlation algorithm. The YOLOv11 model automatically identifies key waveform features, such as node waves and end-face waves, even in noisy or distorted signals, and outputs their precise positions in the time domain, thereby adaptively determining the effective sampling range of ultrasonic signals. Building on this, an energy-based weight function is introduced in the cross-correlation calculation, assigning greater weight to high-energy segments with prominent main wave characteristics, effectively suppressing noise interference and enhancing the main wave response. Experimental results demonstrate that this method significantly reduces time-delay calculation errors compared with the traditional cross-correlation algorithm, producing more continuous and stable extraction results. Notably, the improved method maintains high-precision performance even at temperatures of 1200 °C and above, achieving an average error reduction of over 35%. These findings confirm that combining YOLOv11 feature recognition with a weighted cross-correlation algorithm can effectively improve the accuracy and reliability of ultrasonic temperature measurement systems in extreme environments, offering new approaches and technical support for high-precision measurements under complex conditions.

Disclosure statement

The authors declare no conflict of interest.

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