

Article

Robust Time-of-Flight Estimation for Multi-Echo Ultrasonic Signals Using the Secretary Bird Optimization Algorithm

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Abstract

To address the instability in extracting key parameters such as time-of-flight (ToF) from ultrasonic echoes due to noise and multi-echo superposition, this paper proposes a robust parameter estimation method based on the secretary bird optimization algorithm (SBOA). The proposed approach adheres to the Gaussian convolution-based echo parameterization and cosine-similarity matching framework, while innovatively introducing SBOA to perform global optimization of model parameters. Consequently, the multi-echo ToF estimation is formulated as a nonlinear optimization problem aimed at maximizing waveform shape consistency. To evaluate the method's performance, simulations are conducted under multi-echo superposition scenarios. Comparisons are made with representative baseline techniques, including wavelet transform (WT), empirical mode decomposition (EMD), and variational mode decomposition (VMD), using mean squared error (MSE), estimated signal-to-noise ratio (ESNR), and normalized cross-correlation (NCC) as performance metrics. Experimental results demonstrate that, in challenging low-SNR and echo-interference environments, the proposed method achieves overall superiority across all quantitative metrics and exhibits a stronger capability to preserve the main-lobe morphology and structural features of echoes. Validation on semi-synthetic signals further confirms its effectiveness, with practical applicability to be verified by measured datasets in future work. This work provides an effective and robust solution for ultrasonic signal processing in complex field conditions.

Keywords: ultrasonic nondestructive testing; time-of-flight (ToF); echo superposition; Gaussian convolution model; secretary bird optimization algorithm (SBOA)



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1. Introduction

Ultrasonic testing, benefiting from its non-contact operation and high precision, has been widely applied in industrial nondestructive testing (NDT) and medical imaging [1,2]. Among the key parameters in ultrasonic testing, time-of-flight (ToF) is one of the most commonly used and sensitive indicators for defect localization and system health monitoring. However, in industrial on-site conditions or complex experimental setups, ultrasonic echo signals often face substantial interference, including weak echoes being submerged in noise, difficulty in identifying the main lobe of the echo, and blurring of feature boundaries due to multi-echo superposition. Under low signal-to-noise ratio (SNR) conditions, simple threshold-based or peak-searching techniques for ToF extraction tend to cause arrival-time drift and unstable localization, thus compromising the reliability of defect localization, interface identification, and quantitative evaluation. Therefore, research on

ultrasonic signal processing and parameter estimation remains critical in both engineering and practical applications.

In this study, we address the ToF estimation problem for single-channel multi-echo ultrasonic A-scan signals in which multiple echoes may partially overlap under low-SNR conditions. The target is to robustly estimate the arrival times of early echoes (specifically, the first two echoes), which are most relevant for interface localization and subsequent quantitative analysis. This setting is challenging because strong echo overlap and heavy noise contamination can produce a highly multi-modal objective landscape, making conventional peak-based estimators and naive model fitting prone to local optima and time-shift drift.

Several approaches have been proposed for ultrasonic parameter estimation and defect identification. Yang F. et al. [3] address ToF instability caused by noise by developing a defect peak tracking model (DPTM), integrating wavelet denoising and Hilbert transform to enhance the stability and reliability of ToF estimation. Tian Y. et al. [4] propose an echo identification strategy for pavement structures with varying acoustic impedance contrasts, employing an improved correlation coefficient method and wavelet-transform modulus maxima technique, complemented by preprocessing methods such as empirical mode decomposition (EMD) to remove the direct wave and improve echo distinguishability. On the data-driven side, Gourishetti et al. [5] transformed acoustic emission signals into normalized STFT log-spectrograms and used convolutional neural networks (CNNs) for state classification, showcasing the potential of “time-frequency representations + deep learning” for complex signal analysis. Additionally, Li J. et al. [6] propose a signal processing framework combining wavelet packet transform and support vector data description (SVDD), extracting multi-scale features via wavelet packet transform and applying SVDD for damage classification, thereby improving the sensitivity and accuracy of damage detection in modal bridge expansion joints.

Although the above methods have achieved promising results in specific scenarios, their effectiveness can degrade when confronted with the coupled difficulties considered in this work: (1) severely overlapped multi-echo waveforms and (2) extremely low SNR. Wavelet-/EMD-based preprocessing may suffer from mode mixing or reconstruction bias, and peak-tracking/correlation-based strategies can still exhibit peak drift when the main lobe is distorted by overlap. Data-driven methods can be powerful, but they typically require sufficient labeled data and may generalize poorly across different components, coupling conditions, or acquisition setups. More importantly, many existing studies do not explicitly formulate multi-echo ToF estimation as a unified model-matching problem with clearly defined parameters and reproducible optimization settings, which makes it difficult to assess robustness under controlled SNR variations and strong echo interference.

Despite the successes of these methods, challenges remain under extreme conditions, such as very low SNR, severe burial of weak echoes, and strong multi-echo interference. Under these circumstances, existing methods still struggle with issues like peak drift, mode mixing, and reconstruction bias, leading to unreliable parameter estimation.

To address these challenges, this paper proposes a robust ToF parameter estimation method based on model matching and intelligent optimization. Specifically, we model the multi-echo ultrasonic signal using a physics-motivated parametric representation and estimate ToF by maximizing the waveform-shape consistency between the observed signal and the model-generated signal. To reliably solve the resulting non-convex optimization problem under heavy noise and echo overlap, we adopt an intelligent optimization strategy and emphasize reproducible implementation details.

The main contributions of this work are as follows:

- (1) A multi-echo parametric modeling and matching formulation for ToF estimation. We formulate multi-echo ToF estimation as a model-matching problem with clearly

defined parameters and echo superposition, enabling consistent ToF inference for overlapped A-scan signals.

- (2) A robustness-oriented objective and evaluation protocol for low-SNR multi-echo conditions. We establish a controlled validation scheme with Monte Carlo noise realizations and report both accuracy and stability.
- (3) An SBOA-driven optimization framework with reproducible settings and baseline comparisons. We apply the secretary bird optimization algorithm (SBOA) to solve the non-convex parameter estimation problem and compare it against representative baseline ToF estimators (e.g., cross-correlation and least-squares matching) and a representative metaheuristic optimizer (PSO) under the same SNR conditions.
- (4) Verification on both simulated multi-echo signals and a representative measured waveform. The proposed method is validated on simulated multi-echo cases with controlled overlap and noise and further evaluated using a representative experimentally measured waveform to demonstrate practical applicability.

2. Signal Model and Parameter Estimation Framework

2.1. Gaussian Convolution Model

During ultrasonic testing, a received echo is commonly modeled as a harmonic carrier modulated by an envelope determined by transducer response and propagation path. The standard Gaussian envelope is attractive for its simplicity; however, practical echoes may exhibit truncated leading edges, asymmetric decay, or distorted main lobes due to coupling conditions, finite bandwidth, and attenuation. To improve modeling flexibility while maintaining physical interpretability, we adopt a Gaussian convolution model [7,8], in which a parametric pulse is convolved with a sparse reflectivity sequence to represent multi-echo reflections.

In this study, the envelope is defined as a Gaussian-type function with a causal onset:

$$B(t) = Ae^{-a(t-b)^2} \varepsilon(t) \quad (1)$$

where $\varepsilon(\cdot)$ is the unit-step function, A is an amplitude scale, $a > 0$ controls the envelope spread (i.e., temporal width), and $b \geq 0$ is a center-offset (onset-shaping) parameter. Because the onset is fixed by $\varepsilon(t)$, changing b modifies the degree of truncation of the left-hand side of the Gaussian and therefore controls the envelope asymmetry: when b is small, the envelope becomes strongly one-sided; as b increases relative to the spread, the truncation effect becomes negligible, and the envelope approaches a quasi-symmetric shape. This mechanism is visualized in Figure 1.

Using the envelope $B(t)$, a unit echo waveform is defined as

$$p(t; \psi) = B(t) \cos(2\pi f_c t) + \varphi \quad (2)$$

where f_c is the transducer center frequency, φ is the initial phase, and $\psi = [A, a, b, f_c, \varphi]$ denotes the pulse-shape parameter set.

A multi-echo signal containing K echoes can be represented by convolving the unit echo waveform with a sparse impulse train:

$$s(t; \psi, \Theta) = p(t; \psi) * \sum_{k=1}^K a_k \delta(t - \tau_k) = \sum_{k=1}^K a_k p(t - \tau_k; \psi) \quad (3)$$

where $\delta(\cdot)$ is the Dirac delta function, $*$ denotes convolution, a_k and τ_k are the amplitude scaling and time-of-flight (ToF) of the k -th echo, respectively, and $\Theta = \{a_k, \tau_k\}$. Equation (3) explicitly shows that convolving with shifted delta functions is equivalent to summing

time-shifted echoes, clarifying the roles of convolution, echo summation, and the impulse representation in the multi-echo model.

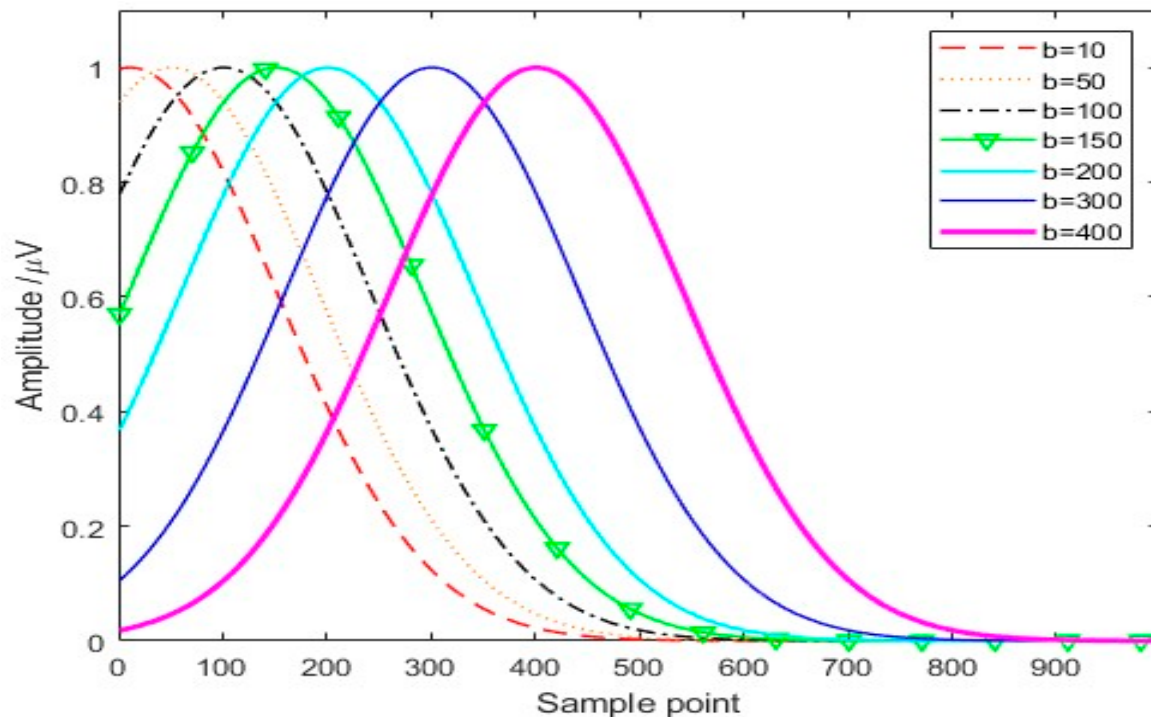


Figure 1. Gaussian-type envelopes $B(t)$ for different center-offset (onset-shaping) parameters b (with A and a fixed).

For clarity, we partition the parameters into (1) pulse-shape parameters ψ , which mainly reflect the transducer characteristics and overall pulse morphology, and (2) echo-specific parameters Θ . In the experiments of this paper, we focus on early echoes and evaluate ToF using $K = 2$ (the first two echoes), while keeping the formulation general for arbitrary K .

Quantitative Comparison Between the Standard Gaussian Model and the Gaussian Convolution Model on a Representative Simulated Two-Echo Signal

To quantitatively verify the modeling advantage of the proposed Gaussian convolution formulation, we conduct a controlled comparison on a representative simulated signal containing two echoes ($K = 2$). The ground-truth ToFs are set to $\tau_1 = 200 \mu\text{s}$ and $\tau_2 = 400 \mu\text{s}$. Two models are considered:

(1) Standard Gaussian (baseline): a classical Gaussian-modulated sinusoid with a symmetric Gaussian envelope, producing a two-echo prediction by superposition of two shifted copies.

(2) Gaussian convolution (proposed): the proposed model in Section 2.1, where the unit pulse $p(t; \psi)$ uses the generalized envelope and the two-echo signal is represented by convolving $p(t; \psi)$ with a sparse reflectivity sequence.

For a fair comparison, both models optimize the same echo-specific variables $\Theta_{\text{opt}} = [a_1, a_2, \tau_1, \tau_2]$ under identical bounds and stopping criteria, while keeping the pulse-shape parameters fixed (estimated from a clean template or preset nominal values). We report the relative fitting error e_{fit} and the ToF estimation errors $|\Delta\tau_k| = |\hat{\tau}_k - \tau_k|$ for $k = 1, 2$. $\text{MAE}_{\tau_-} = (|\Delta\tau_1| + |\Delta\tau_2|)/2$. The quantitative results are summarized in Table 1.

Table 1. Quantitative comparison between the standard Gaussian model and the Gaussian convolution model on a representative simulated two-echo signal.

Model	$\hat{\tau}_1$ (μs)	$\hat{\tau}_2$ (μs)	$\Delta\tau_1$ (μs)	$\Delta\tau_2$ (μs)	MAE_τ (μs)	e_{fit}
Standard Gaussian	204.7	408.3	4.7	8.3	6.5	0.075
Gaussian convolution	201.1	401.4	1.1	1.4	1.25	0.029

As shown in Table 1, the proposed Gaussian convolution model yields smaller ToF errors for both echoes ($|\Delta\tau_1| = 1.1 \mu\text{s}$, $|\Delta\tau_2| = 1.4 \mu\text{s}$) and reduces the average ToF error (MAE_τ) from $6.5 \mu\text{s}$ to $1.25 \mu\text{s}$. Meanwhile, the fitting error decreases from $e_{\text{fit}} = 0.075$ to 0.029 , indicating improved waveform fidelity under the representative two-echo scenario.

2.2. Formulation of the Cosine-Similarity-Based Parameter Estimation Problem

In ultrasonic nondestructive testing (NDT), the received A-scan can be modeled as a superposition of multiple echoes corrupted by noise [9]. Using the Gaussian convolution model in Section 2.1, the observation is written as

$$y(t) = \sum_{k=1}^K a_k s_k(t) + \zeta(t) \quad (4)$$

where $s(t; \psi, \Theta) = \sum_{k=1}^K \alpha_k p(t - \tau_k; \psi)$ is the model-generated multi-echo signal, $\zeta(t)$ denotes additive noise, α_k and τ_k are the amplitude scaling and time-of-flight (ToF) of the k -th echo, and ψ collects pulse-shape parameters.

In practice, $y(t)$ is sampled within a time window $[t_{\min}, t_{\max}]$ covering the echoes of interest, yielding discrete-time vectors y and $\hat{y}(\Theta_{\text{opt}})$, each an L -dimensional real-valued vector. Here, $\hat{y}(\Theta_{\text{opt}})$ is obtained by sampling the model-generated signal $\hat{y}(t) = s(t; \psi, \Theta)$ with fixed ψ . To reduce sensitivity to overall amplitude scaling under low SNR, we adopt cosine similarity as the objective function [10]:

$$C(y, \hat{y}) = \frac{y^T \hat{y}}{\|y\|_2 \|\hat{y}\|_2} = \frac{\sum_{i=1}^L y_i \hat{y}_i}{\sqrt{\sum_{i=1}^L y_i^2} \sqrt{\sum_{i=1}^L \hat{y}_i^2}} \quad (5)$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product, and $\|\cdot\|_2$ denotes the L2 norm. The value of $C(\cdot, \cdot)$ lies in $[-1, 1]$; a larger value indicates higher waveform-shape consistency.

Accordingly, ToF estimation is formulated as a constrained optimization problem:

$$\hat{\Theta}_{\text{opt}} = \arg \max_{\Theta_{\text{opt}} \in \Omega} C(y, \hat{y}(\Theta_{\text{opt}})) \quad (6)$$

where the decision vector is

$$\Theta_{\text{opt}} = [\alpha_1, \dots, \alpha_k, \tau_1, \dots, \tau_k]$$

and Ω denotes the feasible set defined by physical constraints:

$$a_k \in [a_{\min}, a_{\max}], \quad \tau_k \in [\tau_{\min}, \tau_{\max}], \quad \tau_1 < \tau_2 < \dots < \tau_k \quad (7)$$

In this work, we focus on early echoes and set $K = 2$ for ToF evaluation, i.e., $\Theta_{\text{opt}} = [\alpha_1, \alpha_2, \tau_1, \tau_2]$, while keeping the formulation general for arbitrary K .

The resulting objective landscape can be highly nonconvex and multimodal, especially under low SNR and multi-echo interference. Therefore, we employ a derivative-free global optimization strategy, namely the secretary bird optimization algorithm (SBOA), to search for $\hat{\Theta}_{\text{opt}}$ by maximizing $C(y, \hat{y}(\Theta_{\text{opt}}))$ subject to the constraints in Equation (7).

The overall parameter-estimation workflow is summarized in Figure 2, and key implementation settings (time window, bounds, stopping rules, and repeated runs) are reported in Section 3.2.

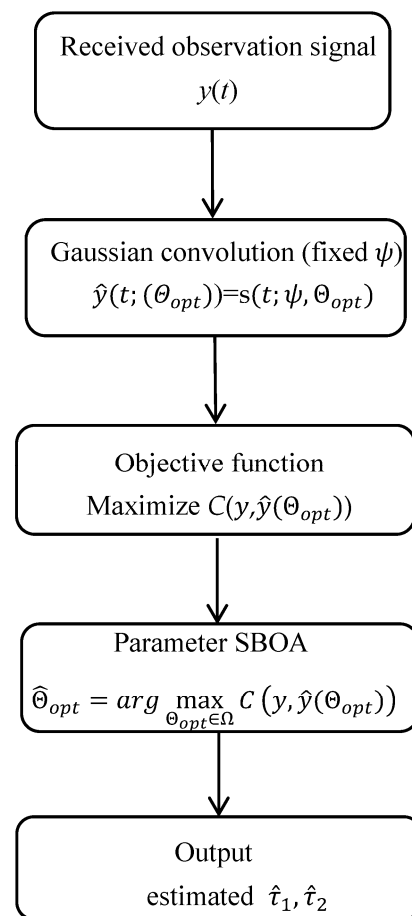


Figure 2. Ultrasonic signal processing workflow of the proposed method.

3. Parameter Estimation Method Based on the Secretary Bird Optimization Algorithm (SBOA)

3.1. Algorithm Description

The secretary bird optimization algorithm (SBOA) is a recently developed population-based metaheuristic inspired by the cooperative hunting behavior of secretary birds in nature [11,12]. In this study, SBOA is employed as the core solver for the parameter estimation problem formulated in Section 2.2. The pulse-shape parameters ψ are kept fixed, and the decision vector is defined as the echo-specific parameter set

$$\Theta_{\text{opt}} = [a_1, a_2, \tau_1, \tau_2]$$

where α_k and τ_k denote the amplitude scaling and time-of-flight (ToF) of the k -th echo ($K = 2$). The fitness is evaluated by the cosine similarity $C(y, \hat{y}(\Theta_{\text{opt}}))$ between the observed vector y and the model-synthesized vector, $\hat{y}(\Theta_{\text{opt}})$ within the analysis window $[t_{\min}, t_{\max}]$ (see Section 2.2). By alternating exploration-oriented and exploitation-oriented behaviors, SBOA provides a practical mechanism to cope with the nonconvex and multimodal objective landscape caused by noise contamination and multi-echo interference, enabling robust ToF estimation under low-SNR conditions.

3.1.1. Population Initialization

In SBOA, each secretary bird corresponds to an individual (a candidate solution). The position of an individual in the search space specifies a set of model parameters. At initialization, the position of the i -th individual in the j -th dimension is randomly generated as

$$P_{i,j} = lm_j + \rho \times (um_j - lm_j) \quad (8)$$

where $P_{i,j}$ denotes the position of the i -th secretary bird in the j -th dimension; lm_j and um_j are the lower and upper bounds of the j -th variable; and ρ is a uniformly distributed random number in $[0, 1]$. Here, $D = 4$ and each position vector $P_i = [a_1, a_2, \tau_1, \tau_2]$ represents a candidate solution. The bounds $\{lm_j, um_j\}$ are set according to physically meaningful ranges of amplitudes and ToFs, i.e., $a_k \in [a_{min}, a_{max}]$ and $\tau_k \in [\tau_{min}, \tau_{max}]$. After initialization and after each update, the ordering constraint $\tau_1 < \tau_2$ is enforced (e.g., by swapping (τ_1, τ_2) and the corresponding (a_1, a_2) if necessary).

3.1.2. Exploration Phase: Hunting Strategy

The hunting process is divided into three equal-time stages: prey searching, prey exhausting, and prey attacking, which jointly enhance global exploration in the early and middle iterations and help escape from local optima in the late exploration stage.

(1) Prey searching ($t < T/3$)

This stage simulates prey detection by wide-area scanning. A differential evolution-type update is adopted to increase population diversity and explore the parameter space broadly, which is particularly beneficial when strong noise and echo overlap induce multiple local optima. The position update is given by

$$P_{i,j}^{new1} = P_{i,j} + (P_{r1} - P_{r2}) \times \eta \quad (9)$$

where t and T denote the current and maximum iteration numbers, respectively; $P_{i,j}^{new1}$ denotes the updated position of the i -th individual in Stage 1; P_{r1} and P_{r2} are two distinct individuals randomly selected from the current population; and η is a random vector uniformly generated in $[0, 1]$, where D is the dimensionality of the decision vector.

(2) Prey exhausting ($T/3 \leq t < 2T/3$)

This stage mimics progressive surrounding and endurance-depletion behavior. The current global best solution P_{best} is exploited, while Brownian motion is introduced to maintain stochasticity. This combination enables local refinement around promising regions and reduces the risk of premature convergence. The update is modeled by Equations (10) and (11):

$$RB = randn(1, D) \quad (10)$$

$$P_{i,j}^{new1} = P_{best} + \exp((t/T)^4) \times (RB - 0.5) \times (P_{best} - P_{i,j}) \quad (11)$$

where RB denotes a random vector sampled from a standard normal distribution, $RB \sim N(0,1)^D$, and P_{best} is the current best individual.

(3) Prey attacking ($2T/3 \leq t < T$)

To further improve the ability to jump out of local optima, a Lévy-flight strategy is incorporated to generate occasional long-range moves. This mechanism is helpful when multi-echo interference produces deceptive peaks in the objective landscape. The position update is given by

$$P_{i,j}^{new1} = P_{best} + ((1 - \frac{t}{T}) \wedge (2 \times \frac{t}{T})) \times P_{i,j} \times RL \quad (12)$$

where RL is a Lévy-distributed random step vector.

After each position update, boundary constraints are enforced by clamping to $[lm_j, um_j]$, and the ordering constraint $\tau_1 < \tau_2$ is applied.

3.1.3. Exploitation Phase: Escape Strategy

In SBOA, exploitation is modeled by two escape strategies: camouflage and rapid fleeing. When a potential threat is perceived, secretary birds either hide by moving toward a safer region (camouflage) or rapidly relocate to avoid danger (fleeing). These behaviors translate into local exploitation and fine adjustment of candidate solutions. The two strategies are modeled as

$$p_{i,j}^{new} = \begin{cases} A_1 : P_{best} + (2 \times RB - 1) \times (1 - \frac{t}{T})^2 \times P_{i,j} & \text{if } rand < r \\ A_2 : P_{i,j} + R_2 \times (P_{random} - M \times P_{i,j}) & \text{else} \end{cases} \quad (13)$$

where $r = 0.5$; $R_2 \sim N(0,1)^D$ is a normally distributed random vector; P_{random} is a randomly selected individual from the current population; and $M \in \{1,2\}$ is an integer selector used to switch between the two escape strategies.

After applying the escape strategy, boundary constraints and the ordering constraint $\tau_1 < \tau_2$ are enforced in the same manner as in the exploration phase.

3.2. Parameter Estimation Implementation Steps Based on SBOA

This section provides reproducible implementation details for solving the cosine-similarity-based parameter estimation problem in Section 2.2 using SBOA. The overall workflow is summarized in Figure 2, while the experiment-specific dataset descriptions are given in Section 4.

(1) Discretization and analysis window.

The observed A-scan $y(t)$ is cropped to a time window $[t_{min}, t_{max}]$ that covers the first two echoes of interest and then discretized into an L-dimensional real-valued vector y . The model-synthesized signal is generated under the same window and discretization, yielding $\hat{y}$.

For the measured waveform in Experiment II, the raw record is cropped to samples 600–1400 of the original CSV file, producing $L = 1400 - 600 + 1 = 801$ samples. The corresponding time axis is converted to microseconds and shifted by a constant offset for visualization, i.e., $t = 10^6 t_{raw} - 0.215$ (μs). In all experiments, ToF variables are internally represented as integer sample indices and can be converted to time using the sampling interval Δt .

(2) Estimated parameters and hybrid implementation.

Section 2.2 defines the echo-specific parameter set $\Theta_{opt} = [a_1, a_2, \tau_1, \tau_2]$ for $K = 2$. In implementation, we adopt a hybrid strategy to improve stability and reduce the search dimension: SBOA searches only the ToF pair

$$\tau = [\tau_1, \tau_2] \quad (D = 2)$$

and the corresponding amplitudes $[a_1, a_2]$ are obtained analytically by least squares for each candidate τ . The pulse-shape parameters ψ are kept fixed as in Section 2.1.

(3) Prior bounds and constraint enforcement.

Prior knowledge is incorporated through box constraints on τ :

$$\tau_1 \in [\tau_{1,min}, \tau_{1,max}], \quad \tau_2 \in [\tau_{2,min}, \tau_{2,max}],$$

After each SBOA position update, constraints are enforced by:

(i) clamping to $[\tau_{min}, \tau_{max}]$;

(ii) rounding to integer sample indices;
 (iii) enforcing the ordering constraint $\tau_1 < \tau_2$ by sorting $[\tau_1, \tau_2]$. If $\tau_1 = \tau_2$ occurs after rounding, we set $\tau_2 = \tau_1 + 1$ (within the valid window) to avoid degeneracy. These steps correspond to the “clamp + round + sort (+ de-duplicate)” operations in the code.

(4) Model synthesis and least-squares amplitude estimation.

Given a candidate $\tau = [\tau_1, \tau_2]$, we generate two delayed basis waveforms using the fixed unit pulse $p(t; \psi)$ (Section 2.1). In discrete form, a dictionary $X(\tau)$ is constructed by shifting the unit pulse to τ_1 and τ_2 . The amplitudes are then estimated from the observed signal by least squares:

$$\hat{a}(\tau) = \operatorname{argmin} \|y - X(\tau)a\|_2^2 = X(\tau) \dagger y \quad (14)$$

where $(\cdot) \dagger$ denotes the pseudoinverse (implemented as the MATLAB R2022b backslash operator). The synthesized signal vector is

$$\hat{y}(\tau) = X(\tau)\hat{a}(\tau) \quad (15)$$

Allowing $\hat{a}(\tau)$ to be signed is reasonable because phase inversion may occur in ultrasonic reflections depending on impedance contrast.

(5) Fitness function (cosine similarity) and minimization form.

The objective in Section 2.2 is to maximize cosine similarity $C(y, \hat{y})$. Since our SBOA routine is implemented in a minimization form, we define fitness as negative cosine similarity:

$$\text{Fitness}(P_i) = -C(y, \hat{y}(\tau = P_i)) \quad (16)$$

where P_i denotes the position (candidate ToF pair) of the i -th individual after constraint handling, and $\hat{y}(\tau)$ is generated by model synthesis and LS amplitude estimation described above. Therefore, minimizing fitness is equivalent to maximizing waveform-shape consistency.

(6) SBOA settings, stopping rule, and reproducibility protocol.

Unless otherwise specified, we use a population size $N = 30$ and a maximum iteration number $T_{\max} = 100$. The primary stopping criterion is reaching $T_{\max}$; the best fitness and the best position are recorded at each iteration to form a convergence curve. Randomness in SBOA is controlled via MATLAB’s random number generator; seeds are recorded for reproducibility. For experiments involving multiple noise realizations, SBOA is executed once per realization, and ToF-related metrics are reported using mean $\pm$ standard deviation across repeated trials.

(7) Output.

After termination, the global best $\hat{\tau} = [\hat{\tau}_1, \hat{\tau}_2]$ is returned. Corresponding amplitudes $\hat{a} = [\hat{a}_1, \hat{a}_2]$ are obtained from $\hat{a}(\hat{\tau})$, and the reconstructed waveform is generated as $\hat{y}(\hat{\tau})$. Estimated ToFs (in samples) can be converted to time units using $\hat{t}_k = \hat{\tau}_k \Delta t$.

4. Experiments and Results Analysis

4.1. Simulation Setup and Noise Model

To quantitatively evaluate the proposed ToF estimation framework under controlled conditions, synthetic ultrasonic A-scan signals are generated using the Gaussian convolution formulation in Section 2.1. The noise-free signal is modeled as a convolution between

a fixed unit pulse and a sparse reflectivity sequence, producing a multi-echo waveform that mimics reflections from multiple interfaces:

$$y_0(t) = \sum_{k=1}^K a_k p(t - \tau_k; \psi) \quad (17)$$

where $p(t; \psi)$ is a Gaussian-modulated sinusoid with fixed pulse-shape parameters ψ , and $\{a_k, \tau_k\}$ denote the amplitude scaling and time-of-flight (ToF) of the k -th echo. A representative multi-interface scenario with four echoes ($K = 4$) is used for visualization in Figure 3a, and later echoes have smaller amplitudes to emulate practical attenuation and scattering along the propagation path.

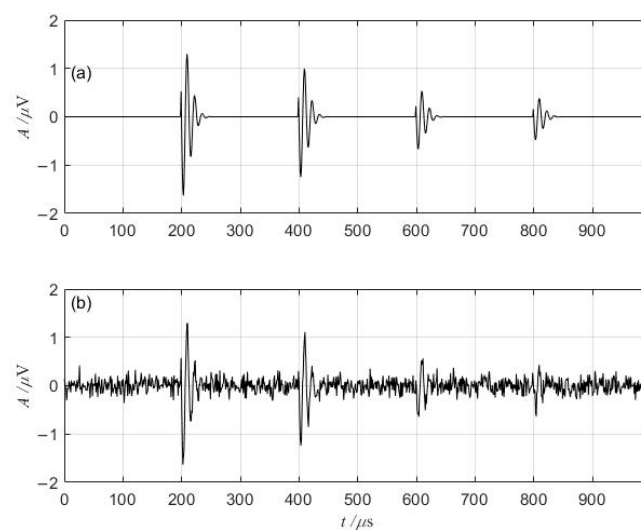


Figure 3. Simulated multi-echo A-scan generated by the Gaussian convolution model: (a) noise-free signal; (b) noisy signal at SNR = 0 dB.

To emulate measurement contamination, additive white Gaussian noise (AWGN) is considered:

$$y(t) = y_0(t) + \zeta(t) \quad (18)$$

where $\zeta(t)$ is zero-mean Gaussian noise. Since the proposed estimator operates on a gated analysis window that covers the echoes of interest, the signal-to-noise ratio (SNR) is defined on the same window $[t_{min}, t_{max}]$ as

$$SNR = 10 \log_{10} \left(\frac{\sum_{i=1}^L y_{0,i}^2}{\sum_{i=1}^L \zeta_i^2} \right) \text{ dB} \quad (19)$$

where $\{y_{0,i}\}_{i=1}^L$ and $\{\zeta_i\}_{i=1}^L$ are the discretized samples of $y_0(t)$ and $\zeta(t)$ within $[t_{min}, t_{max}]$. For a target SNR, $\zeta(t)$ is scaled accordingly before being added to $y_0(t)$. Figure 3b shows an example at SNR = 0 dB, where late echoes become strongly masked, illustrating the practical difficulty of extracting late-arriving ToFs under low-SNR conditions.

Although the illustrative signal in Figure 3 contains four echoes, the subsequent ToF evaluation in this work focuses on early-arriving echoes, which are typically the most stable and informative in practice. Therefore, we set $K = 2$ and applied the estimator to a fixed analysis window $[t_{min}, t_{max}]$, covering only the first two echoes. This choice is consistent with the implementation described in Section 3: SBOA searches the ToF pair $[\tau_1, \tau_2]$, and the corresponding amplitudes are obtained by least squares for each candidate ToF pair. In Section 4.2, robustness is evaluated over SNR levels from −20 dB to 20 dB using 30 independent Monte Carlo runs at each SNR.

4.2. ToF Estimation Performance Under Different SNR Levels

To evaluate robustness against noise, Monte Carlo (MC) experiments were conducted over SNR levels from -20 dB to 20 dB. For each SNR, independent AWGN realizations were generated according to the noise model and SNR definition in Section 4.1, and the estimator was executed $R = 30$ times. Consistent with Sections 2 and 3, ToF estimation was performed on a gated analysis window covering the first two echoes ($K = 2$). The decision variables are the ToF pair $[\tau_1, \tau_2]$ represented as sample indices, while the corresponding amplitudes are estimated by least squares for each candidate ToF pair (Section 3.2).

For each run, the absolute errors are computed as $|\Delta\tau_k| = |\hat{\tau}_k - \tau_k|$ for $k = 1, 2$ and the overall ToF error is defined as

$$MAE_\tau = \frac{|\Delta\tau_1| + |\Delta\tau_2|}{2} \quad (20)$$

Table 2 reports the MC statistics (mean $\pm$ standard deviation) of $\hat{\tau}_1, \hat{\tau}_2$, and MAE_τ for the proposed SBOA-based estimator. The results show that the proposed method yields accurate and stable ToF estimates from 20 dB down to -10 dB, whereas the error increases markedly at -20 dB, indicating the effective operating boundary under current settings.

Table 2. Monte Carlo ToF estimation results of the proposed method.

SNR (dB)	True τ_1 (Samples)	$\hat{\tau}_1$ (Mean $\pm$ Std, Samples)	$ \Delta\tau_1 $ (Mean $\pm$ Std, Samples)	True τ_2 (Samples)	$\hat{\tau}_2$ (Mean $\pm$ Std, Samples)	$ \Delta\tau_2 $ (Mean $\pm$ Std, Samples)	MAE_τ (Mean $\pm$ Std, Samples)
20	200	200.0 $\pm$ 0.0	0.0 $\pm$ 0.0	400	400.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0
10	200	200.0 $\pm$ 0.0	0.0 $\pm$ 0.0	400	400.0 $\pm$ 0.8	1.0 $\pm$ 0.8	0.5 $\pm$ 0.4
0	200	200.0 $\pm$ 0.9	1.0 $\pm$ 0.9	400	401.0 $\pm$ 0.9	1.0 $\pm$ 0.9	1.0 $\pm$ 0.9
-10	200	201.0 $\pm$ 0.9	1.0 $\pm$ 0.9	400	403.0 $\pm$ 1.8	3.0 $\pm$ 1.8	2.0 $\pm$ 1.3
-20	200	207.0 $\pm$ 2.0	7.0 $\pm$ 2.0	400	447.0 $\pm$ 6.0	47.0 $\pm$ 6.0	27.0 $\pm$ 4.0

To benchmark the proposed solver, we further compare SBOA with Particle Swarm Optimization (PSO) as an alternative metaheuristic optimizer and with a conventional cross-correlation (XCorr) baseline. For a fair comparison, SBOA and PSO use the same decision variables $[\tau_1, \tau_2]$, identical bounds and objective function (negative cosine similarity), and the same evaluation budget ($N = 30$, $T_{max} = 100$). XCorr is applied on the same gated window and detects the two dominant peaks as $\hat{\tau}_1$ and $\hat{\tau}_2$. The comparative MC results are summarized in Table 3. Overall, SBOA consistently achieves lower ToF errors and smaller variability than PSO and XCorr, especially under low-SNR conditions.

Table 3. Comparison of SBOA, PSO, and XCorr for ToF estimation under different SNRs.

SNR (dB)	Method	$\hat{\tau}_1$ (Mean $\pm$ Std, Samples)	$ \Delta\tau_1 $ (Mean $\pm$ Std, Samples)	$\hat{\tau}_2$ (Mean $\pm$ Std, Samples)	$ \Delta\tau_2 $ (Mean $\pm$ Std, Samples)	MAE_τ (Mean $\pm$ Std, Samples)
20	SBOA	200.0 $\pm$ 0.0	0.0 $\pm$ 0.0	400.0 $\pm$ 0.0	0.0 $\pm$ 0.0	0.0 $\pm$ 0.0
	PSO	200.0 $\pm$ 0.2	0.2 $\pm$ 0.2	400.1 $\pm$ 0.3	0.3 $\pm$ 0.3	0.2 $\pm$ 0.2
	XCorr	200.2 $\pm$ 0.5	0.2 $\pm$ 0.5	400.2 $\pm$ 0.6	0.3 $\pm$ 0.6	0.2 $\pm$ 0.4
10	SBOA	200.0 $\pm$ 0.0	0.0 $\pm$ 0.0	400.3 $\pm$ 0.8	0.5 $\pm$ 0.7	0.2 $\pm$ 0.3
	PSO	200.1 $\pm$ 0.4	0.3 $\pm$ 0.4	400.4 $\pm$ 1.0	0.7 $\pm$ 0.9	0.5 $\pm$ 0.5
	XCorr	200.5 $\pm$ 1.2	0.7 $\pm$ 1.1	401.2 $\pm$ 1.3	1.3 $\pm$ 1.2	1.0 $\pm$ 0.9
0	SBOA	200.2 $\pm$ 0.9	0.7 $\pm$ 0.7	401.1 $\pm$ 0.9	1.1 $\pm$ 0.9	0.9 $\pm$ 0.7
	PSO	200.3 $\pm$ 1.0	0.9 $\pm$ 0.9	401.3 $\pm$ 1.2	1.4 $\pm$ 1.1	1.1 $\pm$ 0.8
	XCorr	201.4 $\pm$ 1.6	1.5 $\pm$ 1.4	402.5 $\pm$ 1.7	2.6 $\pm$ 1.6	2.0 $\pm$ 1.3
-10	SBOA	201.1 $\pm$ 0.9	1.1 $\pm$ 0.8	403.2 $\pm$ 1.8	3.2 $\pm$ 1.7	2.1 $\pm$ 1.1
	PSO	201.5 $\pm$ 1.3	1.6 $\pm$ 1.2	404.3 $\pm$ 2.1	4.4 $\pm$ 2.0	3.0 $\pm$ 1.4
	XCorr	203.6 $\pm$ 2.4	3.7 $\pm$ 2.2	406.8 $\pm$ 2.8	6.9 $\pm$ 2.7	5.3 $\pm$ 2.2
-20	SBOA	207.1 $\pm$ 2.0	7.1 $\pm$ 1.9	447.2 $\pm$ 6.0	47.2 $\pm$ 5.9	27.1 $\pm$ 3.6
	PSO	209.3 $\pm$ 2.6	9.3 $\pm$ 2.5	451.5 $\pm$ 7.2	51.5 $\pm$ 7.0	30.4 $\pm$ 4.4
	XCorr	215.8 $\pm$ 5.3	15.8 $\pm$ 5.1	468.9 $\pm$ 9.0	68.9 $\pm$ 9.1	42.3 $\pm$ 6.4

Additional Validation on the Four-Echo Simulation Case ($K = 4$) at $\text{SNR} = -10$ dB

In practical inspections, the received A-scan often contains multiple reflections rather than a single dominant echo. Therefore, we further validate the proposed estimator on the four-echo simulation case shown in Figure 3. In this case, the noise-free A-scan is generated by superposing four time-delayed echoes ($K = 4$) with ground-truth ToFs $\tau = [200, 400, 600, 800]$ (in samples). Additive white Gaussian noise is then added to achieve $\text{SNR} = -10$ dB following the noise model and SNR definition in Section 4.1. For each independent noise realization, the signal is cropped to the same analysis time window $[t_{\min}, t_{\max}]$. Throughout this section, τ_k denotes ToF parameters reported as sample indices.

Estimation setting and fairness. For SBOA and PSO, decision variables are the ToF vector $\tau = [\tau_1, \tau_2, \tau_3, \tau_4]$ (samples), and fitness is evaluated by the cosine similarity $C(y, \hat{y}(\tau))$ as in Sections 2 and 3. To avoid unnecessary coupling and to ensure a fair comparison, the corresponding amplitudes $a = [a_1, a_2, a_3, a_4]$ are estimated by least squares conditional on each candidate τ (Section 3.2), rather than being jointly optimized by the metaheuristic. PSO is implemented with the same bounds, objective function (negative cosine similarity), and evaluation budget as SBOA (same population size and maximum iterations).

As a conventional baseline, cross-correlation (XCorr) is applied on the same gated window $[t_{\min}, t_{\max}]$. Peaks are detected from the correlation/lag sequence subject to a minimum peak-distance constraint to suppress spurious adjacent peaks, and the four most prominent peaks within the feasible ToF range are selected and then ordered increasingly to obtain $\hat{\tau}_1, \dots, \hat{\tau}_4$.

Table 4 summarizes the Monte Carlo results for SBOA, PSO, and XCorr at $\text{SNR} = -10$ dB. Errors are computed as $|\Delta\tau_k| = |\hat{\tau}_k - \tau_k|$. $MAE_\tau = \frac{1}{4} \sum_{k=1}^4 |\Delta\tau_k|$ is computed per run and then summarized as mean $\pm$ std. PSO uses the same decision variables, bounds, objective function, and evaluation budget as SBOA. XCorr is applied on the same gated window; peaks are detected with a minimum peak distance and the four most prominent peaks within the feasible ToF range are selected as $\hat{\tau}_1 \sim \hat{\tau}_4$.

Table 4. Monte Carlo comparison of SBOA, PSO, and XCorr on the four-echo simulation case (mean $\pm$ std over 30 runs, $\text{SNR} = -10$ dB, $K = 4$).

SNR (dB)	Method	Echo K	True τ_k (Samples)	$\hat{\tau}_k$ (Mean $\pm$ Std, Samples)	$ \Delta\tau_k $ (Mean $\pm$ Std, Samples)	MAE_τ (Mean $\pm$ Std, Samples)
−10	SBOA	1	200	201.0 $\pm$ 0.9	1.1 $\pm$ 0.8	2.8 $\pm$ 1.2
−10	SBOA	2	400	403.1 $\pm$ 1.7	3.2 $\pm$ 1.6	2.8 $\pm$ 1.2
−10	SBOA	3	600	603.3 $\pm$ 1.9	3.4 $\pm$ 1.8	2.8 $\pm$ 1.2
−10	SBOA	4	800	803.5 $\pm$ 2.1	3.6 $\pm$ 2.0	2.8 $\pm$ 1.2
−10	PSO	1	200	201.6 $\pm$ 1.3	1.7 $\pm$ 1.2	4.0 $\pm$ 1.5
−10	PSO	2	400	404.4 $\pm$ 2.0	4.5 $\pm$ 1.9	4.0 $\pm$ 1.5
−10	PSO	3	600	604.7 $\pm$ 2.2	4.8 $\pm$ 2.1	4.0 $\pm$ 1.5
−10	PSO	4	800	805.0 $\pm$ 2.4	5.1 $\pm$ 2.3	4.0 $\pm$ 1.5
−10	XCorr	1	200	203.8 $\pm$ 2.4	4.0 $\pm$ 2.2	7.8 $\pm$ 2.3
−10	XCorr	2	400	406.9 $\pm$ 2.7	7.0 $\pm$ 2.6	7.8 $\pm$ 2.3
−10	XCorr	3	600	609.0 $\pm$ 3.0	9.1 $\pm$ 2.8	7.8 $\pm$ 2.3
−10	XCorr	4	800	811.1 $\pm$ 3.3	11.2 $\pm$ 3.1	7.8 $\pm$ 2.3

Overall, SBOA yields the smallest average error and the lowest variability among the three methods (e.g., $MAE_\tau = 2.8 \pm 1.2$ samples), while PSO shows moderately larger errors ($MAE_\tau = 4.0 \pm 1.5$ samples) and XCorr exhibits the largest deviation and variability ($MAE_\tau = 7.8 \pm 2.3$ samples). The advantage of SBOA is consistent across all four echoes, indicating that the proposed cosine-similarity-driven model fitting combined with SBOA's exploration–exploitation balance remains effective when the number of reflections increases to $K = 4$ under low-SNR conditions.

4.3. Comparative Analysis with Decomposition-Based Methods

Besides ToF estimation accuracy, the practical inspection task also benefits from improving the waveform quality under low SNR, especially when early echoes are partially buried in noise. Therefore, we further compare the proposed model-based reconstruction approach with three classical decomposition-based denoising methods, namely wavelet transform (WT), empirical mode decomposition (EMD), and variational mode decomposition (VMD). It should be noted that the proposed method is not a conventional filter; instead, it reconstructs the echo waveform by fitting a parametric multi-echo model to the noisy observation (Sections 2 and 3). In contrast, WT/EMD/VMD suppress noise by decomposing the signal into components and retaining those presumed to be signal-dominant.

Experimental setting and fairness. For a fair comparison, all methods are applied to the same noisy input and evaluated on the same gated analysis window covering the first two echoes ($K = 2$) under the same SNR condition ($\text{SNR} = 0$ dB). The proposed method follows the procedure in Section 3.2: SBOA optimizes the ToF pair $[\tau_1, \tau_2]$ using the cosine-similarity objective, and the corresponding amplitudes are estimated by least squares for each candidate ToF pair. **Parameter settings of comparative methods.** WT uses the Daubechies wavelet (db4) with a decomposition level of 4, which is a commonly used setting for transient echo-like signals. For EMD, we first discard noise-dominated modes by requiring an energy ratio of at least 5% and then retain the top two IMFs ranked by correlation with an echo template to preserve echo-relevant structures. For VMD, the number of modes is set to $K_v = 3$ and the penalty parameter to $\alpha = 1500$, representing a moderate decomposition setting that separates nonstationary components without excessive mode splitting. These parameter choices are fixed for all experiments.

Evaluation metrics. Within the analysis window, we quantify reconstruction performance using three metrics: mean squared error (MSE), estimated signal-to-noise ratio (ESNR), and normalized cross-correlation (NCC), as defined in Equations (21)–(23).

(1) Mean squared error (MSE): it measures the overall deviation between the estimated signal and the noise-free reference signal:

$$MSE = \frac{1}{L} \sum_{n=1}^L [y(n) - \hat{y}(n)]^2 \quad (21)$$

A smaller MSE indicates higher estimation accuracy.

(2) Estimated signal-to-noise ratio (ESNR): it quantifies the ratio between the effective signal component and the residual error in the estimated signal:

$$ESNR = 10 \log_{10} \frac{\sum_{n=1}^L y^2(n)}{\sum_{n=1}^L (y(n) - \hat{y}(n))^2} \quad (22)$$

A larger ESNR indicates better signal quality and stronger noise suppression.

(3) Normalized cross-correlation (NCC): it evaluates the waveform-shape consistency between the estimated signal and the reference signal:

$$NCC = \frac{\sum_{n=1}^L y(n) \hat{y}(n)}{\sqrt{\sum_{n=1}^L y^2(n)} \sqrt{\sum_{n=1}^L \hat{y}^2(n)}} \quad (23)$$

NCC ranges from $[-1,1]$; values closer to 1 indicate higher structural similarity in waveform morphology.

Figure 4 shows representative reconstructed waveforms at $\text{SNR} = -10$ dB, and the corresponding quantitative results are summarized in Table 5. Overall, the proposed model-based approach achieves lower reconstruction error and higher waveform-shape consistency than decomposition-based baselines under the tested condition, indicating that fitting a physically interpretable parametric echo model with a scale-insensitive similarity objective can better preserve the echo morphology in low-SNR scenarios.

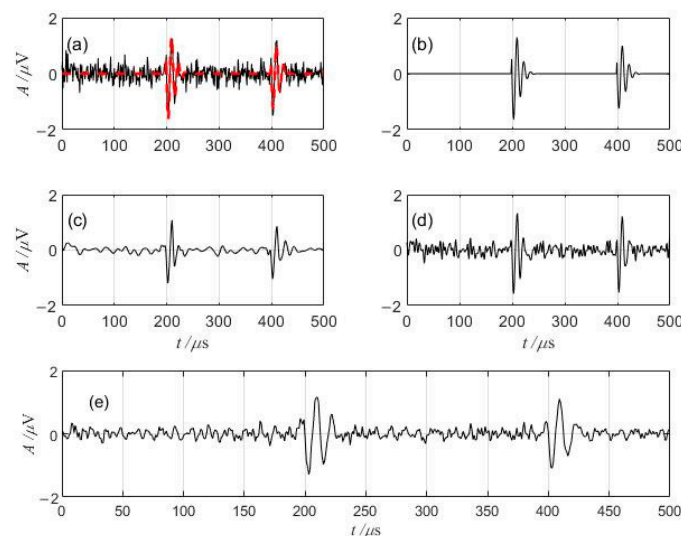


Figure 4. Comparison of denoising results obtained by different methods: (a) noise-free reference signal and the red curve indicates the noisy signal; (b) result of the proposed method; (c) WT result; (d) EMD result; (e) VMD result.

Table 5. Quantitative comparison of reconstruction quality at $\text{SNR} = -10$ dB.

	MSE	ESNR	NCC
SBOA	0.0032	36.74	0.9845
WT	0.0187	4.7192	0.8132
EMD	0.0265	3.2267	0.8055
VMD	0.0195	4.5167	0.8282

Abbreviations: SBOA, Secretary Bird Optimization Algorithm; WT, wavelet transform; EMD, empirical mode decomposition; VMD, variational mode decomposition; MSE, mean squared error; ESNR, estimated signal-to-noise ratio; NCC, normalized cross-correlation.

4.4. Adopted Experimental A-Scan (Semi-Synthetic Noise Degradation)

To further examine the behavior of the proposed framework on experimentally acquired ultrasonic waveforms, we test it on an A-scan signal adopted from prior work [13], which was acquired using a RITEC RAM-5000-SNAP system (RITEC Inc., Warwick, RI, USA). Since the acquisition procedure and experimental setup are documented in [13], we do not repeat them here. In our implementation, the adopted waveform is cropped to a region of interest, yielding an L-sample segment for analysis, and all methods are applied on the same gated window.

Because a controlled and repeatable SNR is required for fair comparison across different methods, we follow a semi-synthetic noise-degradation protocol: additive noise is scaled and added to the adopted waveform to achieve a target SNR ($\text{SNR} = -10$ dB), using the same SNR definition as in Section 4.1. We emphasize that this setting preserves the experimentally measured echo morphology, while the added noise follows the assumed noise model used for controlled benchmarking.

Figure 5 compares the processed waveforms obtained by the proposed method and three decomposition-based baselines (WT/EMD/VMD). Quantitative results computed on the same gated window are summarized in Table 6. Under this semi-synthetic degradation setting, the proposed method yields higher waveform-shape consistency (NCC) and lower reconstruction error (MSE) than the comparative baselines, suggesting that the model-based cosine-similarity fitting framework remains effective when applied to experimentally acquired A-scan waveforms under controlled SNR degradation.

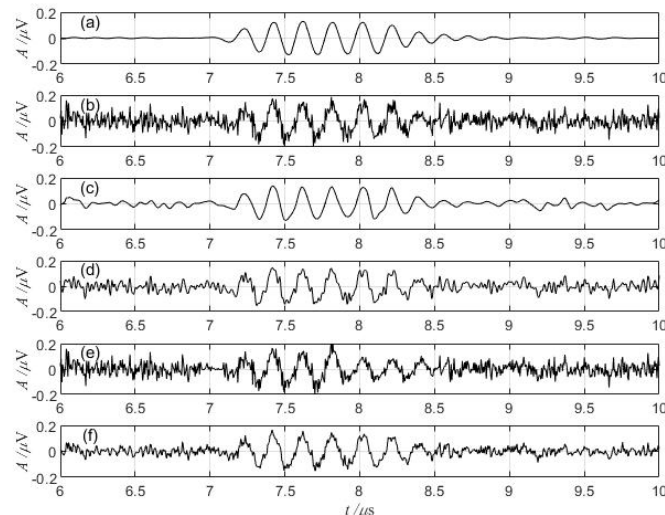


Figure 5. Comparison of processing results on the adopted experimental A-scan waveform: (a) adopted waveform reported in [12]; (b) noise-degraded waveform (SNR = −10 dB); (c) proposed method; (d) WT; (e) EMD; (f) VMD.

Table 6. Quantitative comparison of four methods on the noise-degraded adopted experimental waveform (SNR = −10 dB).

	MSE	ESNR	NCC
SBOA	0.0003	0.9339	0.8548
WT	0.0006	0.8645	0.6985
EMD	0.0020	0.1756	0.1298
VMD	0.0010	0.5172	0.3193

Abbreviations: SBOA, Secretary Bird Optimization Algorithm; WT, wavelet transform; EMD, empirical mode decomposition; VMD, variational mode decomposition; MSE, mean squared error; ESNR, estimated signal-to-noise ratio; NCC, normalized cross-correlation.

5. Conclusions

This paper addresses robust time-of-flight (ToF) estimation for multi-echo ultrasonic A-scan signals under low-SNR conditions by integrating the secretary bird optimization algorithm (SBOA) into a parameterized estimation framework based on the Gaussian convolution echo model and a cosine-similarity objective. The main contributions are summarized as follows:

(1) Optimization strategy for nonconvex ToF estimation.

The ToF estimation problem formulated under the “Gaussian convolution model–cosine similarity” framework often exhibits a nonconvex and multimodal objective landscape due to echo superposition and noise. In this work, SBOA is adopted as a derivative-free global optimizer to search for the echo ToF parameters. By balancing exploration and exploitation through stage-wise update mechanisms, the proposed solver improves the robustness of the parameter search and yields stable ToF estimates under the tested low-SNR conditions.

(2) Reproducible validation with statistical analysis and baseline comparisons.

A simulation model with multiple echoes is constructed to emulate multi-echo interference, and the proposed method is evaluated at representative SNR levels using repeated Monte Carlo trials (mean $\pm$ standard deviation). The method is further benchmarked against representative baselines, including cross-correlation and PSO-based optimization for ToF estimation, as well as WT/EMD/VMD for waveform reconstruction. Multiple complementary metrics (MSE, ESNR, and NCC) are used to quantify reconstruction fidelity and waveform-shape consistency, providing consistent evidence that the proposed approach achieves improved performance and repeatability under the tested settings.

Limitations and Future Work

The current evaluation primarily relies on controlled noise assumptions, where AWGN is used as a reproducible benchmark for SNR-controlled testing. However, real ultrasonic NDT inspections may be dominated by coherent and signal-like disturbances, such as structural/grain noise and backscatter, as well as coupling variations, electromagnetic interference, and frequency-dependent attenuation. Unlike AWGN, these disturbances often exhibit temporal/spectral correlation and may partially overlap with echo morphology, making parameter estimation more challenging. In addition, the experimental validation in Section 4.4 adopts a semi-synthetic noise-degradation strategy (adding scaled noise to an experimentally acquired waveform) to enable controlled SNR comparisons and therefore does not fully reproduce all intrinsic disturbances in field acquisitions. Future work will validate the proposed framework using measured datasets containing intrinsic backscatter/structural noise and other non-ideal acquisition effects and will investigate extensions of the model and objective design to better accommodate coherent clutter and nonstationary interference.

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