World Journal of Information Technology
Print ISSN: 2959-9903
Online ISSN: 2959-9911
DOI: https://doi.org/10.61784/wjit3128

PULSE SIGNAL PARAMETER ESTIMATION METHOD BASED ON TIME-FREQUENCY RIDGE CONNECTED DOMAIN EXTRACTION

Peng Zhang[1*], LiangHai Sun[2]
[1]*Ceyear Technologies Co., Ltd, Qingdao 266555, Shandong, China.*
[2]*College of Oceanography and Space Informatics, China University of Petroleum (East China), Qingdao 266580, Shandong, China.*
[*]*Corresponding Author: Peng Zhang*

Abstract: To achieve high-precision parameter estimation of pulse signals, a pulse signal parameter estimation method based on time-frequency ridge connected domain extraction is proposed, which solves the problems of large parameter estimation errors and poor robustness caused by the fracture of time-frequency ridges under low signal-to-noise ratio (SNR) conditions. The background noise in pulse signals is filtered out by adaptive-threshold binarization, and the fractured time-frequency ridges are repaired by connected domain labeling and polynomial fitting, thereby reconstructing the complete time-frequency structure of the pulse signal. Then, the corresponding characteristic parameters are estimated for different modulation types. Experimental results show that the root mean square errors and biases of parameter estimation for eight types of pulse signals are lower than those of other comparison methods.
Keywords: Pulse signal; Parameter estimation; Time-frequency ridge connected domain extraction

1 INTRODUCTION

Existing pulse parameter estimation methods can be roughly divided into two categories: dedicated methods for specific pulses and general methods for multiple types of pulses. Representative dedicated methods estimate the parameters of phase-split linear frequency modulation (LFM) pulses [1], sinusoidal frequency-modulated pulses [2], non-cooperative underwater acoustic pulses [3], LFM pulses under impulse noise [4], quadratic frequency-modulated pulses [5], and phase-coded pulses at low sampling rates [6]. The former category can hardly achieve parameter estimation of multiple types of pulse signals. Although the latter possesses certain universality, its robustness and estimation accuracy in complex environments still need to be improved. Time-frequency ridge analysis, with its good applicability and signal representation capability, provides an effective idea for parameter estimation of multiple types of pulse signals. Gu et al. addressed the challenge of sub-pulse identification for complex combined pulse signals in non-cooperative underwater sonar detection and proposed a time-frequency ridge extraction and fitting method based on STFT peak search [7]. An et al. proposed an improved time-frequency ridge method for multi-user wideband frequency-hopping signals [8], which performs parallel extraction and differential processing of the highest and lowest ridges combined with sliding-window merging and least-squares fitting, achieving high-precision and low-complexity estimation of the hopping rate and hopping time. Zhai et al. proposed a combined pulse signal identification and parameter estimation method based on time-frequency connected region reconstruction [9], which separates sub-pulses by connected domain labeling and then reconstructs discontinuous signals with a linear model and adaptive morphological dilation and erosion operations, effectively solving the problem of correct separation and complete parameter estimation of discontinuous combined pulse signals under low SNR conditions. Hao et al. proposed an iterative multi-ridge extraction method based on a sliding window and the second-order synchrosqueezing transform (SST) [10-12]. However, in complex electromagnetic environments, such methods are easily disturbed by noise and environmental factors, which causes problems such as fracture and blurring of time-frequency ridges, seriously reduces the completeness and accuracy of ridge extraction, and further increases parameter estimation errors.

2 TIME-FREQUENCY RIDGE EXTRACTION METHOD FOR PULSE SIGNALS

First, the signal pixel ratio of the time-frequency distribution matrix is calculated to evaluate its time-frequency feature density, which is the basis of time-frequency analysis of non-stationary signals. The signal pixel ratio is defined as the proportion of the significant-energy part in the time-frequency image, and its calculation formula is:

$$r_\rho = \frac{\sum_{t=1}^{N_t}\sum_{f=1}^{N_f} I(S(t,f) > T_b)}{\rho_t \times \rho_f} \tag{1}$$

where r_ρ represents the signal pixel ratio of the radar pulse signal, ρ_t and ρ_f represent the pixel sizes of the time axis and the frequency axis of the time-frequency image, respectively, $I(\cdot)$ represents the indicator function, which takes the value of 1 when the condition is satisfied and 0 otherwise, and T_b is the threshold for background noise energy estimation.

© By the Author(s) 2026, under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0).

Second, the binarization threshold is adaptively selected according to the signal pixel ratio r_ρ of the radar pulse signal [13]. When the signal energy distribution is relatively ideal, that is, the pixel ratio is within a reasonable range, the mean threshold method, which is simple and efficient, is adopted. Its threshold calculation formula is:

$$T_\rho = \mu_\rho + \omega \cdot \sigma_\rho \tag{2}$$

where μ_ρ represents the energy mean of all pixels in the time-frequency image, σ_ρ represents its standard deviation, and ω represents the adjustment coefficient. In scenarios where the signal and background noise are well separated, this method can quickly achieve effective binarization segmentation. When the signal pixel ratio is too small, it indicates that the pulse signal energy is sparse in the time-frequency domain, which usually results from a weak signal or a high noise floor. In this case, if the mean threshold method is used, the threshold will be dominated by the large-area low-energy background, causing weak signals to be misjudged as noise and lost. Conversely, when the ratio is relatively large, it indicates that high-energy regions are widely distributed in the time-frequency image, which is often caused by broadband interference or the large bandwidth of the signal itself. At this time, the mean threshold will be too low due to the elevated overall energy statistics, failing to effectively suppress noise, so that the binarization result contains a large number of false components.

To overcome the above limitations, when the pixel ratio exceeds the ideal range, a percentile threshold method based on data sorting is adopted instead, and its calculation formula is:

$$T_\rho = P_\alpha(E) \tag{3}$$

where E represents the time-frequency energy set, and $P_\alpha(\cdot)$ represents the operation of taking the α-th percentile. This method directly retains the $\alpha\%$ pixels with the highest energy, which can effectively extract weak signals at low ratios and significantly suppress noise at high ratios, thereby adapting to environments with different SNRs.

The time-frequency image is binarized using the determined threshold T_ρ to generate a binary matrix B_m:

$$B_m(t,f) = \begin{cases} 1, \text{if } S(t,f) \geq T_\rho \\ 0, \text{otherwise} \end{cases} \tag{4}$$

Next, the local frequency-domain maxima at different time points are extracted from the binary image B_m. For each time point t_i, the set of maximum points is defined as:

$$M_\rho(t_i) = \{f_i \mid B_m(t_i,f_i) = 1 \cap B_m(t_i,f_j) \geq B_m(t_i,f_{j+\Delta})\} \tag{5}$$

where Δ represents the local neighborhood radius, which is used to determine the extremum search range.

Eight-connected domain labeling is then performed on the maximum point sets [14-15], clustering spatially adjacent pixels into initial connected domains CR_k. To solve the problem of ridge fracture, the multi-dimensional similarity DS_{ij} between any two connected domains CR_i and CR_j is calculated:

$$DS_{ij} = w_t e^{\left(-\frac{|\bar{t}_i-\bar{t}_j|}{\gamma_t}\right)} + w_f e^{\left(-\frac{|\bar{f}_i-\bar{f}_j|}{\gamma_f}\right)} + w_b\left(1-\frac{|B_{wi}-B_{wj}|}{\max(B_{wi},B_{wj})}\right) + w_d\left(1-\frac{|D_{\rho i}-D_{\rho j}|}{\max(D_{\rho i},D_{\rho j})}\right) \tag{6}$$

where $\bar{t}$ and $\bar{f}$ represent the centroids of the connected domain in the time and frequency dimensions, respectively, B_w represents the frequency bandwidth, D_ρ represents the pixel density, w_t, w_f, w_b, w_d represent the weights of each dimension and satisfy $w_t + w_f + w_b + w_d = 1$, and γ_t, γ_f represent normalization parameters. If DS_{ij} is greater than the fusion threshold, the two connected domains are merged.

Finally, time-frequency ridge fitting is performed on the fused connected domains.

3 PARAMETER ESTIMATION OF PULSE SIGNALS

Based on the extracted continuous and smooth time-frequency ridges, parameter estimation can be transformed into mathematical calculation of the ridge trajectories. For the basic characteristic parameters shared by various radar pulse signals, including time of arrival (TOA), pulse width (PW) and pulse repetition interval (PRI) [16], a general estimation method based on time-frequency ridges is proposed.

First, parameters are extracted and estimated sequentially for each obtained time-frequency ridge $R_i = \{(t_{i,j}, f_{i,j})\}$. For the i-th ridge, its time of arrival TOA and time of end TOE can be obtained directly from the time coordinates of the ridge data points:

$$\text{TOA} = \min_j t_{i,j}, \quad \text{TOE} = \max_j t_{i,j} \tag{7}$$

Then, the pulse width PW is estimated by calculating the duration of the time-frequency ridge along the time axis:

$$\text{PW} = \text{TOE} - \text{TOA} \tag{8}$$

After the above parameter extraction is completed for all time-frequency ridges, the estimation stage of the pulse repetition interval begins. To improve the estimation accuracy and anti-interference capability, all time-frequency ridges belonging to the same modulation type are grouped and classified [17], which can effectively filter out interference such as the interleaving of non-homologous pulse signals and noise artifacts, ensuring that the subsequent analysis is carried out only on homologous pulse sequences. Through direct extraction and statistical calculation of the time endpoint information of the time-frequency ridges, this process achieves efficient and intuitive estimation of the basic parameters of pulse signals, such as time of arrival, pulse width and pulse repetition interval.

4 EXPERIMENTAL ANALYSIS

Table 1 shows the performance comparison results of four different methods in estimating the basic parameters of pulse signals. In terms of TOA estimation, the RMSE of the proposed method is only 1.25 μs, which is 31.7%, 59.9% and 48.1% lower than those of the SST method, the local extremum method and the multi-component fitting method, respectively. Its estimation bias is also controlled within 0.22 μs, far lower than those of the other methods, indicating that the proposed method can effectively suppress systematic errors and achieve high-precision localization of the pulse start time. In PW estimation, the RMSE of the proposed method is 1.89 μs, which is 29.2% to 58.6% lower than those of the other three methods, and its bias is only 0.31 μs, showing that the method has good stability and consistency in pulse duration estimation. In terms of PRI estimation, the proposed method also performs outstandingly, with an RMSE of 3.76 μs, 28.2% to 57.9% lower than those of the comparison methods, and a bias of 0.58 μs, which further verifies the effectiveness of the proposed method in extracting the temporal structure features of pulses.

Table 1 Error Comparison of Basic Pulse Parameter Estimation

Method	TOA		PW		PRI	
	RMSE	Bias	RMSE	Bias	RMSE	Bias
SST method	1.83 μs	0.45 μs	2.67 μs	0.62 μs	5.24 μs	1.28 μs
Local extremum method	3.12 μs	1.21 μs	4.56 μs	1.85 μs	8.93 μs	3.42 μs
Multi-component fitting method	2.41 μs	0.78 μs	3.34 μs	1.12 μs	6.57 μs	2.15 μs
Proposed method	1.25 μs	0.22 μs	1.89 μs	0.31 μs	3.76 μs	0.58 μs

The main reason for the error differences among the different methods in basic pulse parameter estimation lies in their different abilities to deal with time-frequency ridge fracture and noise interference. The local extremum method directly relies on the local extrema of the time-frequency image for ridge extraction, is sensitive to noise, and has difficulty in handling ridge fracture, so its estimation error is the largest. The multi-component fitting method fits the time-frequency distribution through a preset signal model. Although it improves the anti-noise capability to a certain extent, its performance is limited by the degree of model matching. By virtue of the high time-frequency resolution of the synchrosqueezing transform, the SST method performs relatively well in the continuity of ridge extraction, but it is still affected by noise-induced energy diffusion under low SNR conditions. The proposed method effectively reconstructs the fractured time-frequency ridges through adaptive-threshold binarization and connected domain labeling and fusion, and performs parameter estimation on this basis, thereby significantly suppressing noise interference while maintaining ridge continuity and achieving higher estimation accuracy and lower systematic bias.

5 CONCLUSION

Focusing on the problem of accurate parameter estimation of pulse signals under low SNR conditions, this paper proposes a robust estimation method based on time-frequency ridge connected domain extraction. The study first analyzes the limitations of traditional methods under strong noise environments, such as ridge fracture and estimation bias. On this basis, a three-stage technical route centered on time-frequency image binarization, connected-domain ridge repair and modulation feature extraction is systematically described. Experimental results show that, compared with the traditional SST method, the local extremum method and the multi-component fitting method, the proposed method exhibits lower estimation errors and better stability in key indicators, with particularly significant advantages under extremely low SNR conditions, which verifies the practicability and robustness of the method in complex electromagnetic environments.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Hui S Y, Yang L, Xing S Q, et al. An Extraction and Parameter Estimation Method of LFM Signals Under Pulse Splitting Conditions. Radar Science and Technology, 2025, 23(2): 158-166+175.
[2] Bai G, Cheng Y F, Tang W B, et al. Estimation of Sinusoidal Frequency-Modulated Signal Parameters by Two Branches and Two Stages. IEEE Transactions on Signal Processing, 2020, 68: 4959-4970.
[3] Deng H C, Zhang G Q, Liu B Q. Blind detection of non-cooperative underwater acoustic signals based on time-frequency domain association. Ship Science and Technology, 2023, 45(1): 157-162.
[4] Zhang Y H, Zhang Y X, Zhang C, et al. Parameter estimation method for LFM signals suppressing impulse noise. Journal of Xidian University, 2022, 49(6): 23-31+102.
[5] Yang Y, Cheng Y Q, Wu H, et al. Parametric Instantaneous Frequency Estimation via PWSR With Adaptive QFM Dictionary. IEEE Signal Processing Letters, 2023, 30: 738-742.
[6] Zhu H, Xu X G, Zou X J, et al. Method for Estimating the Key Parameters of Phase-Coded Signals With Low Sampling Rate Based on Wavelet Analysis and Periodic Annihilating Filtering. IEEE Transactions on Instrumentation and Measurement, 2025, 74: 1-18.
[7] Gu X, Wang X Y, Cao H L. Instantaneous Frequency Estimation of Noncooperative Underwater Acoustic Short-Pulse Signals Using the Peak of the STFT. 2024 OES China Ocean Acoustics (COA), 2024: 1-6.

[8] An J, Liu X D, Lv F F, et al. Parameter Estimation Method of Multi-broadband Frequency Hopping Signal Based on Improved Time-frequency Ridge. Computer Measurement & Control, 2025, 33(4): 225-231.
[9] Zhai Y, Wang X Y, Cao H L. Combined Pulse Signal Identification and Parameter Estimation Method Based on Time-Frequency Connected Region Reconstruction. 2024 OES China Ocean Acoustics (COA), 2024: 1-5.
[10] Hao Z Y, Zhang X X, Feng H P. Variable speed fault diagnosis of rolling bearings based on sliding-window multiple time-frequency ridge extraction. Journal of Hebei University (Natural Science Edition), 2025, 45(5): 551-560.
[11] Oberlin T, Meignen S, Perrier V. Second-Order Synchrosqueezing Transform or Invertible Reassignment? Towards Ideal Time-Frequency Representations. IEEE Transactions on Signal Processing, 2015, 63(5): 1335-1344.
[12] Daubechies I, Lu J F, Wu H T. Synchrosqueezed wavelet transforms: An empirical mode decomposition-like tool. Applied and Computational Harmonic Analysis, 2011, 30(2): 243-261.
[13] Otsu N. A Threshold Selection Method from Gray-Level Histograms. IEEE Transactions on Systems, Man, and Cybernetics, 1979, 9(1): 62-66.
[14] Suzuki S, Abe K. Topological structural analysis of digitized binary images by border following. Computer Vision, Graphics, and Image Processing, 1985, 30(1): 32-46.
[15] He L F, Ren X W, Gao Q H, et al. The connected-component labeling problem: A review of state-of-the-art algorithms. Pattern Recognition, 2017, 70: 25-43.
[16] Bang J H, Park D H, Kim H N. Improved TOA and Pulse Width Estimation for Wideband Signal in Electronic Warfare Systems. 2022 19th European Radar Conference (EuRAD), 2022: 73-76.
[17] Han Z Z, Zhao Z H, Gao Z B, et al. Radar Signal Sorting Algorithm Based on Pulse Repetition Interval. 2020 5th International Conference on Electromechanical Control Technology and Transportation (ICECTT), 2020: 163-166.