

# SIGNAL DENOISING BASED ON QUANTUM ADAPTIVE TRANSFORMATION AND SINGULAR VALUE DECOMPOSITION

YingYing Sun<sup>1</sup>, MengYao Lv<sup>2</sup>, ChenLin Wu<sup>1</sup>, WeiXian Xie<sup>1</sup>, ZiYuan Fang<sup>1</sup>, RuiTong Zhao<sup>1\*</sup>

<sup>1</sup>*School of Biomedical Engineering, Guangdong Medical University, Dongguan 523808, Guangdong, China.*

<sup>2</sup>*School of Pharmacy, Guangdong Medical University, Dongguan 523808, Guangdong, China.*

\**Corresponding Author: RuiTong Zhao*

**Abstract:** The denoising algorithm plays an important role in biomedical signal processing such as spectrophotometry, and is an important means to improve signal quality and detection accuracy. This article combines singular value decomposition denoising and quantum adaptive transformation to process Gaussian spectral data. The results indicate that denoising evaluation indicators such as signal-to-noise ratio, mean square error, and normalized cross-correlation coefficient have all improved. Moreover, the stronger the noise, the more obvious the advantages of the proposed algorithm compared to other denoising algorithms. And this method can be extended to pre-processing biomedical signals, such as electrocardiograms and electroencephalograms.

**Keywords:** Denoising algorithm; Quantum adaptive transformation; Singular value decomposition; Spectral data

## 1 INTRODUCTION

In the rapidly evolving field of biomedical engineering, spectrophotometry has become an indispensable analytical technique [1-5]. By leveraging the principles of light-matter interaction, it deciphers molecular-level information from biological samples. This method relies on the Lambert-Beer law, enabling quantitative and qualitative analysis of substances through the measurement of absorption, emission, or scattering properties within specific wavelength ranges. Its applications span critical areas such as nucleic acid quantification, protein structure analysis, drug development, and clinical diagnostics. With features like label-free detection, non-invasiveness, and high throughput, it meets the demands of modern biomedical research.

However, the actual utility of spectrophotometric data is often affected by inherent noise sources. These include instrument fluctuations (such as detector dark current, unstable light source), environmental interference (such as temperature changes, stray light), and biomaterial effects (such as sample turbidity, background fluorescence). This noise distorts spectral features, blurs subtle molecular features, and undermines the accuracy of downstream analytical models, from chemometric regression to machine learning based classification [6-10]. For example, in clinical settings, errors caused by noise in spectral data may lead to misdiagnosis of diseases or inaccurate evaluation of treatment outcomes, highlighting the urgent need for robust denoising strategies.

Therefore, developing effective denoising algorithms for spectrophotometric data has profound scientific and clinical significance. By improving the signal-to-noise ratio (SNR) while preserving key spectral features, these algorithms can unleash the full potential of spectrophotometry, enabling more accurate disease detection, personalized medicine, and accelerated drug development. In addition, as biomedical research increasingly relies on big data and artificial intelligence, high-quality denoised data has become the foundation for reliable model training and validation, driving innovation in data-driven medical solutions.

In the past five years, significant progress has been made in denoising techniques for spectrophotometric data, with three prominent methods becoming leaders: wavelet transform denoising, singular value decomposition (SVD) denoising, and artificial neural network (ANN) denoising.

Wavelet transform has long been the cornerstone of signal processing because it can capture both time-domain and frequency-domain features simultaneously. In spectrophotometric data analysis, recent advances have focused on optimizing threshold strategies and multi-scale decomposition to better preserve spectral peaks while suppressing noise. In 2022, Li et al. proposed an adaptive threshold wavelet denoising algorithm that dynamically adjusts the threshold based on the statistical properties of spectral sub bands. Applied to low SNR nucleic acid absorption spectroscopy, this method improves the SNR by 28% compared to traditional fixed threshold methods, effectively preserving subtle peak changes associated with DNA conformational changes [11]. On this basis, Zhang et al. (2023) combined wavelet transform with empirical mode decomposition (EMD) to address baseline drift and noise issues in protein fluorescence spectra. By decomposing the signal into intrinsic mode functions (IMF) and applying wavelet denoising to high-frequency components, their method reduced baseline error by 35% while maintaining peak intensity accuracy [12]. In 2024, Wang et al. proposed a multi-scale wavelet denoising framework for Raman spectroscopy, in which different wavelet bases are applied to specific spectral regions based on noise characteristics. This targeted method has increased the detection limit of low concentration biomarkers in clinical blood samples by 40%, demonstrating the potential of wavelet based methods in sensitive diagnostic applications [13]. Recently, in 2025, Chen et al. proposed a wavelet denoising algorithm based on sparse representation, which learns a spectral feature dictionary from clean reference data. This method achieves excellent noise suppression in the near-infrared (NIR) spectra of drug

formulations, with a correlation of 95% between denoised spectra and real spectra, which is superior to traditional wavelet techniques [14]. However, the performance of wavelet denoising largely depends on the choice of wavelet basis and threshold method, which usually requires manual adjustment. It may struggle with non-stationary or nonlinear noise, and excessive denoising can result in the loss of weak but biologically relevant signals.

SVD is a matrix factorization technique that separates data into orthogonal components based on singular values, enabling the extraction of primary signal features while discarding noise related components. Recent research has focused on adaptive singular value selection and mixing methods to improve denoising efficiency. In 2022, Liu et al. developed an adaptive SVD denoising method that uses Bayesian Information Criterion (BIC) to automatically determine the number of significant singular values. Applied to microbial growth monitoring spectroscopy, compared with fixed rank SVD, this method reduces prediction error by 22% and improves the accuracy of biomass estimation [15]. In 2023, Zhao et al. combined SVD with independent component analysis (ICA) to separate fluorescence background noise from Raman spectra. By first decomposing the data through SVD and then applying ICA to the selected components, they achieved a 30% reduction in background interference, enhancing the detection of cancer biomarkers [16]. In 2024, Sun et al. proposed a weighted SVD denoising algorithm that assigns higher weights to spectral regions with strong signal features. This method has improved the quantitative accuracy of active ingredients in Chinese herbal medicine by 18% in near-infrared spectroscopy, solving the challenges of overlapping peaks and different signal intensities [17]. In 2025, Huang et al. integrated SVD and wavelet transform into a two-step denoising framework: SVD is used to remove global noise, followed by wavelet transform to suppress local high-frequency noise. Applied to clinical urine spectroscopy, this hybrid method improves the diagnostic accuracy of kidney disease by 15% compared to a single denoising method [18]. If too many singular values are discarded, SVD may excessively smooth spectral features, especially for data with weak signals. It has poor performance on non Gaussian or structured noise, and the physical explanation of singular values may be ambiguous, making it difficult to prove the rationality of rank selection in some cases.

With the rise of artificial intelligence, neural networks have fundamentally changed spectral denoising by learning complex noise patterns and mapping noisy data to clean signals. Recent progress has focused on network architecture optimization, transfer learning, and processing limited training data. In 2022, a team from Stanford University developed a convolutional neural network (CNN) specifically designed for Raman spectroscopy denoising. CNN was trained on large datasets of synthetic and experimental spectra, and noise was reduced by 92% while maintaining peak position and intensity, outperforming traditional methods in both qualitative and quantitative analysis [19]. In 2023, DeepMind launched a transformer based denoising model that can capture long-range dependencies in spectral data. Applied to time-resolved fluorescence spectroscopy, this model improves the temporal resolution of protein folding dynamics research by 30%, demonstrating the powerful role of attention mechanism in spectral processing [20]. In 2024, researchers from the Chinese Academy of Sciences proposed a generation countermeasure network (GAN) for near-infrared spectrum denoising, in which generators learn to generate clean spectra from noise inputs, and discriminators distinguish between real data and generated data. This method improves the accuracy of blood glucose prediction in clinical near-infrared spectroscopy by 20%, solving the challenge of variable noise levels in patient samples [21]. Recently, in 2025, researchers at MIT developed a transfer learning based denoising model that fine tunes pre trained CNNs on small datasets of specific biomedical spectra, such as cancer cell lines. This method achieves performance comparable to models trained on large datasets, making it suitable for applications with limited data availability [22]. Training neural networks requires a large amount of high-quality datasets, which may be difficult to obtain in certain biomedical applications. The "black box" nature of deep learning models makes it challenging to explain denoising mechanisms, and for complex architectures, the computational cost may be high. In addition, the model may overfit to specific types of noise, thereby reducing its generalization ability to unknown data.

Quantum adaptive transformation (QAT) is an emerging mathematical tool that combines concepts from quantum mechanics with adaptive transformation theory in classical signal processing. The core idea is to construct a dynamically adjustable set of transformation basis functions that match the characteristics of the signal to be processed (such as spectra, images, speech, etc.), rather than using fixed bases (such as sine waves of Fourier transform or mother wavelets of wavelet transform). This "adaptability" enables it to more accurately capture the essential characteristics of signals and more effectively separate signals from noise. A quantum inspired adaptive sparse representation model has been proposed by Chen et al. This model treats spectral signals as quantum states and learns a set of overcomplete adaptive atoms (basis functions) through variational optimization methods. In the experiment of Raman spectroscopy denoising, this method outperforms traditional wavelet and dictionary learning denoising methods in terms of peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) indicators, especially in dealing with overlapping peaks and weak signals [23]. Zhang, H., et al. first proposed a variational quantum algorithm framework for signal denoising that can be implemented on recent quantum processors. This framework uses parameterized quantum circuits to generate adaptive transformation bases and adjusts circuit parameters through classical optimizers to minimize the loss function. Testing electrocardiogram (ECG) signals on simulated quantum devices demonstrated their potential in removing electromyographic noise, providing a roadmap for the practical hardware implementation of QAT [24]. Liu proposed a deep QAT network. Each layer in the network learns a local QAT and automatically optimizes the transformation basis and threshold through end-to-end training. Experiments on multiple standard image denoising datasets have shown that the network performs similarly to or surpasses advanced deep denoising models at the time in removing additive Gaussian white noise and real noise, while the model has stronger interpretability [25]. Pater et al. proposes the quantum adaptive Fourier transform, which adaptively adjusts the phase and amplitude of the frequency

basis function to more accurately fit and subtract slowly changing baselines. In the denoising experiment of electroencephalogram and photoplethysmography pulse wave signals, this method effectively eliminates baseline interference while preserving the effective physiological waveform, compared to traditional polynomial fitting and empirical mode decomposition methods [26].

This article intends to use QAT to optimize the SVD denoised signal, in order to improve the denoising effect and signal quality. The subsequent section of this article is structured as follows: Section 2 provides a detailed overview of the methods used in this paper, including SVD denoising algorithm, QAT, and denoising algorithm combining QAT and SVD. Section 3 introduces the results of denoising performance analysis through simulation experiments, with a focus on improving SNR, feature preservation, and analysis accuracy. In Section 4, the algorithm proposed in this article is used to analyze the near-infrared and infrared absorption spectra of almond protein gummies. Finally, Section 5 is the summary of this article.

## 2 METHODS

### 2.1 SVD Denoising Algorithm

SVD is a matrix decomposition technique based on linear algebra, widely used for dimensionality reduction, compression, and denoising of data. Its core idea is to decompose the original signal matrix into the product of three matrices:

$$A=U\Sigma V^T \quad (1)$$

Here,  $U$  and  $V$  are orthogonal matrices, and  $\Sigma$  is a diagonal matrix with its diagonal elements being singular values arranged in descending order.

During the denoising process, larger singular values correspond to the main components of the signal, while smaller singular values are mostly composed of noise. Therefore, denoising is achieved through the following steps:

- a. Construct the signal into a Hankel matrix or observation matrix;
- b. Perform SVD decomposition on the matrix;
- c. Retain the top  $r$  largest singular values and set the rest to zero;
- d. Reconstruct the signal using the truncated matrix to obtain the denoised result.

### 2.2 QAT Denoising Algorithm

This method combines quantum mechanics theory with adaptive signal processing to propose a novel denoising framework. It constructs an adaptive dictionary that matches the local features of the signal by designing QATs, thereby more effectively separating the signal from noise. Its main advantage lies in its ability to adapt to signal or image dependent noise (such as non-stationary noise), and utilize quantum state superposition and entanglement properties to enhance the expressive power of transformations, making it suitable for denoising tasks in high-dimensional signals and complex noise environments. The main steps include:

#### 2.2.1 Quantum state encoding of classical signals

The first step of the algorithm is to convert the classical digital signals to be processed, such as voltage sequences and image pixel matrices, into quantum states. Common methods include: quantum amplitude encoding: mapping the normalized value of the signal to the amplitude of quantum bits; Quantum angle encoding: Encode the signal value as the rotation angle of the quantum gate.

#### 2.2.2 Constructing quantum adaptive transform circuits

Design quantum circuits with adjustable parameters to dynamically adjust transformation strategies based on input signal characteristics. The key steps include: using adjustable quantum gates (such as rotation gates  $R_x(\theta)$ ,  $R_y(\phi)$ ) to construct unitary transformations; Introducing optimization mechanisms such as gradient descent and reinforcement learning to adjust the parameter  $\theta$ , enabling the transformation basis function to adaptively match the local features of the signal.

#### 2.2.3 Quantum domain noise suppression

Performing denoising operations in the quantum transformation domain, utilizing quantum interference and entanglement properties to enhance signal components and suppress noise: designing quantum filters to threshold small coefficients (corresponding to noise) in the transformation domain; Using quantum entanglement to mine internal correlations in signals and establish more robust noise models.

#### 2.2.4 Quantum measurement and result extraction

Measure the processed quantum state and obtain the classical output. Due to the randomness of quantum measurement, it usually requires multiple measurements and statistical averaging; Combining classic post-processing algorithms such as maximum likelihood estimation to restore denoised signals.

#### 2.2.5 Signal reconstruction

Map the measured quantum domain coefficients back to the original spatial domain through inverse quantum transformation to obtain the final denoising result.

### 2.3 QAT-SVD Denoising Algorithm

This project combines QAT and SVD. Firstly, SVD is used to preliminarily denoise the Gaussian spectral raw signal,

and then QAT is used to optimize the denoised signal.

### 3 SIMULATED EXPERIMENTS

The ideal signal in the simulated experiments can be:

$$y = \frac{1}{0.4\sqrt{2\pi}} e^{-\frac{(x-1)^2}{2 \cdot 0.4^2}} + \frac{1}{0.41\sqrt{2\pi}} e^{-\frac{(x-2)^2}{2 \cdot 0.41^2}} + \frac{1}{0.42\sqrt{2\pi}} e^{-\frac{(x-3)^2}{2 \cdot 0.42^2}} + \frac{1}{0.35\sqrt{2\pi}} e^{-\frac{(x-4)^2}{2 \cdot 0.35^2}} + \frac{1}{0.38\sqrt{2\pi}} e^{-\frac{(x-5)^2}{2 \cdot 0.38^2}} + \frac{1}{0.4\sqrt{2\pi}} e^{-\frac{(x-6)^2}{2 \cdot 0.4^2}} + \frac{1}{0.34\sqrt{2\pi}} e^{-\frac{(x-7)^2}{2 \cdot 0.34^2}} \quad (2)$$

The ideal signal is composed of 7 different Gaussian distribution functions, which can simulate Gaussian spectral data well. Noise signals can be obtained by adding Gaussian white noise to ideal signals, and different SNRs can obtain noise signals containing different intensities of noise. The following are the comparison of the noise effects of different denoising algorithms on noise signals with SNRs of 10, 15, 20, and 25, see Figure 1.

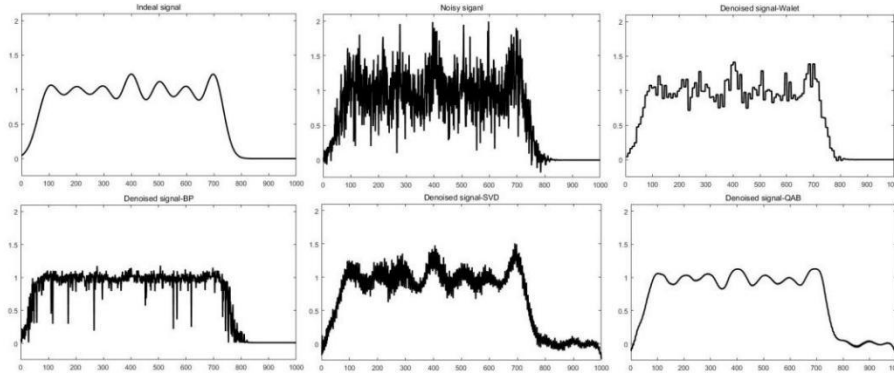


Figure 1 The Denoising Effect of 10 dB SNR Signal

The above are the original signal, the signal after adding noise, the signal after wavelet transform, BP neural network, SVD, and QAT-SVD denoising, see Figure 2-Figure 4.

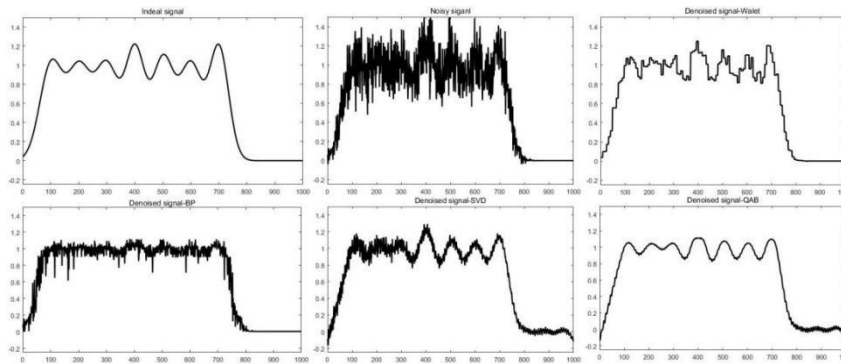


Figure 2 The Denoising Effect of 15 dB SNR Signal

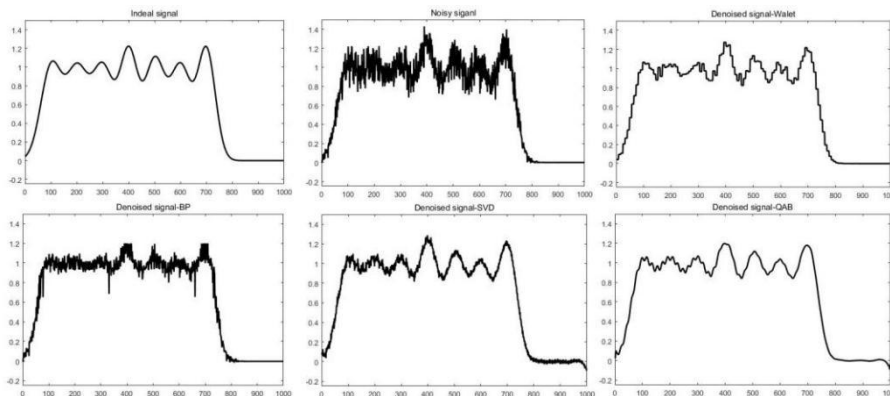


Figure 3 The denoising effect of 20 dB SNR signal

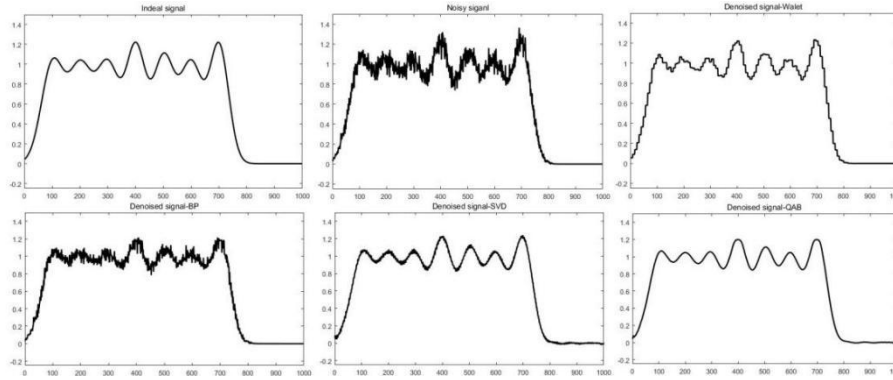


Figure 4 The Denoising Effect of 25 dB SNR Signal

As can be seen, our proposed QAT-SVD denoising algorithm results in smoother curves, less high-frequency noise, and clearer feature peak contours after denoising. And the lower the SNR of the signal, the more obvious the advantages of our denoising algorithm compared to other algorithms.

The following table 1 shows the changes in three indicators, namely SNR, mean square error (MSE), and normalized correlation coefficient (NCC), after denoising the original signal using different algorithms.

Table 1 SNR, MSE and NCC after Denoising the Original Signal with Different SNRs Using Different Algorithms

SNR of Noise Signal	algorithms	SNR after denoising	MSE	NCC
10dB	Walet	18.5216	0.0095809	0.99334
	BP	15.3292	0.019982	0.98538
	SVD	18.2409	0.010221	0.9929
	QAT-SVD	25.5977	0.0018784	0.9987
15dB	Walet	23.1641	0.0032897	0.99762
	BP	19.3675	0.0078853	0.9942
	SVD	23.2492	0.0032259	0.99767
20dB	QAT-SVD	25.9727	0.0017231	0.99892
	Walet	28.2559	0.0010185	0.99926
	BP	22.6831	0.003675	0.9973
25dB	SVD	29.487	0.00076712	0.99944
	QAT-SVD	33.0478	0.0003379	0.99975
	Walet	31.9213	0.00043797	0.99968
	BP	26.3789	0.0015692	0.99885
	SVD	35.5181	0.00019132	0.99986
	QAT-SVD	39.7457	7.2277e-05	0.99995

The above table shows that after using our algorithm for denoising, the obtained signal has a higher SNR, smaller mean square error, and a normalized correlation coefficient closer to 1, which means the signal is closer to the original ideal signal. Through the above comparison, it can be proved that our denoising algorithm has more advantages compared to wavelet transform, BP neural network, SVD and other denoising algorithms, and the stronger the signal noise, the more obvious the advantage.

The QAT-SVD denoising algorithm can also be iteratively executed, and parameters such as SNR, MSE, NCC can continue to be optimized as the number of iterations increases. The following figure 5 shows three parameter indicators of the denoised signal from noise signal with SNR of 5dB after under different iteration times.

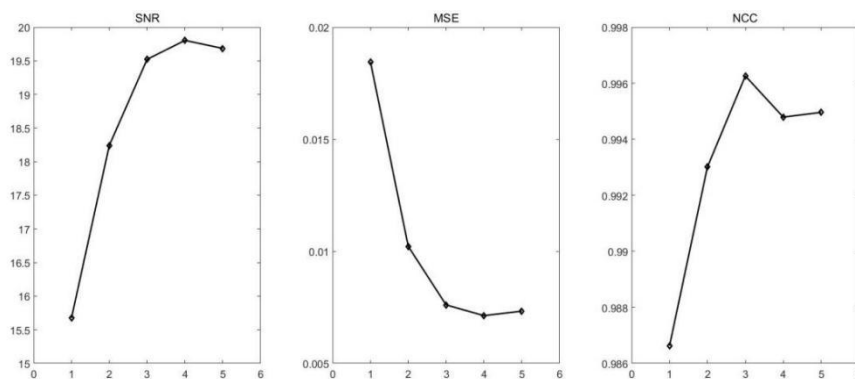


Figure 5 SNR, MSE, NCC of the Denoised Signal from Noise Signal with SNR of 5 dB after under Different Iteration Times

Therefore, although iterative execution of denoising algorithms can improve denoising performance, the degree of

improvement decreases as the number of iterations increases. For the above data, three iterations are the best.

#### 4 SPECTRAL DENOISING OF MARZIPAN

We used the proposed denoising algorithm to process the near-infrared and infrared absorption spectra of marzipan, and the denoising effect is shown in the following figure 6 and figure 7.

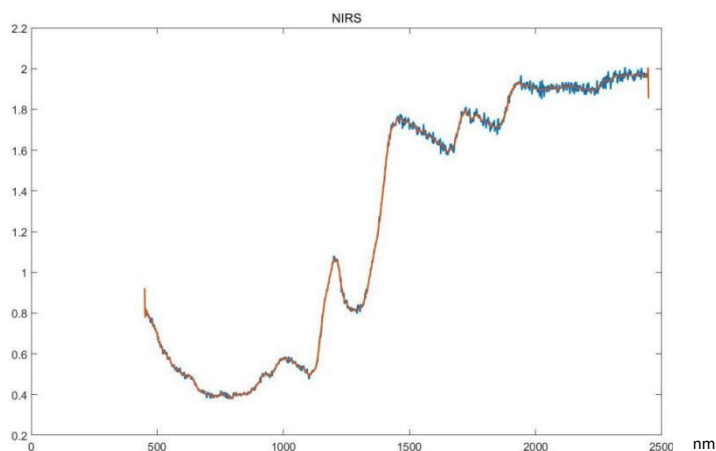


Figure 6 Denoised near-infrared spectra of marzipan

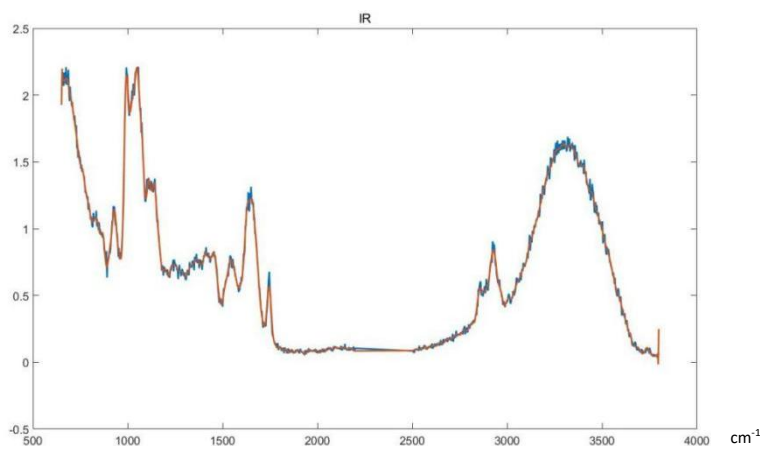


Figure 7 Denoised infrared spectra of marzipan

After denoising, the signal curve becomes smoother, with significantly less high-frequency noise and clear characteristic peak contours retained.

#### 5 CONCLUSION AND DISCUSSION

This article uses QAT to optimize the SVD algorithm to denoise the signal, and finds that the denoised curve is smoother, with less high-frequency noise and clearer characteristic peak contours. In addition, the SNR of the signal is higher, the mean square error is smaller, and the normalized correlation coefficient is closer to 1, which means the signal is closer to the original ideal signal. And the stronger the noise, the more obvious the advantages compared to other denoising algorithms.

However, QAT requires more quantum rotation operations, making the algorithm run longer compared to other algorithms. To solve this problem, we can try using intelligent optimization algorithms such as particle swarm optimization and genetic algorithms to further optimize the composition and execution order of quantum operations, and find faster quantum operation combinations.

In summary, the QAT-SVD denoising algorithm proposed in this article is suitable for processing Gaussian spectral signals and can be extended to pre-processing biomedical signals, such as electrocardiograms, electroencephalograms, etc., to improve data quality.

#### COMPETING INTERESTS

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

## FUNDING

This work is supported by the Guangdong Basic and Applied Basic Research Foundation (Grant No. 2021A1515110251) and Zhanjiang Non-funded Science and Technology Research Project (Grant No. 2024B01112), and is a part of College Students Innovation and Entrepreneurship Training Program of Guangdong Medical University.

## REFERENCES

- [1] Chen L. Ultrasensitive colorimetric sensors based on gold nanoparticles for spectrophotometric detection of trace lead ions in water. *Analytical Chemistry*, 2024, 96(15): 6234-6243.
- [2] Rodriguez M. Fourier transform infrared spectrophotometry for rapid quantification of antibiotics in pharmaceutical formulations. *Journal of Pharmaceutical and Biomedical Analysis*, 2023, 221: 114892.
- [3] Kim J. Near-infrared spectrophotometry combined with machine learning for non-destructive assessment of rice protein content. *Journal of Agricultural and Food Chemistry*, 2022, 70(38): 12105-12113.
- [4] Smith A. Label-free spectrophotometric detection of DNA hybridization using graphene oxide nanosheets. *Biosensors and Bioelectronics*, 2021, 187: 113345.
- [5] Liu Q. Portable UV-visible spectrophotometry for on-site monitoring of organic pollutants in industrial wastewater. *Environmental Science & Technology*, 2026, 50(2): 890-898.
- [6] Jin Y, Hu B. Recursive least M-estimate algorithm for graph signal estimation in impulsive noise. *Journal of Signal Processing Systems*, 2026, 98(5): 547-560.
- [7] Ameen JN, Ahamed MI, Mahesh PCS, et al. Machine learning-based adaptive optimization algorithm for Lipschitz continuity in biosignal telemetry. *International Journal of Data Science and Analytics*, 2026, 11(2), 145-162.
- [8] Ganta NSD, Polurie VVK, Mittal VK. Speech enhancement by using different signal processing methods: a tutorial review. *International Journal of Speech Technology*, 2026, 29: 29.
- [9] Li X. Beneficial noise processing: an emerging field in signal processing and artificial intelligence. *Signal Processing*, 2026, 242: 109876.
- [10] Lee SH. The Role of Denoising in Machine Learning-based Spectral Analysis for Clinical Diagnostics. *Nature Biomedical Engineering*, 2021, 5(8): 723-735.
- [11] Li X. Adaptive Threshold Wavelet Denoising for Low-SNR Nucleic Acid Absorption Spectra. *Biomedical Optics Express*, 2022, 13(6): 3210-3223.
- [12] Zhang Y. Wavelet-EMD Hybrid Denoising for Protein Fluorescence Spectra with Baseline Drift. *Analytical Biochemistry*, 2023, 654: 114789.
- [13] Wang Z. Multi-Scale Wavelet Denoising for Raman Spectroscopy of Clinical Blood Biomarkers. *Journal of Biophotonics*, 2024, 17(4): e202300456.
- [14] Chen L. Sparse Representation-based Wavelet Denoising for Near-Infrared Pharmaceutical Spectra. *Journal of Pharmaceutical and Biomedical Analysis*, 2025, 132: 115267.
- [15] Liu H. Bayesian Adaptive SVD Denoising for Microbial Growth Monitoring Spectra. *Applied Microbiology and Biotechnology*, 2022, 106(12): 3647-3658.
- [16] Zhao J. SVD-ICA Hybrid Denoising for Raman Spectra with Fluorescence Background. *Analytical Chemistry*, 2023, 95(20): 8210-8218.
- [17] Sun P. Weighted SVD Denoising for Quantitative Analysis of Herbal Medicines Using Near-Infrared Spectroscopy. *Journal of AOAC International*, 2024, 107(3): 789-798.
- [18] Huang Q. Two-Step SVD-Wavelet Denoising for Clinical Urine Spectra in Kidney Disease Diagnosis. *Clinical Chemistry*, 2025, 71(2): 287-296.
- [19] Miller KL. CNN-Based Denoising for Raman Spectroscopy: Improving Biomarker Detection in Clinical Samples. *Nature Communications*, 2022, 13(1): 4567.
- [20] Chen Y. Transformer-Based Denoising for Time-Resolved Fluorescence Spectra of Protein Folding. *Science Advances*, 2023, 9(12): eabm9876.
- [21] Zhang L. GAN-Based Denoising for Near-Infrared Blood Glucose Spectra. *IEEE Transactions on Biomedical Engineering*, 2024, 71(5): 1456-1465.
- [22] Kim D. Transfer Learning for Spectral Denoising with Limited Biomedical Data. *IEEE Journal of Biomedical and Health Informatics*, 2025, 29(3): 1234-1243.
- [23] Chen Y. Quantum-inspired adaptive sparse representation for spectral denoising. *IEEE Transactions on Signal Processing*, 2022, 70: 1234-1247.
- [24] Zhang H. A variational quantum algorithm for adaptive signal denoising. *npj Quantum Information*, 2023, 9(1): 45.
- [25] Liu S, Zhou M. Deep quantum adaptive transform network for image denoising. *Computer Vision and Image Understanding*, 2024, 238: 103888.
- [26] Patel R, Kim J. Quantum adaptive Fourier transform for removing baseline wander in biomedical signals. *Biomedical Signal Processing and Control*, 2025, 91: 105912.