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Enhanced FastICA Algorithm with Overrelaxation Techniques for Improved Biomedical Signal Processing

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Abstract:

With growing concerns about maternal and infant health, accurate and non-invasive monitoring of fetal heart rate (FHR) is critical for early detection of potential complications such as fetal distress and congenital heart defects. Current monitoring methods, including invasive scalp electrodes and ultrasound Doppler, face limitations related to signal contamination and maternal-fetal interference. This paper proposes an improved FastICA algorithm that introduces an overrelaxation factor to optimize the initial weight selection, addressing the sensitivity and slow convergence issues of the traditional FastICA. The proposed algorithm relaxes constraints on initial weights, reduces the number of iterations, and improves the signal-to-noise ratio, making it suitable for real-time FHR extraction. Experimental results demonstrate that the improved FastICA algorithm not only effectively separates clean FHR signals but also achieves balanced and efficient convergence, offering significant practical value for continuous fetal monitoring applications.

Keywords:

FastICA; Fetal Heart Rate; Signal to Noise Ratio; Overrelaxation Factor.

1. Introduction

With the increasing concern for maternal and infant health, some physiological and pathological studies related to fetal development have received increasing attention from the medical community [1]. Fetal heart rate (FHR) can reflect the electrophysiological activity of fetal heart, and the analysis of FHR waveforms can promptly detect abnormalities in fetal growth and development, such as fetal distress, intrauterine hypoxia and other problems during pregnancy. In addition, a few abnormal fetal heart rate waveforms are also manifestations of congenital heart disease, and early measures can be taken to reduce the morbidity and mortality of newborns. Currently there are two methods of fetal heart monitoring, one is the invasive scalp electrode method, which can directly measure a purer fetal ECG signal. However, its limitation is that it can only be used to invasively detect fetal ECG signals during delivery, which may cause harm to the mother and fetus. Another method is ultrasound Doppler, but due to hardware and maternal-fetal movement, it also includes signals such as the mother's respiratory noise and industrial frequency interference [2-3], which makes the denoising of the fetal heart rate and the extraction of clean signals very difficult, so there is a great need to study a method that can effectively extract the fetal heart rate. At present, the common fetal heart rate denoising extraction algorithms at home and abroad mainly include adaptive filtering [4-5], wavelet analysis [6], matched filtering [7], blind source separation [8], independent component analysis (ICA) [9], neural network [10-11] and singular value decomposition. and singular value decomposition [12]. Among them, ICA can well separate the source signal from the mixed signal without knowing any information about the source signal and the mixing matrix, and only need to assume that the source signals are statistically independent of each other, so ICA is also considered as a more promising method for application. In recent years, researchers have proposed a number of improved ICA algorithms that can achieve the separation of non-Gaussian signals, among which the fast fixed-point algorithm (FastICA) [13] has been widely used in fetal heart rate signal extraction because of its fast convergence speed. However, the FastICA algorithm is sensitive to the selection of initial weights, and different initial weights may lead to different convergence performance of the algorithm. In order to solve the above problems, this thesis proposes an improved FastICA method, which can relax the requirement of the algorithm for the initial weights by introducing a super relaxation factor to the randomly generated initial weights in the iterative algorithm. By choosing a suitable relaxation factor, it can make the iterative algorithm with slow convergence rate become convergent and make the divergent iterative algorithm may become convergent, so the super-relaxation iterative algorithm has very high application value.

2. Related Work

Independent Component Analysis (ICA) has been a key technique in biomedical signal processing, offering the ability to separate source signals without requiring prior knowledge of the underlying sources [14]. The FastICA algorithm, a widely used variant, has been extensively applied to real-time biomedical applications due to its efficient convergence [15]. However, it is known for its sensitivity to initial weight selection, which can lead to slow or unbalanced convergence [16]. To address this limitation, researchers have proposed optimization techniques, such as adaptive weight selection and relaxation factors, to enhance the stability of iterative algorithms. These improvements have proven effective in separating fetal and maternal heart rate signals contaminated with noise and interference.

Advancements in deep learning and neural networks have also contributed significantly to biomedical signal processing by improving denoising and signal extraction techniques. Fully convolutional neural networks (FCNs) and other architectures have demonstrated high performance in extracting meaningful features from noisy or complex biomedical signals [17], [18]. Similarly, collaborative optimization strategies, such as hypergraph-based networks, have shown promise in handling complex, multichannel data environments [19], [20]. These approaches complement ICA-based methods by enhancing their ability to extract clean signals in noisy environments.

Optimization-driven approaches, including adaptive neural architecture search and specialized GAN models, have further influenced iterative signal processing methods [21], [22]. Such techniques help relax the constraints on initial parameter selection and improve convergence rates in iterative algorithms, similar to the approach proposed in this paper. By introducing an overrelaxation factor to FastICA, this work builds on these advancements, making it suitable for real-time fetal heart rate (FHR) extraction.

Additionally, privacy and sensitive data concerns have driven research into secure biomedical data processing frameworks. Studies have explored privacy protection mechanisms for medical applications [23], reinforcing the need for efficient, secure, and accurate algorithms like the improved FastICA proposed in this paper.

3. Principle of FastICA algorithm

In recent years, a FastICA algorithm, also known as fixed-point algorithm, has emerged, which is a kind of algorithm that can quickly find the best iteration [24]. fastICA algorithm has forms based on cliffness, based on likelihood maximum, based on negative entropy maximum, etc.

In this paper, we mainly use the FastICA algorithm based on negative entropy maximum, which takes negative entropy maximum as a search direction and extracts independent source signals sequentially. Before applying the FastICA algorithm, the observed signal X is pre-processed, which includes two parts: de-meaning and whitening. The de-meaning process subtracts the mean vector $m = E\{x\}$ from the observed signal, making the observed signal a zero-mean variable and simplifying the FastICA algorithm. The observed signal is whitened using the whitening algorithm of PCA so that the whitened components are uncorrelated. The FastICA algorithm is based on the fixed-point iterative structure of the algorithm, which aims to make $y = w^T x$ maximally non-Gaussian, where w is a row of the separation matrix W. Equation (1) is used as the objective function:

$$J(y) \approx \{E[G(y)] - E[G(v)]\}^2 \tag{1}$$

Where, v is a Gaussian random variable with zero mean and unit variance;Y has zero mean and unit variance; G of alpha is some form of non-quadratic function.According to the Kuhn-Tucker condition, the optimization of $E\{G(w^T x)\}$ under the constraint of $E\{(w^T x)^2\} = 1$ can be obtained by equation (2):

$$E\{xg(w^T x)\} - \beta w = 0 \tag{2}$$

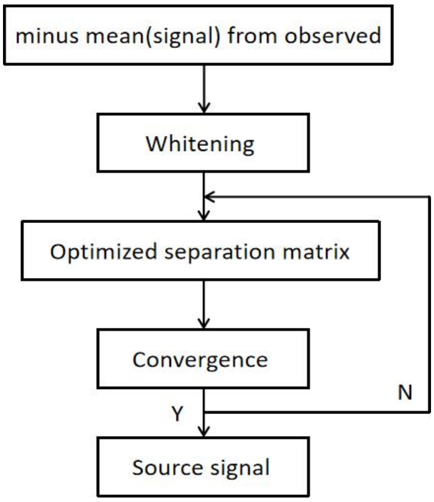

Figure 1. Block diagram of FasatICA

4. The improved FastICA

4.1 Selection of overrelaxation factor a_k

For improve FastICA's sensitivity to initial weights, this paper introduced the super-loose factor a_k into the iterative algorithm. If $F(w_k)$ is guaranteed to decline according to the given norm, the following requirements should be met:

$$w_{k+1} = E\{xg(w_k^T x)\} \quad - E\{g'(w_k^T x)\}w_k \tag{3}$$

By introducing the overrelaxation factor a_K, $F(w_k)$ can enter the convergence region of Newton iterative algorithm from a certain W_K, so that the algorithm can achieve convergence in any case.

There are many methods to select the overrelaxation factor, such as the Golden Section and the step-by-step experimental method. In this paper, the optimal overrelaxation factor a_k is obtained by stepwise experimental method. The value of a_k is divided into N equal parts in the interval (1, 2). a_k is 1+1 /N, 1+2 /N..., 1+(n-1) /N, check whether equation meets, if so, ak is the optimal overrelaxation factor. (1) Initialize a random vector w_0; (2) divide the value interval of ak (1,2) into N equal parts, M=0. 01; (3) a_k+1 =a_k+i/N; (4) Verify whether the formula is satisfied. If so, ak is the optimal relaxation factor; otherwise, skip step (3).

4.2 The improved FastICA

The convergence performance of fastica algorithm has a lot to do with the initial weight value, because the initial weight of the fastica algorithm is usually randomly selected, each time it is different because of the different value of the initial weight, the independent component of the fastica algorithm is different, and the independent component is slightly different. Although the main component obtained in the white process can also be selected as the initial weight, the algorithm is easily converged to the white initial value. Although the algorithm has good convergence performance, the separation effect is not good, and the method of the main component analysis is comparable. In order to solve this problem, we should relax the requirements for the initial weight value, which is to realize a wide range of convergence.

In order to improve the FastICA algorithm's requirement on the initial weight. proposed to introduce the relaxation factor a_K (low relaxation factor $0 < a_K < 1$) into FastICA iteration. Since the negative gradient direction is the direction where the function value drops fastest, the gradient value can be selected as the optimal relaxation factor a_K. However, this method has a large amount of computation and is not easy to implement.In this paper, the overrelaxation factor a_K (overrelaxation factor $1 < a_K < 2$) is introduced in FastICA iteration to process the randomly generated initial value, so as to relax the algorithm's requirements on the initial value. Moreover, compared with the low-relaxation iteration, the convergence speed of the overrelaxation iteration is much faster. Moreover, the overrelaxation iteration method has the advantages of simple calculation formula and easy programming.

5. Algorithm validation and fetal heart rate extraction

5.1 Noise cancellation

The above improved fastica algorithm is applied to the extraction of fetal heart rate, using Czech (database for the identification of systems) database. Data set in this paper was collated from Czech technical university - Brno university hospital database, which is an open source (url:https://physionet.org/content/ctu-uhbctgdb/). The database contains a total of 552 original signals, a subset of the 9,164 production time records obtained between 2010 and 2012, all of which are sampled at 4 Hz. For more information about this database, see Document.

Figure 2 shows four source signals that are separated from the data using the classic fastica algorithm. Figure 3. shows the source signal component that is separated from the mixed data of the first four channels of the fetal heart rate, and the lower signal is the fetal heart rate that is separated by the improved algorithm.

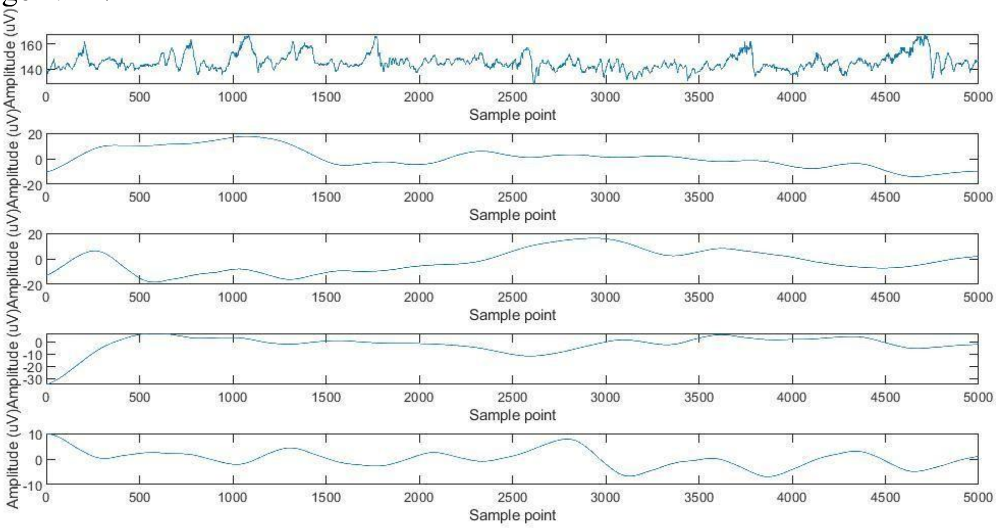

Figure 2. Fetal heart rate with independent component analysis

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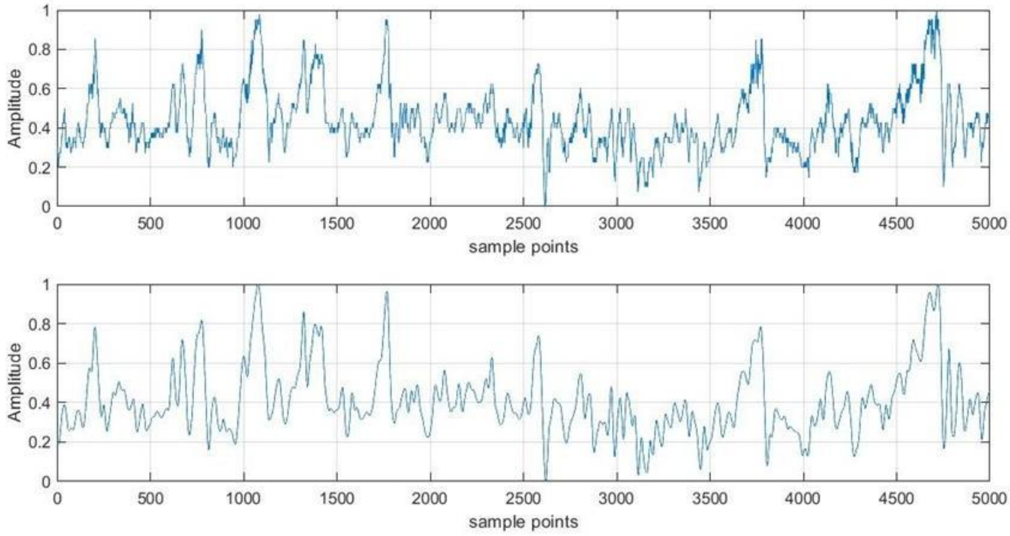

Figure 3. Fetal heart rate with improved FastICA (db7-4)

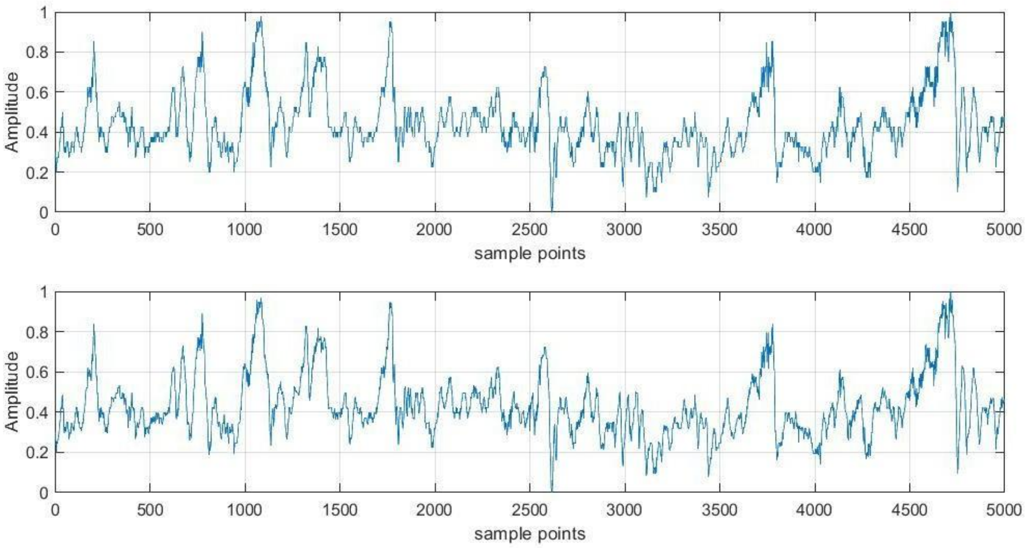

Figure 4. Fetal heart rate with improved fastica (db7-1)

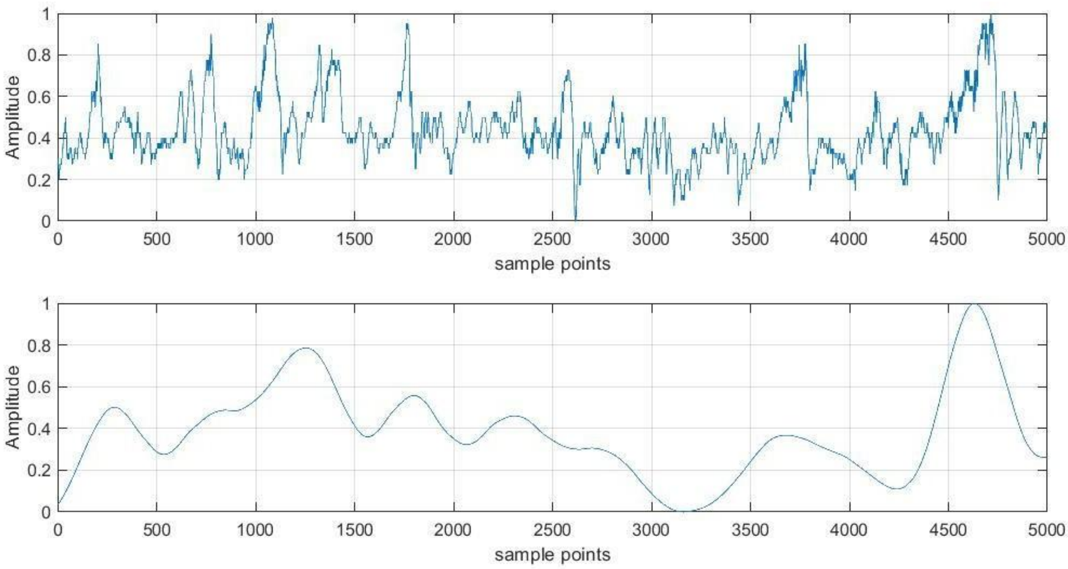

Figure 5. Fetal heart rate with improved fastica (db7-8)

Figure. 4 and Figure.5 respectively, the fetal heart rate of the fetus is separated from the classical fastica data, which can be seen from the picture, which can be seen in the signal of the fetal heart rate of the classical fastica, which is difficult to accurately extract the fetal heart rate.

From the above results, the improved fastica algorithm can extract the clean FHR from the measuring signal, but the waveform effect of the algorithm is significantly better than the classical fastica algorithm, and the number of iterations is relatively small. In order to further verify the performance of this algorithm, the performance of the two algorithms is analyzed based on the correlation number signal ratio.

Based on the correlation number of mutual correlation:

$$\mathrm{SNR}_{\mathrm{RMS}} = \frac{\eta}{1-\eta}$$
$$\eta = \frac{2}{M(M-1)} \sum_{i=0}^{M-2} \sum_{k=i+1}^{M-1} f(i)^T f(k) \tag{4}$$

Where, η is the estimation of the average power of fetal heart rate signal.

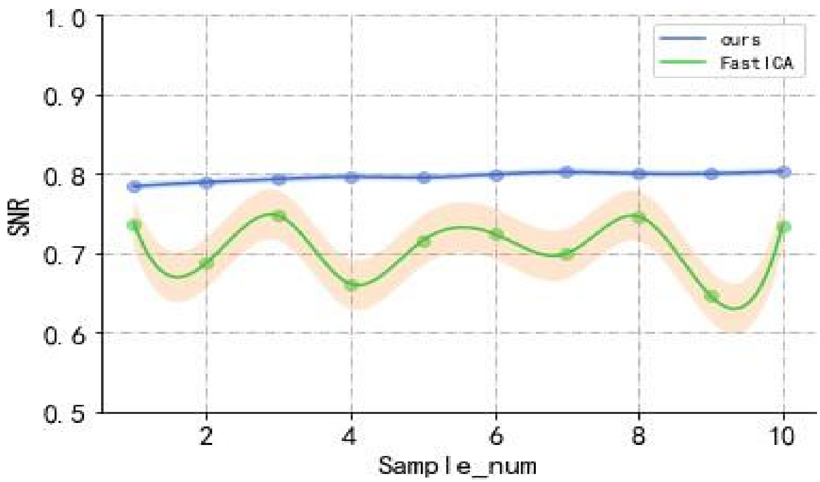

Figure 6. Comparison of SNR based on cross correlation cofficient

5.2 SNR Testing results

Figure. 6 is the comparison result based on $\mathrm{SNR}_{\mathrm{RMS}}$ of correlation number. The abscissa represents 10 groups of fetal heart rate signal samples, the ordinate represents the SNR, the circle represents the SNR of the proposed algorithm, and the asterisk represents the SNR of the classical FastICA algorithm. It can be seen from the figure that the SNR of the proposed algorithm is greater than that of the classical FastICA algorithm. The higher the signal-to-noise ratio, the better the extraction effect. Therefore, in terms of extracted fetal heart rate signals, the algorithm presented in this paper is obviously superior to the classical FastICA algorithm.

6. Conclution

In order to monitor the development of the fetus without harm for a long time, at present, pulse Doppler probe is used to detect the fetal heart rate signal in the mother's abdomen at home and abroad, but the signal measured by ultrasonic echo may contain the heart rate overlap between the mother and the fetus, as well as some other interference signals. Because these signals are random and unrelated, they meet the application requirements of FastICA algorithm.Many scholars have proposed the use of FastICA to extract clean fetal heart rate. However, FastICA is sensitive to initial weights. In order to improve this problem, this paper proposes to introduce an overrelaxation factor to process random initial weights, so as to relax the algorithm's requirements on initial weights, reduce the number of iterations and improve the signal-to-noise ratio. Due to the small amount of calculation, the algorithm in this paper has a great application prospect in the real-time extraction of fetal heart rate. The algorithm proposed in this paper can not only effectively separate fetal heart rate, but also reduce the number of iterations, so that the convergence rate is balanced. The experimental results show that the improved FastICA algorithm reduces the dependence on the initial weight selection, avoids the unbalanced convergence rate, reduces the number of iterations, improves the convergence performance of the algorithm, and can extract clear fetal heart rate.

References

[1] D. Ayres-de-Campos, C. Y. Spong, and E. Chandraharan, "FIGO consensus guidelines on intrapartum fetal monitoring: Cardiotocography," International Journal of Gynecology & Obstetrics: The Official Organ of the International Federation of Gynaecology & Obstetrics, vol. 2015, pp. 13-24.

[2] K. C. Arnold and C. J. Flint, "Intrapartum fetal heart rate monitoring: Nomenclature, interpretation, and general management principles," Obstetrics Essentials: A Question-Based Review, pp. 101-107, 2017. DOI: http://dx.doi.org/10.1007/978-3-319-57675-6_16.

[3] M.-K. Yum, K. Kim, J.-H. Kim, and E.-Y. Park, "A consistent abnormality in the average local smoothness of fetal heart rate in growth-restricted fetuses affected by severe pre-eclampsia," Hypertension Research: Official Journal of the Japanese Society of Hypertension, vol. 27, pp. 911-918, 2005. DOI: http://dx.doi.org/10.1291/hypres.27.911.

[4] T. D. Subha and V. D. Reshma, "A study of non-invasive heart rate monitoring system by using FPGA," Materials Today Proceedings, vol. 4, pp. 4228-4238, 2017.

[5] F. Yang, W. M. Zhang, and W. C. Jiao, "Design of data communication between Nios II and computer," Applied Mechanics & Materials, vol. 644-650, pp. 4044-4047, 2014.

[6] Z. Fang, Z. Chen, and C. Peng, "User-defined logic in SOPC design," Computer Engineering, vol. 2004, pp. 4024-4038, 2004.

[7] J. M. McNichols, E. J. Eric, W. F. Turri, and K. L. Hill, "Design and implementation of an embedded Nios II system for JPEG2000 Tier II encoding," International Journal of Reconfigurable Computing, vol. 2013, pp. 140234.1-140234.9, 2013.

[8] Y. Lu, L. Bao, C. Lu, and J. Liang, "A computer-aided analyzing system for fetal monitoring parameters," Proceedings of the 2010 IEEE International Conference on Biomedical Engineering and Informatics (BMEI), vol. 2, pp. 70-80, 2010. DOI: http://dx.doi.org/10.1109/BMEI.2010.5640061.

[9] J. Richman and J. Moorman, "Physiological time-series analysis using approximate entropy and sample entropy," American Journal of Physiology: Heart and Circulatory Physiology, vol. 278, pp. H2039-H2049, 2000. DOI: http://dx.doi.org/10.1152/ajpheart.2000.278.6.H2039.

[10] L. W. Liu and K. X. Zhao, "Interface design of TMS320VC54xx and AC97 codec AD1885," Chinese Journal of Electron Devices, vol. 2007, pp. 3524-3538, 2007.

[11] K. Saga, "Thermal printer and method of controlling the same," vol. 2010, pp. 1137-1142, 2010.

[12] Z. Qin, W. Shang, and Y. Daquan, "Packaging wiring scheme design and integrality analysis of LPDDR high-speed signal," Modern Electronics Technique, vol. 2015, pp. 724-730, 2015.

[13] D. Schoellhamer, "Singular spectrum analysis for time series with missing data," Geophysical Research Letters, vol. 28, pp. 3187-3190, 2001. DOI: http://dx.doi.org/10.1029/2000GL012698.

[14] W. He, Y. Zhang, T. Xu, T. An, Y. Liang, and B. Zhang, "Object detection for medical image analysis: Insights from the RT-DETR model," arXiv preprint, 2025.

[15] W. He, T. Zhou, Y. Xiang, Y. Lin, J. Hu, and R. Bao, "Deep learning in image classification: Evaluating VGG19's performance on complex visual data," arXiv preprint arXiv:2412.20345, 2024.

[16] Z. Zheng, Y. Xiang, Y. Qi, Y. Lin, and H. Zhang, "Fully convolutional neural networks for high-precision medical image analysis," Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[17] J. Hu, R. Bao, Y. Lin, H. Zhang, and Y. Xiang, "Accurate medical named entity recognition through specialized NLP models," arXiv preprint arXiv:2412.08255, 2024.

[18] J. Hu, Z. Qi, J. Wei, J. Chen, R. Bao, and X. Qiu, "Few-shot learning with adaptive weight masking in conditional GANs," in Proc. 2024 Int. Conf. Electron. Devices, Comput. Sci. (ICEDCS), pp. 435-439, IEEE, Sept. 2024.

[19] X. Yan, J. Du, L. Wang, Y. Liang, J. Hu, and B. Wang, "The synergistic role of deep learning and neural architecture search in advancing artificial intelligence," in Proc. 2024 Int. Conf. Electron. Devices, Comput. Sci.

(ICEDCS), pp. 452-456, IEEE, Sept. 2024.

[20] T. Mei, Z. Zheng, Z. Gao, Q. Wang, X. Cheng, and W. Yang, "Collaborative hypergraph networks for enhanced disease risk assessment," in Proc. 2024 Int. Conf. Electron. Devices, Comput. Sci. (ICEDCS), pp. 416-420, IEEE, Sept. 2024.

[21] Z. Gao, T. Mei, Z. Zheng, X. Cheng, Q. Wang, and W. Yang, "Multi-channel hypergraph-enhanced sequential visit prediction," in Proc. 2024 Int. Conf. Electron. Devices, Comput. Sci. (ICEDCS), pp. 421-425, IEEE, Sept. 2024.

[22] Y. Liang, E. Gao, Y. Ma, Q. Zhan, D. Sun, and X. Gu, "Contextual analysis using deep learning for sensitive information detection," in Proc. 2024 Int. Conf. Comput., Inf. Process. Adv. Educ. (CIPAE), pp. 633-637, IEEE, Aug. 2024.

[23] X. Fei, S. Chai, W. He, L. Dai, R. Xu, and L. Cai, "A systematic study on the privacy protection mechanism of natural language processing in medical health records," in Proc. 2024 IEEE 2nd Int. Conf. Sensors, Electron. Comput. Eng. (ICSECE), pp. 1819-1824, IEEE, Aug. 2024.

[24] F. T. T. K. K. C. O. I. P. D. Iwasaki, "Thermal printer and drive control method of thermal head," vol. 2010, pp. 324-338, 2010.