Research on FastICA Algorithm Based on Improved Secant Method (Postprint)

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Abstract

Blind source separation represents one of the active research areas in signal processing. Among numerous blind source separation algorithms, the fixed-point algorithm (FastICA) has garnered significant attention due to its rapid convergence; however, the convergence of FastICA is vulnerable to the selection of initial values for the demixing matrix. To remedy the deficiencies of FastICA, this work incorporates gradient descent to mitigate sensitivity to initial value selection and proposes an improved secant method to expedite convergence. Experimental results indicate that the FastICA algorithm based on the improved secant method, compared with other FastICA variants, not only enhances separation performance but also reduces iteration counts and improves convergence stability. Consequently, the improved FastICA algorithm surmounts the issue of initial value sensitivity, attaining more rapid and robust speech separation performance.

Full Text

Research on FastICA Algorithm Based on Improved Secant Method

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Abstract

Blind source separation (BSS) is a prominent research topic in signal processing. Among numerous BSS algorithms, the fixed-point algorithm (FastICA) has attracted considerable attention due to its rapid convergence rate. However, the convergence performance of FastICA is highly susceptible to the initial value selection of the demixing matrix. To address this limitation, this paper introduces the gradient descent method to reduce sensitivity to initial values and proposes an improved secant method to accelerate convergence speed. Experimental results demonstrate that compared with other FastICA algorithms, the proposed algorithm based on the improved secant method not only enhances separation performance but also reduces the number of iterations and improves convergence stability. Consequently, the improved FastICA algorithm overcomes the sensitivity to initial value selection and achieves faster and more robust speech separation performance.

Keywords: blind source separation; fixed-point algorithm; gradient descent method; improved secant method; speech separation

1. FastICA Algorithm Overview

Blind source separation (BSS) has long been a critical problem in signal processing. Independent component analysis (ICA) can effectively solve this problem by extracting signal components with non-Gaussian distributions and independent characteristics from random signals. ICA is a statistical signal processing method that has demonstrated excellent application results in numerous fields, including signal separation, digital image processing, and data analysis. In the early 1980s, Jutten and Christian first proposed the ICA technique prototype at a neurophysiology conference, successfully separating two mixed signals. Subsequently, many improved ICA algorithms have been proposed, such as Infomax ICA, JADE, SOBI, and FastICA. Among these, the fixed-point algorithm (FastICA) proposed by Hyvarinen et al. in 1997 has gained attention for its faster convergence speed and better robustness compared to other ICA improvement algorithms.

FastICA is a method that maximizes the non-Gaussianity of independent components hidden in mixed signals based on Newton' s iteration method. Since its proposal, many scholars have researched and improved FastICA. Some have optimized its convergence speed and computational complexity. For instance, in 2013, Tahir et al. proposed using an eighth-order convergent Newton' s method to optimize FastICA, significantly improving convergence speed. In 2017, He et al. proposed the EFICA algorithm, which replaced the original nonlinear approximation function with two new rational polynomials, improving separation performance and accelerating convergence. However, since the core iteration formula remains Newton' s iteration method, the algorithm' s sensitivity to initial values was not addressed. Other scholars have focused on improving FastICA' s convergence stability regarding initial value selection for the demixing matrix. In 2013, James et al. proposed a gradient iteration ICA algorithm that enabled faster convergence of the initial value matrix and achieved better stability under Gaussian noise. In 2014, Ji Ce et al. introduced a super-relaxation factor to process the initial value matrix, ensuring convergence speed while avoiding convergence imbalance caused by improper initial value selection. In 2015, Guo Wei et al. introduced Newton’ s downhill method to improve initial value sensitivity and achieved more stable speech separation results. In 2016, Ge et al. proposed the SparseFastICA algorithm, which used the sparsity of source signals as a constraint for FastICA, achieving better robustness in fMRI analysis. However, since SparseFastICA first uses FastICA to calculate the separation matrix and then constrains the demixing matrix based on the sparsity of the calculated source signals, its separation efficiency is insufficient. Despite over 20 years of development and many improved FastICA algorithms, none have simultaneously improved convergence speed and overcome initial value sensitivity. Therefore, this paper attempts to find a method that can better reduce the impact of initial value sensitivity while accelerating convergence speed.

FastICA is an iterative algorithm that continuously adjusts the demixing matrix until reaching a local optimum, making it a fast method for finding the optimal demixing matrix. The algorithm mainly consists of two parts: data preprocessing and independent component extraction.

1.1 Data Preprocessing

Data preprocessing typically includes centering and whitening. Centering subtracts the mean value from the observed signal vector, making it a zero-mean vector. This step simplifies the mixed signal and reduces noise effects. Whitening performs eigenvalue decomposition on the covariance matrix of the zero-mean vector to obtain the whitened vector. Whitening removes correlation from the centered data while performing dimensionality reduction to decrease computational complexity, typically using principal component analysis (PCA).

1.2 Independent Component Extraction

This paper studies the FastICA algorithm based on negentropy maximization, which uses negentropy as an approximate measure of the non-Gaussianity of independent components to estimate observed signals. The negentropy function is defined as:

$$J(y) = \rho\{E[G(y)] - E[G(v)]\}^2$$

where $J(y)$ represents the negentropy of random variable y, v is a standardized Gaussian random variable with zero mean and unit variance, ρ is a constant coefficient, and $E[\cdot]$ denotes the expectation operator. To obtain a more robust estimation, function G should not grow too fast with its argument. Proven useful functions include:

$$G_1(y) = \frac{1}{a_1} \log\cosh(a_1 y)$$

$$G_2(y) = -\exp\left(-\frac{y^2}{2}\right)$$

$$G_3(y) = \frac{y^4}{4}$$

where $a_1 \in [1, 2]$ and $a_1 \approx 1$.

FastICA can be understood as finding a direction, i.e., a unit vector w, such that the projection of independent components hidden in the mixed signal achieves maximum non-Gaussianity. The negentropy approximation typically reaches its maximum at the extreme points of $E[G(w^T z)]$. According to Lagrange conditions, the extreme value under the constraint $E[(w^T z)^2] = \|w\|^2 = 1$ is obtained where the gradient of the Lagrange function equals zero. Therefore, the problem of maximizing negentropy can be transformed into finding the maximum of $E[G(w^T z)]$. The optimization problem can be expressed as:

$$J_G(w) = E[G(w^T z)] + \beta(\|w\|^2 - 1)$$

where β is the Lagrange multiplier. Taking partial derivatives on both sides and setting them to zero yields the objective function:

$$F(w) = E\{zg(w^T z)\} + \beta w = 0$$

where $g(\cdot)$ is the derivative of $G(\cdot)$. Using Newton' s method to solve Equation (6) and find the extreme points of the objective function, the Newton iteration is:

$$w_{n+1} = w_n - \frac{E\{zg(w_n^T z)\} + \beta w_n}{E\{g'(w_n^T z)\} + \beta}$$

After normalization processing of w to improve iteration stability, the basic iteration formula of the negentropy-based FastICA algorithm is obtained:

$$w_{n+1} = E\{zg(w_n^T z)\} - E\{g'(w_n^T z)\} w_n$$

To obtain the optimal demixing matrix W, after n iterations, the separation matrix W makes the separated signals Y and Z uncorrelated, and the separated signals y_i can approximate the source signals as closely as possible.

From the FastICA principle, the algorithm depends on the selection of the initial demixing matrix and the iteration formula calculation, resulting in two main problems: a) **Initial value sensitivity**: When FastICA randomly selects the initial demixing matrix w_0, only when w_0 is close to the convergence extreme point w^* can better convergence be guaranteed. Therefore, initial value selection affects FastICA' s convergence stability. b) **High computational complexity in iteration**: Each iteration must compute $E\{g(w^T z)\}$ and $E\{g'(w^T z)\}$. Whether based on derivative operations of the objective function or Jacobian matrix operations, the computational complexity throughout the iteration process is substantial.

2. Improved Secant Method Principle

To reduce computational complexity during iteration and accelerate convergence speed, this paper proposes an iteration method based on the improved secant method to avoid derivative calculations in Newton' s iteration.

2.1 Secant Method

The secant method, also known as the difference quotient method, is an improvement on Newton' s iteration method. It approximates the tangent slope at x_n using the slope of the secant line formed by two points $(x_{n-1}, f(x_{n-1}))$ and $(x_n, f(x_n))$ on the function $f(x)$ curve:

$$f'(x_n) \approx \frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}}$$

From Newton' s iteration formula and Equation (11), the iteration formula can be derived as:

$$x_{n+1} = x_n - \frac{f(x_n)(x_n - x_{n-1})}{f(x_n) - f(x_{n-1})}$$

This is the secant method iteration formula.

2.2 Improved Secant Method

Literature [17] compares several different iteration methods, where the secant method has a convergence order of 1.618. Although slightly lower than Newton' s method' s second-order convergence, and the iteration speed is somewhat insufficient, it avoids the time-consuming derivative calculation required in each Newton iteration. To overcome the secant method' s insufficient convergence order and slightly slow iteration speed, this paper proposes an improved secant method that can accelerate iteration speed while reducing computational complexity per iteration. The improved secant method is:

$$\begin{cases} x_{n+1} = x_n - \frac{f(x_n)(x_n - x_{n-1})}{f(x_n) - f(x_{n-1})} \\ \tilde{x}_{n+1} = x_n - \frac{f(x_n)(x_n - \tilde{x}_{n-1})}{f(x_n) - f(\tilde{x}_{n-1})} \end{cases}$$

where $\tilde{x}_n$ is a non-zero real number. According to the formula:

$$\tilde{x}_{n+1} = x_n - \frac{f(x_n)(x_n - \tilde{x}_{n-1})}{f(x_n) - f(\tilde{x}_{n-1})}$$

where $\tilde{x}_n$ is a non-zero real number. From the definition, we know $e_n = x_n - x^*$, and based on these formulas:

$$e_{n+1} = ke_n^p$$

The improved secant method has at least 2.414-order convergence, which is significantly higher than Newton' s method' s second-order convergence.

2.3 Convergence Order of Improved Secant Method

Referencing the proof of convergence order for first-order secant methods [17-19], we prove that the improved secant method has a convergence order of 2.414. The proof is as follows:

The secant method is a variant of Newton' s iteration. According to Newton' s method definition, given equation $f(x) = 0$ with real root x^*, let iteration sequence $\{x_n\}$ converge to root x^*, where x_n is the value at each iteration. Let $e_n = x_n - x^*$ represent the error at iteration n. If there exists real constant $k \neq 0$ such that:

$$\lim_{n\to\infty} \frac{e_{n+1}}{e_n^p} = k$$

then iteration sequence $\{x_n\}$ is said to be p-order convergent.

From the first fraction of Equation (12):

$$x_{n+1} = x_n - \frac{f(x_n)(x_n - x_{n-1})}{f(x_n) - f(x_{n-1})}$$

Combining iteration error $e_n = x_n - x^*$:

$$e_{n+1} = e_n - \frac{f(x_n)(e_n - e_{n-1})}{f(x_n) - f(x_{n-1})}$$

According to the Lagrange mean value theorem, there exists ξ_n between x_n and x^* such that:

$$f(x_n) - f(x^*) = f'(\xi_n)(x_n - x^*)$$

This leads to the transformation:

$$e_{n+1} = e_n - \frac{f'(\xi_n)e_n(e_n - e_{n-1})}{f'(\xi_n)e_n - f'(\xi_{n-1})e_{n-1}}$$

Simplifying:

$$e_{n+1} \approx \frac{f'(\xi_{n-1})e_{n-1}e_n}{f'(\xi_n)e_n - f'(\xi_{n-1})e_{n-1}}$$

From the definition $e_{n+1} = ke_n^p$, we have:

$$ke_n^p \approx \frac{f'(\xi_{n-1})e_{n-1}e_n}{f'(\xi_n)e_n - f'(\xi_{n-1})e_{n-1}}$$

Since $e_{n-1} = k^{-1/p}e_n^{1/p}$, substituting yields:

$$ke_n^p \approx Ce_n^{1+1/p}$$

Equating exponents gives $p = 1 + 1/p$, solving which yields $p \approx 2.414$. Therefore, the improved secant method has a convergence order of 2.414, significantly higher than Newton' s method.

3. Algorithm Implementation

3.1 Optimization of Initial Demixing Matrix

To enable rapid convergence of the initial demixing matrix and reduce initial value sensitivity, we introduce gradient descent to optimize the initial matrix, referencing gradient methods [12,21]. Gradient descent, also known as the steepest descent method, typically finds the minimum point x^* of function $f(x)$ by starting from x_0 and finding a direction p_n where:

$$x_{n+1} = x_n + \lambda_n p_n$$

with λ_n as the iteration step size (correction parameter). The gradient descent objective function is:

$$p_n = -\frac{\partial f(x_n)}{\partial x_n}$$

For FastICA, the correction parameter at each iteration can be expressed as:

$$\lambda_n = \arg\min_{\lambda} f(x_n + \lambda p_n)$$

Combining with FastICA algorithm Equation (6), we have:

$$F(w) = E\{zg(w^T z)\} + \beta w$$

The iteration formula for w is:

$$w_{n+1} = w_n + \lambda_n p_n = w_n - \lambda_n \frac{\partial F(w_n)}{\partial w_n}$$

According to the Lagrange mean value theorem, there exists ξ_n between w_n and w_{n+1} such that:

$$F(w_{n+1}) - F(w_n) = F'(\xi_n)(w_{n+1} - w_n)$$

This yields the transformation:

$$w_{n+1} = w_n - \lambda_n E\{zg(w_n^T z)\}$$

The algorithm steps for optimizing the initial matrix are: a) Randomly select initial demixing matrix w_0; b) Compute the negative gradient value $p_n = -E\{zg(w_n^T z)\}$ at w_n; c) Update $w_{n+1} = w_n + \lambda_n p_n$; d) If w_n converges, i.e., $|w_{n+1} - w_n| < \varepsilon$, where independent components follow a Gaussian distribution according to normal distribution 3σ with $\varepsilon = 0.00135$, then w_{n+1} is the locally optimal initial value and iteration stops. Otherwise, return to step c).

Gradient descent reduces initial value selection sensitivity and corrects the random initial matrix, effectively improving FastICA' s initial value sensitivity problem. Additionally, gradient descent converges rapidly in early iterations, accelerating FastICA' s convergence speed and enhancing algorithm stability.

3.2 FastICA Based on Secant Method

To reduce FastICA' s computational complexity, literature [22] proposed a FastICA algorithm based on Newton' s correction method, which significantly reduced iteration computational load. Inspired by this, combining objective function Equation (6) and secant method Equation (11), we obtain the iteration form for demixing matrix w:

$$w_{n+1} = w_n - \frac{E\{zg(w_n^T z)\} - E\{g'(w_n^T z)\} w_n}{E\{g'(w_n^T z)\} - E\{g''(w_n^T z)\} w_n^T z} \cdot \frac{w_n - w_{n-1}}{E\{zg(w_n^T z)\} - E\{zg(w_{n-1}^T z)\}}$$

This yields the iteration formula for the secant method-based FastICA algorithm (SFastICA):

$$\begin{cases} w_{n+1} = w_n - \frac{F(w_n)(w_n - w_{n-1})}{F(w_n) - F(w_{n-1})} \\ \tilde{w}_{n+1} = w_n - \frac{F(w_n)(w_n - \tilde{w}_{n-1})}{F(w_n) - F(\tilde{w}_{n-1})} \end{cases}$$

The SFastICA algorithm has two initial iteration matrices and, like standard FastICA, is susceptible to initial value selection. However, introducing gradient descent to optimize the initial matrix compensates for SFastICA' s insufficient convergence speed. Thus, SFastICA can reduce initial value sensitivity while improving convergence speed and stability to some extent.

3.3 FastICA Based on Improved Secant Method

Higher convergence order leads to faster iteration convergence. To further improve the secant method' s convergence speed, this paper proposes the FastICA algorithm based on improved secant method (ISFastICA). Section 2.3 proved that the improved secant method has a convergence order of 2.414, higher than Newton' s method' s second-order convergence, with significantly faster convergence speed. Combining objective function Equation (6) and improved secant method Equation (12), we obtain the iteration formula:

$$\begin{cases} w_{n+1} = w_n - \frac{F(w_n)(w_n - w_{n-1})}{F(w_n) - F(w_{n-1})} \\ \tilde{w}_{n+1} = w_n - \frac{F(w_n)(w_n - \tilde{w}_{n-1})}{F(w_n) - F(\tilde{w}_{n-1})} \end{cases}$$

This yields the iteration formula for ISFastICA:

$$\begin{cases} w_{n+1} = w_n - \frac{E\{zg(w_n^T z)\} - E\{g'(w_n^T z)\}w_n}{E\{g'(w_n^T z)\} - E\{g''(w_n^T z)\}w_n^T z} \cdot \frac{w_n - w_{n-1}}{E\{zg(w_n^T z)\} - E\{zg(w_{n-1}^T z)\}} \\ \tilde{w}_{n+1} = w_n - \frac{E\{zg(w_n^T z)\} - E\{g'(w_n^T z)\}w_n}{E\{g'(w_n^T z)\} - E\{g''(w_n^T z)\}w_n^T z} \cdot \frac{w_n - \tilde{w}_{n-1}}{E\{zg(w_n^T z)\} - E\{zg(\tilde{w}_{n-1}^T z)\}} \end{cases}$$

The ISFastICA algorithm steps are: a) Center the observed signals: $x_i \leftarrow x_i - \frac{1}{n}\sum_{j=1}^{n} x_j$; b) Whiten the data: $z = Vx = ED^{-1/2}E^T x$; c) Randomly select two initialization vectors w_0 and w_1 with unit norm, and optimize the initial matrix using gradient descent; d) Update w_{n+1}: substitute the optimized demixing matrix into Equation (33); e) If w_n converges, i.e., $|w_{n+1} - w_n| < \varepsilon$, where according to normal distribution 4σ with $\varepsilon = 0.0000315$, the algorithm converges and stops. Otherwise, return to step d); f) Multiply the converged optimal demixing matrix W with observed signal x to obtain the estimated source signals $Y = WX$.

4. Experimental Results and Analysis

To evaluate the performance of ISFastICA, we conducted comparative experiments with FastICA, EFICA [11], SparseFastICA [15] (S-FICA), SFastICA, and ISFastICA. We used speech signals from three different speakers (s2_bbbs5p.wav, s5_bbiy7s.wav, s6_bbwz7n.wav) from the Two-talker dataset

[23,24]. First, we read three clean speech signals, multiplied them by a randomly generated mixing coefficient matrix to obtain mixed signals, then used the five algorithms to separate the mixed signals, obtaining three estimated signals. Finally, we statistically analyzed the signal-to-noise ratio (SNR), iteration count, and separation time for each algorithm, and evaluated convergence characteristics and sensitivity to initial value selection.

4.1 Separation Performance Comparison

Separation experiments used SNR as the metric for separation quality. SNR describes the ratio of effective components to noise components in estimated signals—generally, higher SNR indicates better separation [25]. SNR is defined as:

$$SNR = 10 \log_{10} \frac{\sum_{i=1}^{n} s_i^2}{\sum_{i=1}^{n} (s_i - \hat{s}_i)^2}$$

where s_i represents the clean source signal and $\hat{s}_i$ represents the separated estimated signal. We conducted 100 separation experiments, statistically analyzing and averaging the SNR, iteration count, and separation time for the five algorithms, as shown in .

Table 1. Experimental Parameter Comparison

Algorithm	SNR (dB)	Iterations	Separation Time (s)
FastICA			
EFICA			
S-FICA			
SFastICA			
ISFastICA			

Table 1 shows that in terms of SNR, ISFastICA performs better than S-FICA, which performs better than SFastICA, which performs better than FastICA, though ISFastICA is slightly inferior to EFICA. ISFastICA' s SNR is 3.82% higher than FastICA, while SFastICA' s SNR is 2.54% higher than FastICA. In terms of iteration count, ISFastICA requires fewer iterations than S-FICA, which requires fewer than SFastICA, which requires fewer than EFICA, which requires fewer than FastICA. ISFastICA reduces iteration count by 38.89% compared to FastICA, while SFastICA reduces it by 11.11%. In terms of separation time, ISFastICA is faster than EFICA, which is faster than SFastICA, which is faster than FastICA, which is faster than S-FICA. ISFastICA improves separation time by 24.72% compared to FastICA, while SFastICA improves it by 9.44%. Thus, ISFastICA offers significant improvements in both separation performance and efficiency.

4.2 Convergence Characteristics Comparison

We read three source signals. [Figure 1: see original paper] shows the sampled waveforms of the clean speech signals, with the x-axis representing sample points and the y-axis representing waveform amplitude.

We linearly mixed the three source signals by multiplying them with a randomly generated mixing coefficient matrix to obtain three mixed signals, as shown in [Figure 2: see original paper].

Using the five algorithms to separately estimate the mixed signals yielded different separation results, as shown in [Figure 3: see original paper].

To evaluate algorithm convergence characteristics, we examined the relationship between demixing matrix iteration differences and iteration counts. Faster decreasing iteration differences indicate faster convergence. The 3D bar chart of convergence characteristics is shown in [Figure 4: see original paper], where bars from outer to inner represent FastICA, EFICA, S-FICA, SFastICA, and ISFastICA, with bar height representing iteration differences and the x-axis representing iteration numbers.

[Figure 4: see original paper] shows that FastICA, EFICA, S-FICA, SFastICA, and ISFastICA required 18, 13, 14, 16, and 11 iterations, respectively. Clearly, the convergence speeds from fastest to slowest are ISFastICA, EFICA, S-FICA, SFastICA, and FastICA. Therefore, ISFastICA demonstrates superior convergence performance.

4.3 Initial Value Sensitivity Comparison

To compare how initial demixing matrix selection affects algorithm convergence, we conducted 10 separation experiments on the three mixed signals, each with randomly generated different initial matrices. We then statistically analyzed iteration count variations across algorithms, as shown in .

Table 2. Iteration Count Statistics

Experiment	FastICA	EFICA	S-FICA	SFastICA	ISFastICA
1					
2					
...					
10					
Mean					
Variance					

Table 2 shows that ISFastICA has the smallest mean iteration count, followed by EFICA, S-FICA, SFastICA, and FastICA. ISFastICA also has the smallest iteration count variance, followed by SFastICA, EFICA, and FastICA, though slightly larger than S-FICA. Thus, ISFastICA requires the fewest iterations and demonstrates good convergence stability for different initial demixing matrices, with less sensitivity to varying initial values.

To more intuitively observe how randomly generated initial matrices affect convergence performance in each experiment, we plotted iteration counts as histograms in [Figure 5: see original paper], where each group from left to right represents ISFastICA, EFICA, S-FICA, SFastICA, and FastICA, with bar height representing iteration counts and the x-axis representing experiment number.

[Figure 5: see original paper] shows that in each group, ISFastICA has the lowest bars with minimal variation between groups, reflecting that ISFastICA has the most stable convergence performance for different initial demixing matrices. In other words, ISFastICA is least affected by initial value sensitivity among the five algorithms and has the fastest iterative convergence.

4.4 Experimental Analysis

Statistical analysis of experimental results comparing the five algorithms yields the following conclusions: a) As shown in Table 1, ISFastICA' s separation performance is superior to EFICA, S-FICA, SFastICA, and FastICA. b) As shown in [Figure 4: see original paper], ISFastICA has the fastest convergence speed. c) Initial value sensitivity experiments demonstrate that ISFastICA not only converges faster but also has better convergence stability than the other four algorithms.

Compared to standard FastICA, ISFastICA not only reduces initial value selection sensitivity but also achieves faster convergence and better stability. Compared to SFastICA, ISFastICA improves separation performance and accelerates convergence. Compared to EFICA, ISFastICA has slightly lower SNR but faster convergence and better robustness. Compared to S-FICA, ISFastICA has slightly inferior convergence stability but significantly improved convergence speed and SNR. Comparing FastICA, SFastICA, and ISFastICA shows that gradient descent effectively reduces initial value sensitivity, resulting in smaller iteration count variance and more stable convergence. Therefore, the improved secant method enhances separation performance while reducing initial value sensitivity, accelerating convergence speed, and improving convergence stability.

5. Conclusion

This paper introduces gradient descent to overcome FastICA' s sensitivity to initial value selection and proposes an improved secant method to enhance convergence speed and stability. Through theoretical proof and experimental verification, ISFastICA converges faster than FastICA and SFastICA, with better convergence stability than SFastICA and FastICA. Additionally, compared with state-of-the-art FastICA improvements EFICA and SparseFastICA (S-FICA), ISFastICA demonstrates improved convergence stability and separation performance. Thus, the FastICA algorithm based on improved secant method not only accelerates convergence but also enhances stability. However, since the improved algorithm lacks prior knowledge, it cannot distinguish and extract a specific person' s speech from mixed speech. Future research will focus on deep clustering-based speech separation.

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Note: Figure translations are in progress. See original paper for figures.