# Postprint: Application of Invasive Weed Optimization with Chaotic Position Reconstruction in Blind Source Separation

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## Abstract

Traditional blind source separation (BSS) optimization algorithms have very limited application scenarios and low separation performance. To address this, a novel invasive weed optimization (IWO) algorithm employing position chaotic reconstruction is proposed, and its application to blind source separation is investigated. In the early stage of each iteration, the new algorithm drives selected superior individuals to move an appropriate distance toward the current population' s best individual. This not only increases population diversity and prevents premature convergence but also accelerates the convergence speed. Blind signal separation simulation experiments confirm that, compared with standard IWO, particle swarm optimization (PSO), and natural gradient (NG) algorithms, the proposed algorithm demonstrates significant performance advantages, faster convergence speed, and higher separation accuracy.

## Full Text

### Application of Invasive Weed Optimization Based on Location Chaos Reconstruction to Blind Source Separation

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**Abstract:** Traditional optimization algorithms for blind source separation (BSS) suffer from limited applicability and low separation performance. To address these issues, this paper proposes a novel invasive weed optimization (IWO) algorithm based on location chaos reconstruction and investigates its application to BSS. The new algorithm drives selected superior individuals to move a moderate distance toward the current population' s optimal individual at the beginning of each update round. This strategy not only increases population diversity and prevents premature convergence but also accelerates convergence speed. Blind signal separation simulation experiments demonstrate that compared with standard IWO, particle swarm optimization (PSO), and natural gradient (NG) algorithms, the proposed algorithm exhibits superior performance, faster convergence, and higher separation accuracy.

**Key words:** invasive weed optimization; blind source separation; location reconstruction; chaos

## 0 Introduction

Blind source separation (BSS) refers to the technique of recovering independent components of source signals from observed signals (also called mixed signals) without prior knowledge of either the source signals or the mixing system characteristics. As a current research hotspot in signal processing, BSS has found widespread applications in image processing, speech recognition, biomedical engineering, and mechanical fault detection [1~4].

Independent component analysis (ICA) is a process that transforms a set of mixed signal vectors into a set of statistically independent vectors, minimizing the dependencies among vector components. ICA represents an important technique for blind signal separation. Generally, BSS based on ICA comprises two key components: an independence criterion and an optimization algorithm. The independence criterion defines or describes the statistical independence of separated signals, while the optimization algorithm searches for the optimal solution (the optimal separation matrix) within the criterion function space. The optimization algorithm is a critical factor determining the convergence speed and separation accuracy of BSS algorithms. Therefore, selecting an appropriate optimization algorithm is essential for effective BSS implementation.

Traditional BSS optimization algorithms based on natural gradient (NG) not only require the criterion function space to be convex and continuously differentiable but also cannot handle complex multimodal optimization problems, significantly limiting their applicability. To overcome these limitations, intelligent bio-inspired optimization algorithms have been gradually applied to BSS in recent years, including genetic algorithms (GA) [5, 6], PSO [6, 7], and ant colony algorithms (ACA) [8]. These intelligent bio-inspired optimization algorithms, developed by simulating the behavioral characteristics, evolutionary laws, and survival strategies of natural biological populations, represent a new branch of artificial intelligence and evolutionary computation. They generally do not require convexity or continuity of the criterion function, nor do they even demand an analytical expression, demonstrating strong robustness against uncertainty in computational data.

The invasive weed optimization (IWO) algorithm, proposed by Mehrabian et al. [9], mimics the colonization process of weeds in nature, including seed reproduction, dispersal, growth, and competitive extinction. As a novel optimization method, IWO exhibits strong robustness and adaptability. Compared with other swarm intelligence algorithms, IWO allows all individuals in the population to reproduce offspring during evolution, with higher-fitness individuals producing more offspring. This mechanism enhances the algorithm' s search capability and better aligns with natural evolutionary principles. Additionally, the algorithm does not require large memory space to store all individuals' evolutionary trajectories, resulting in lower space complexity. Since its inception, IWO has attracted significant attention from the international academic community and has become a powerful tool for solving practical engineering optimization problems [10~12].

To overcome the limitations of traditional BSS optimization algorithms and further leverage the advantages of IWO, this paper proposes an invasive weed optimization algorithm based on location chaos reconstruction (LCR-IWO) and applies it to blind source separation.

## 1.1 Mathematical Model

The blind signal mixing process can be expressed as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t)$$

where $\mathbf{s}(t) = [s_1(t), s_2(t), \dots, s_n(t)]^T$ represents the source signals, $\mathbf{A}$ is an $m \times n$ mixing matrix, $t$ is the sampling time, $\mathbf{x}(t) = [x_1(t), x_2(t), \dots, x_m(t)]^T$ is the observed signal (the mixed signal data after source signals $\mathbf{s}$ pass through mixing matrix $\mathbf{A}$), and $\mathbf{n}(t)$ denotes noise, which is generally neglected.

The goal of blind source separation is to compute the separation matrix $\mathbf{W}$ based solely on the observed signal $\mathbf{x}(t)$ without any prior knowledge, thereby obtaining an estimate of the source signals:

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t)$$

where $\mathbf{y}(t) = [y_1(t), y_2(t), \dots, y_n(t)]^T$ is also called the separated signal. Since both the source signals and transmission channel characteristics are unknown, the components of the separated signal exhibit randomness in amplitude and order, a phenomenon known as the ambiguity or uncertainty of blind source separation [13].

## 1.2 Signal Preprocessing

In general, observed signal components are correlated, necessitating preprocessing to improve algorithm efficiency. The most common preprocessing methods are centering (zero-mean) and pre-whitening (sphering).

**1) Centering:** Also known as mean removal, this step is not mandatory for all ICA-based BSS algorithms. Centering does not affect subsequent signal separation, and the mean vector can be added back to the recovered signals afterward. The centering expression for observed signals is:

$$\mathbf{x} = \mathbf{x} - E\{\mathbf{x}\}$$

**2) Pre-whitening:** Also called whitening or sphering, this process makes signal components mutually uncorrelated and represents an important preprocessing step in blind separation. Whitening reduces the dimensionality of the mixing matrix, decreases the number of parameters to be estimated, and significantly lowers computational complexity. A common method for pre-whitening observed signals is eigenvalue decomposition (EVD), which essentially computes a whitening matrix $\mathbf{V}$. Let $\lambda_1, \lambda_2, \dots, \lambda_n$ be the eigenvalues obtained from eigendecomposition of the covariance matrix $E\{\mathbf{x}\mathbf{x}^T\}$, and $\mathbf{E}$ be the matrix composed of eigenvectors corresponding to these eigenvalues. With diagonal matrix $\mathbf{D} = \mathrm{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$, the whitening matrix $\mathbf{V}$ is calculated as:

$$\mathbf{V} = \mathbf{E}\mathbf{D}^{-1/2}\mathbf{E}^T$$

The whitened output $\mathbf{z}$ of the observed signal is:

$$\mathbf{z} = \mathbf{V}\mathbf{x}$$

**3) Selection of Independence Criterion:** Kurtosis and negentropy are common statistical independence measures in signal processing. Typically, the kurtosis of a random variable $y_i$ is defined using fourth-order cumulants:

$$\mathrm{kurt}(y_i) = E\{y_i^4\} - 3(E\{y_i^2\})^2$$

Negentropy is difficult to compute accurately but can be approximated by [15]:

$$J(y) \approx \frac{1}{48}(4\mathrm{kurt}(y)^2 - \mathrm{kurt}(y)^4)$$

If the probability distribution of $y$ is symmetric, then $E\{y^3\} = 0$, and negentropy becomes:

$$J(y) \approx \frac{1}{48}\mathrm{kurt}(y)^2$$

Thus, kurtosis can be regarded as a special case of negentropy.

# 2 Invasive Weed Optimization Algorithm

## 2.1 Algorithm Principle

The IWO algorithm guides population colonization through superior individuals, using normally distributed dynamic standard deviation to disperse seeds around parent individuals, balancing global and local search. A parent-offspring survival competition mechanism maximally preserves useful information. Through this evolutionary mechanism, the population ultimately converges to the optimal solution. The algorithm considers both population diversity and evolutionary speed, demonstrating strong search capability and effectively avoiding premature convergence. The invasive weed algorithm consists of four main processes: population initialization, reproduction, spatial dispersal, and survival competition [9].

### 2.2.1 Population Initialization

Determine the initial weed population size $N_0$, maximum population size $N_{\max}$, maximum iterations maxiter, reproduction seed number limits $S_{\max}$ and $S_{\min}$, standard deviation initial value $\sigma_{\text{initial}}$ and final value $\sigma_{\text{final}}$, and the minimum $f_{\min}$ and maximum $f_{\max}$ values of the fitness function. The population individuals are then randomly distributed in the criterion function space.

### 2.2.2 Reproduction

The number of seeds produced by a weed during reproduction is proportional to its fitness value, allowing lower-fitness individuals to produce only a few offspring while higher-fitness individuals generate more. The maximum-fitness weed produces $S_{\max}$ seeds, the minimum-fitness weed produces $S_{\min}$ seeds, and other individuals produce seed numbers following a linear relationship with their fitness values (rounded down). The number of seeds $S_i$ produced by weed $i$ is:

$$S_i = \text{floor}\left(S_{\min} + (S_{\max} - S_{\min})\frac{f_{\max} - f_i}{f_{\max} - f_{\min}}\right)$$

where floor$(\cdot)$ is the floor function and $f_i$ is the fitness value of weed $i$.

[Figure 1: see original paper] illustrates the seed production procedure for weed $i$ [9].

### 2.2.3 Diffusion

Seeds produced by weeds are distributed around parent individuals following a normal distribution $N(0, \sigma^2)$. The relationship between iteration number and standard deviation is:

$$\sigma_{\text{iter}} = \sigma_{\text{final}} + (\sigma_{\text{initial}} - \sigma_{\text{final}})\left(\frac{\text{maxiter} - \text{iter}}{\text{maxiter}}\right)^{\theta}$$

where maxiter and iter represent the maximum and current iteration numbers, respectively, $\theta$ is a nonlinear modulation factor, $\sigma_{\text{initial}}$ is the initial standard deviation, and $\sigma_{\text{final}}$ is the final standard deviation. As shown in the equation, the gradually decreasing standard deviation $\sigma_{\text{iter}}$ reduces the parent search region and population diversity, causing individuals with better fitness values to cluster while those with poorer fitness are eliminated.

### 2.2.4 Survival Competition

After a certain number of iterations, the weed population size reaches the predetermined limit $N_{\max}$. At this point, survival competition occurs: all parent and offspring individuals are sorted by fitness value, and the top $N_{\max}$ individuals with highest fitness are retained for continued evolution, while lower-fitness individuals are eliminated according to the survival-of-the-fittest principle. Thereafter, the population size remains constant at $N_{\max}$, retaining only the most competitive weeds for subsequent searches.

## 2.3 Location Chaos Reconstruction Strategy

Despite its advantages, the standard IWO algorithm has certain drawbacks: for high-dimensional problem spaces, the search time is relatively long; moreover, the algorithm' s reproduction and survival competition mechanisms rely primarily on individual fitness, where low-fitness weeds produce few seeds or are directly eliminated, potentially discarding individuals near global optima and weakening the global dispersal capability of weed seeds, making the algorithm prone to premature convergence.

To address these issues, this paper proposes an IWO algorithm based on location chaos reconstruction. At the beginning of each iteration, selected superior weed individuals undergo location reconstruction, driving them to move toward the current optimal individual. This allows some weeds to escape local optima and quickly guides the entire population toward the global optimum.

The Firefly Algorithm (FA) proposed in literature [16] provides direction for implementing location reconstruction. First, define the attractiveness between weed individuals $i$ and $j$ (essentially the attraction of one weed's field to another) as:

$$\beta_{ij} = \beta_0 e^{-\gamma r_{ij}^2}$$

where $\beta_0$ is the maximum attraction coefficient, introduced because attraction between two weeds weakens as their distance increases, and $r_{ij}$ is the spatial distance between weeds $i$ and $j$.

The distance that weed $i$ moves toward weed $j$ is determined by:

$$x_i(k+1) = x_i(k) + \beta_{ij}(x_j(k) - x_i(k)) + \alpha \cdot (\mathrm{rand} - 0.5)$$

where $x_i$ and $x_j$ are the spatial positions of individuals $i$ and $j$, and $\alpha$ is a random factor following a uniform distribution.

Chaos generally refers to random-like motion states derived from deterministic equations. Chaotic phenomena are ubiquitous in nature and social life, representing a common occurrence in nonlinear systems with complex, random-like behavior. However, behind this apparent disorder lies certain regularity. Chaos exhibits three properties—randomness, regularity, and ergodicity—that make it highly suitable for global optimization problems. Particularly, ergodicity can help improve intelligent optimization algorithms and prevent premature convergence [17].

To further enhance population diversity, chaos theory is applied to process the weights in equations (12) and (13). Various chaotic models exist, each affecting the optimization process differently. While the Logistic chaotic model is common, its non-uniform ergodicity can degrade algorithm performance. The cubic chaotic map offers faster convergence and better ergodic uniformity than the Logistic map. Therefore, this paper employs the cubic chaotic model to construct $\beta_{ij}$ and $\alpha$:

$$\xi_{k+1} = 4\xi_k^3 - 3\xi_k$$

$$\psi_{k+1} = 4\psi_k^3 - 3\psi_k$$

In practical applications, chaos occurs as long as the initial iteration value of the cubic map is not zero.

### 3.1 Algorithm Flowchart

[Figure 2: see original paper] shows the flowchart of the blind separation algorithm based on location chaos reconstruction invasive weed optimization (LCR-IWO).

### 3.2 Algorithm Implementation Steps

Based on [Figure 2: see original paper], the algorithm implementation steps are:

a) Read the observed signal $\mathbf{x}$ and perform mean removal and whitening preprocessing;

b) Initialize parameters $N_0$, $N_{\max}$, maxiter, nonlinear modulation factor $\theta$, $S_{\max}$, $S_{\min}$, $\sigma_{\text{initial}}$, $\sigma_{\text{final}}$, $f_{\min}$, $f_{\max}$, and randomly generate the initial weed population in the solution space;

c) Calculate the fitness values (kurtosis) of weed individuals and record the optimal individual;

d) Perform location chaos reconstruction on the newly formed population individuals;

e) Calculate the number of seeds produced by each weed;

f) Compute the standard deviation for normal distribution of offspring individuals, disperse the generated seeds, and allow them to grow into new weed individuals;

g) Calculate fitness values of parent and offspring weeds, sort them in descending order; if the fitness value of the current optimal weed exceeds the recorded value on the bulletin board, update the bulletin board;

h) If the new population size exceeds $N_{\max}$, retain the top $N_{\max}$ weeds and eliminate others, maintaining the population size at $N_{\max}$ thereafter;

i) If the iteration count meets the termination condition, stop the algorithm and output the results; otherwise, return to step d) and continue.

### 3.3 Computer Simulation Experiments

To validate the effectiveness of the proposed algorithm, this section compares its separation performance with standard IWO, PSO, and NG algorithms through blind signal separation simulations.

### 3.3.1 Experimental Environment and Parameter Values

[Figure 3: see original paper] shows three source signals with 3000 sampling points: $s_1$ is a sawtooth wave, $s_2$ is a random FSK signal, and $s_3$ is the product of sine and cosine functions. The corresponding histograms of source signals are shown in [Figure 4: see original paper]. The experiment uses a randomly generated mixing matrix:

$$\mathbf{A} = \begin{pmatrix} 0.4104 & 0.4782 & 0.6164 \\ 0.0153 & 0.8645 & 0.5361 \\ 0.1435 & 0.8632 & 0.3158 \end{pmatrix}$$

The observed signals $\mathbf{x}$ (after whitening) produced by mixing source signals $\mathbf{s}$ with random matrix $\mathbf{A}$ and their corresponding histograms are shown in [Figure 5: see original paper] and [Figure 6: see original paper], respectively. The parameter values for the LCR-IWO algorithm are listed in .

### 3.3.2 Experimental Results and Analysis

[Figure 7: see original paper] shows the separated signals after 16 updates of the new algorithm (with corresponding histograms in [Figure 8: see original paper]), demonstrating that the source signals have been well recovered. However, comparing [Figure 7: see original paper] with [Figure 3: see original paper] reveals that the order of separated signal components has completely changed compared to the source signals, and most phases and amplitudes have also been altered. This phenomenon is determined by the uncertainty inherent in blind separation.

[Figure 9: see original paper] displays the fitness value curves of the four optimization algorithms, showing that the new algorithm outperforms standard IWO, PSO, and NG in separation performance, achieving the highest convergence speed and recovery accuracy. The convergence speeds rank as: LCR-IWO > PSO > IWO > NG, while the fitness values at convergence rank as: LCR-IWO > PSO > IWO > NG.

lists the fitness values of the four optimization algorithms at certain iteration moments (convergence values are bolded). The algorithms converge at iterations 16, 27, and 37 for LCR-IWO, IWO, and PSO, respectively (NG' s convergence is unknown). The fitness values at convergence are 1.0773 for LCR-IWO, 0.8778 for IWO, and 0.8270 for PSO (NG' s convergence is unknown). These quantitative results clearly demonstrate that LCR-IWO significantly outperforms the other three algorithms.

[Figure 10: see original paper] shows scatter plots of the separated signals versus source signals obtained by the new algorithm, visually confirming that the order, phase, and amplitude of most separated signal components have changed compared to the corresponding source signal components.

## 4 Conclusion

This paper proposes a location chaos reconstruction-based invasive weed optimization algorithm (LCR-IWO). At the beginning of each iteration, selected superior individuals undergo location reconstruction, driving them to move an appropriate distance toward the current optimal individual. This enables some weed individuals to escape local optima and guides the entire population to quickly locate the global optimum. Location reconstruction is then enhanced by applying chaotic processing to certain weights in the movement model to further strengthen population diversity. To overcome the limited applicability and low performance of traditional BSS optimization algorithms, the LCR-IWO algorithm is applied to BSS. Comparative experiments with standard IWO, PSO, and NG algorithms demonstrate the effectiveness of the proposed approach.

The parameter values for the algorithm can be determined following certain rules. The initial population size $N_0$ should not be too large, as this would otherwise affect evolutionary speed without significantly improving separation accuracy. Additionally, $N_0$ should be considered together with the maximum population size $N_{\max}$ to maintain adequate distance and enhance population diversity. For most optimization problems, $N_0$ should be set between 1/8 to 1/2 of $N_{\max}$. A larger $N_{\max}$ benefits population diversity, but simply increasing $N_{\max}$ cannot effectively improve algorithm performance and will increase runtime. Therefore, $N_{\max}$ should be set based on actual conditions, typically between 10 and 50. The maximum seed number $S_{\max}$ is usually set to 1 or 2. For standard deviation, the initial value $\sigma_{\text{initial}}$ must be greater than the final value $\sigma_{\text{final}}$ to achieve the transition from global search in early evolution to local search in later stages. Generally, on the basis of satisfying $\sigma_{\text{initial}} > \sigma_{\text{final}}$, the influence of standard deviation on objective function optimization should be fully considered. The nonlinear modulation factor $\theta$ also significantly impacts the algorithm, with research indicating that the optimal value is typically 3. $S_{\max}$ is generally set to an integer between 3 and 5, while $S_{\min}$ is the lower limit.

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