Research on Signal-to-Noise Ratio Optimization based on Chaotic Immune Difference Algorithm

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Abstract. A new algorithm based on the combination of chaotic sequences and immune differencing is proposed to improve the population diversity capability of the immune differencing algorithm in order to improve the conventional immune differencing algorithm for solving the signal-to-noise optimal problem. The method uses chaotic sequence immune differencing for population expansion, and the accuracy of the algorithm is analysed. In order to test the effectiveness of the algorithm, it is applied to a function optimisation problem. Simulation results show that the method has a lower number of iterations and better accuracy.

Keywords: chaotic sequences, immunodifference, optimal optimization, signal-to-noise ratio

1. Introduction
In previous years two very important techniques for improving the signal-to-noise ratio or spectral efficiency were Geometric Shaping (GS) and Probabilistic Shaping (PS). However, for both methods there is a disadvantage that the cumulative Kerr nonlinearity in PS modulation exhibits stronger than in conventional QAM modulation when transmitted over long distances in optical fibres. The nonlinear effects of such fibres can significantly offset the shaping gain obtained in the linear range. Based on this, the literature [3] provides a new super-Gaussian distribution to solve the problem of nonlinear effects in long-haul fiber transmission, but at this point this case only analyzes the SNR tolerance and the optimization of the SNR is not studied in depth. For such non-convex optimization functions, greedy algorithms such as intelligent optimization algorithms are often used to find the best, and the immunogenetic algorithm is one of the commonly used intelligent algorithms with strong local search capability.

The immune differential algorithm is based on the Immune Clonal Selection Algorithm (ICSA) improved to obtain, is an algorithm to simulate the biological immune system, the main idea is to introduce the binding between antigens and different populations, randomly eliminate the poorly binding populations, the strong binding populations increase the variation, under the optimization of the differential, the parameters of immunization is optimized, the parameters are easy to modify [4].

However, the conventional immunodifference does not complement the diversity of the population well, so in some cases this algorithm cannot obtain the optimal solution quickly, so chaotic sequences are introduced to complement it. In this paper, we propose a new chaotic differential immune cloning algorithm to solve this optimization problem. This algorithm outperforms the conventional differential
immune cloning algorithm in terms of the number of iterations and the correctness of the optimal solution.

2. System model

If it is necessary to design constellation diagrams with higher S/N tolerance, the signal-to-noise ratio of the signal can be increased at the receiving end and the S/N ratio can be expressed as

\[ SNR_{\text{eff}} = \frac{P_e}{\sigma_{\text{eff}}^2} = \frac{P_e}{\sigma_{\text{ASE}}^2 + \sigma_{\text{NL}}^2} \]  

(1)

where \( P_e \) denotes the incident power of the fibre. The noise term is divided into two components, the \( \sigma_{\text{ASE}}^2 \) denotes the spontaneous radiated noise of the amplifier, which can be thought of as the magnitude of the Gaussian noise power. \( \sigma_{\text{NL}}^2 \) denotes the non-linear noise of the signal, where the non-linear noise can also be refined as

\[ \sigma_{\text{NL}}^2 = P_e^3 C_1 + P_e^3 C_2 \left( \frac{\langle |b|^4 \rangle}{\langle |b|^2 \rangle^2} - 2 \right) \]  

(2)

where \( b \) denotes the constellation diagram position of the signal (energy normalised). \( C_1 \) and \( C_2 \) are a set of parameters related to signal filtering in the channel, dispersion, fibre distance and power.

In nonlinear channels, a super-Gaussian distribution was proposed by the authors in the literature.

\[ p(x) = \frac{e^{-\lambda x^k}}{Z(\lambda K)} \]  

(3)

Where \( Z(\lambda, K) \) is the normalisation factor. By adjusting the parameter \( \lambda, K \), a smaller nonlinear noise can be obtained, making the constellation points more adapted to the nonlinear channel.

When introducing both geometric and probabilistic forming techniques, not only the probability distribution of the constellation points of the signal is taken into account, but also the position of the constellation points can be adjusted. Since the information entropy does not increase with the new uncertainty generated by probabilistic segmentation, it can be assumed that the information entropy remains unchanged, and in order to obtain a constellation diagram with a higher signal-to-noise ratio tolerance, it can be assumed at this point that finding the signal-to-noise ratio at this point \( SNR_{\text{eff}} \) the maximum is sufficient.

By integrating the above equations, the final target and constraint equations can be obtained. Due to the practical effects of light communication, the above equations are modified to give the final set of equations as shown in the following equation.
For this constraint, this paper uses a chaotic immunodifferential optimization algorithm to solve it. Compared to existing immunodifferential algorithms, chaotic immunodifferential incorporates a backward iterative process, which improves the speed of finding the optimal solution, and the process is as follows.

3. Chaos immune difference algorithm

3.1. Immunodifferential algorithm

The immune clone selection algorithm is an intelligent method for simulating biological immune systems. By introducing biological affinity, cloning and memory mechanisms, it enhances the diversity of species search of traditional intelligent algorithms and overcomes problems such as poor local search ability; however, at the same time, ICSA also shows the phenomenon of slow evolution and weak local search ability near the optimal solution, which makes it difficult to further improve the solution accuracy. At the same time, ICSA is less robust and has problems such as the operation operator is more sensitive to the feasible domain of the optimization. In order to solve the above problems, this paper adopts the immune differential evolution algorithm, which adds a differential strategy to the traditional ICSA and introduces differential variation and crossover, and its algorithm flow is as follows.

DE-ICSA steps are described as follows:

- generating initial population (P), P was set up by memory cells (M) and retained subset (Pr), P = Pr + M.
- b) Choose n individuals with the greatest affinity were selected to form the antibody population Pn.
- c) A temporary antibody set C is generated by the scaling operation on n individuals with the highest affinity.
- d) The greater the antibody affinity, the more grams of healthy individuals were produced. The temporary antibody set C is mutated to generate the antibody set C*.
- e) Mutate the antibody set C*.
- f) The mutated antibody is crossed to generate the anti-rest set C&
- g) Re-select the individuals with high affinity in the antibody set to be added to the subset of memory cells (M). Some of the individuals in P are replaced by other improvements in C&.
- h) d new antibodies are randomly generated to replace d antibodies with the lowest affinity in P and increase the diversity of antibodies.

The pseudo code is as follows:

\[
SNR_{\text{eff}} = \arg \max_{x, \lambda, P} \frac{P_e}{\sigma_{\text{ASE}}^2 + \sigma_{\text{NLI}}^2}
\]

\[
P(x) = \frac{e^{-\sin(\lambda)x^4}}{z(\lambda, K)}
\]

\[
s.t. \begin{cases} 
\langle |b|^4 \rangle = \frac{E[|X - E(x)|^4]}{(E[|X - E(x)|^2])^{\frac{3}{2}}} \\ 
\langle |b|^2 \rangle^2 = \frac{E[|X|^2]}{(E[|X|^2])^{\frac{1}{2}}} \\ 
f(P) = -\sum P \log_2(P) = C \\ 
P_e = \sum x^2 P(x) 
\end{cases}
\]
3.2. Chaotic sequences

Chaos is the analysis of irregular and unpredictable phenomena and their processes. Chaotic variables in intelligent optimisation algorithms are not only effective in maintaining the diversity of the population, but also facilitate the algorithm to jump out of the local optimum and improve the global search ability. logistic, Tent mapping is a common chaotic system, the introduction of random variables on the original Tent mapping expression can avoid to some extent its falling into small or unstable periodic points, the improvement after adding random variables Tent mapping.

\[ x_{i+1} = \begin{cases} 
2x_i + \text{rand}(0, 1) \times \frac{1}{N}, & 0 \leq x \leq \frac{1}{2} \\
2(1-x_i) + \text{rand}(0, 1) \times \frac{1}{N}, & \frac{1}{2} < x \leq 1 
\end{cases} \]

where \( N \) is the number of particles within the chaotic sequence and \( \text{rand}(0, 1) \) denotes a random number between 0 and 1.

The flow chart of the immune differential evolution algorithm with the addition of chaotic sequences is as follows.

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**Algorithm 2: DE-Ia algorithm**

**Input:** Decision variable : \( x \)

**Output:** Optimization objective : \( y \)

1. **Define:** Population : NP=30 ; Dimensions : D=100 
   F ; Maximum algebra : G =500 ; Clone number : N

2. **PopInitialize:** \( x_{i+1} \leftarrow 2x_i \text{mod}1 + \text{rand} \cdot \frac{1}{N} \) mem

3. **while** \( j < G \) **do**
   
   \( \triangleright \) (Clone based on SNR)
   
   \( P_n = \text{CloneSort}(P_M) \)

4. **for** \( i \leftarrow 1 \) **to** NP **do**
   
   \( v_i \leftarrow x_i^{r_1} + F \cdot (x_i^{r_2} - x_i^{r_3}), i \neq r_1 \neq r_2 \neq \)

5. **end**

6. **\( \triangleright \) (Variation)**

7. **for** \( i \leftarrow 1 \) **to** NP **do**
   
   \( u_i = v_i \)

8. **end**

9. **\( \triangleright \) (Cross)**

10. **for** \( i \leftarrow 1 \) **to** NP **do**

11. **if** \( \text{rand}<C_r \) **or** \( i \leftrightarrow i_{\text{rand}} \) **then**

12. **else**

13. **end**

The flow chart of the immune differential evolution algorithm with the addition of chaotic sequences is as follows.
4. Testing

4.1. CDE-IA performance tests
In order to test the performance of CDE-IA, the signal X with different conditions was first set up and four sets of data were generated according to the randomness of different signals X. They corresponded to four sets of function groups, and with the help of four different sets of functions the algorithm's adaptability to the conditions of different situations could be judged. The algorithm is solved for the functions generated by the model after the set functions have been studied, and these two processes enable a more comprehensive analysis of the accuracy and effectiveness of the algorithm. The specific algorithm performance evaluation is tested using two dimensions: (1) comparison of the number of iterations and the comparison of the answer to the optimal solution (2) comparison of the process for solving the best value case.

(a) Comparison of the number of iterations and the answer to the optimal solution.
As shown in the figure below, firstly, the comparison of the four sets of generating functions shows that for the four different sets of functions F1-F4, only F2 is closer in terms of the number of iterations and the efficiency of solving the optimal solution, among the three tested functions F1, F3 and F4 CDE has a higher number of iterations (all within 100) and a higher efficiency of solving the optimal solution than IA and CIA. It can be seen that with the addition of chaotic sequences, the efficiency of the algorithm in solving the optimal solution has been significantly improved by increasing the diversity of samples.

**Algorithm 2: CDE-IA algorithm**

| Input: Decision variable : $x$ |
| Output: Optimization objective : $y$ |
| Define: Population : NP=30 ; Dimensions : D=100 ; Cross : F ; Maximum algebra : G =500 ; Clone number : Nc = 10; |
| PopInitialize: $x_{i+1} \leftarrow 2x_i mod 1 + rand \cdot \frac{1}{N}$ memory cells |
| while $j<G$ do |
|   $(\text{Clone based on SNR})$ |
|   $P_n = \text{CloneSort}(P_M)$ |
|   $(\text{Variation})$ |
|   for $i \leftarrow 1$ to NP do |
|     $v_i \leftarrow x_i^{r_1} + F \cdot (x_i^{r_2} - x_i^{r_3}), i \neq r_1 \neq r_2 \neq r_3$ |
|   end |
|   $(\text{Cross})$ |
|   for $i \leftarrow 1$ to NP do |
|     if rand $\leq$ Cr or $i$ $==$ $i_{rand}$ then |
|       $u_i = v_i$ ; |
Fig. 1 (F1-F4) Comparison of the number of iterations and the answer to the optimal solution

(b) The case of the process of solving for the optimum.

Fig. 2 The process case for solving for the optimum (F1, F2)
As shown in the figure above, the distribution of the evolutionary solution sets from F1 to F4 in each generation obtained by IA and CDE-IA shows that the evolutionary solution individuals of IA are randomly distributed in the feasible domain, while the evolutionary individuals resulting from CDE-IA are concentrated near the optimal solution, from which it can be seen that CDE-IA has a stronger global search ability compared to IA, on the other hand, the evolutionary individuals resulting from CDE-IA are denser, while the individuals evolved by IA are sparser, and the evolutionary generations are the same. This is because the individuals of the IA algorithm have been stagnating in the local optimum and have not changed more during the evolutionary process, and cannot jump out of the local optimum, while the individuals evolved by CDE-IA can maintain certain local search ability near the optimal solution and keep approaching the optimal solution. From this, it can be seen that CDE-IA has better performance compared to IA in terms of both the global search ability at the beginning and the local search ability at the later stage. It is clear that the addition of chaotic sequences and the variational evolution of the difference strategy effectively improve the reliability of the algorithm.

4.2. Signal-to-noise ratio model optimisation

For the constellation map signal-to-noise ratio model studied in this paper, the IA, CIA and CDE-IA algorithms are used in this paper to solve for each of them, and the following adaptation curves are obtained for the three.
Fig. 4 Comparison of the number of iterations of the model function and the answer to the optimal solution

For the model-generated function, due to the complexity of the model-generated function, both IA and CIA fall into local optimality, and in contrast to this the optimal solution result of CDE-IA is significantly better than the solutions of IA and CIA, what can be seen is that under the condition of limited number of iterations, the efficiency and accuracy of solving the optimal solution of CDE-IA is significantly higher than the remaining two algorithms, indicating that CDE-IA not only effectively adapts to the randomly generated test function, but also passes the model-generated function and can complete the solution of the signal-to-noise ratio optimum more efficiently. The final S/N ratio was determined to be 636.349dB, which is in line with the theoretical reality.

5. Summary
(1) The effectiveness of CDE-IA's search for the global optimum has improved significantly, with none of CDE's solution finding falling into a local optimum in any of the four sets of test functions, and its efficiency in initially finding the optimal solution has improved significantly.
(2) The average number of iterations of CDE-IA is better than both IA and CIA, and the iterations of CDE-IA are also better than IA and CIA for model functions, and CDE also has an advantage in facing complex situations.
(3) The CDE-IA algorithm effectively solves the problem of low population diversity in IA after the introduction of chaotic sequences, making CDE-IA capable of handling problems with complex parameters.

The research on CDE-IA is only in simulation testing, and there has been significant progress in applying it to the optimal solution of signal-to-noise ratio for optical fibre communication. The practical applications of the CDE-IA algorithm are yet to be explored, as the application of CSSA to other problems related to communications, such as image recognition, language processing, etc., is considered later.

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