A Novel Genetic Algorithm for CEC2024

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1 Abstract

In this paper, we introduce a novel genetic algorithm designed to tackle the challenges presented by the CEC2024 benchmark problems [1]. Our approach incorporates advanced selection strategies to enhance convergence speed and solution quality. Specifically, we introduce a local comparison mechanism that preserves near-optimal solutions in the early stages, thereby improving solution diversity. As the algorithm progresses, we gradually expand the comparison range to ensure that the final solutions are globally optimal. For constraint handling, we adopt the i-ε technique, which effectively manages constraints throughout the optimization process.Through rigorous testing and comparative analysis, our algorithm demonstrates superior performance in optimizing complex, high-dimensional functions, making it a promising tool for future research in evolutionary computation.

2 Proposed Algorithm

2.1 Creation of the auxiliary task

In this paper, the auxiliary task can be described as follows:

$$minf(x) = (f_1(x), f_2(x), ..., f_4(x)) \tag{1}$$

s.t.

$$G(x) \leq \epsilon_T$$

$$V = \eta \left(\prod_{m=1}^{M} \left(X_m^{max} - X_m^{min} \right) \right)^{\frac{1}{M}} \tag{2}$$

where T is the current generation, $G(x)$ is the constraint violation value of decision variable x, V is the range of dominance relationship comparison and ϵ_T indicates the constraint boundary value in the T generation.
ϵ_T is calculated by:

$$\varepsilon_T = \varepsilon_0 * \left(1 - \frac{T}{MaxT} \right)^{\frac{-log(\varepsilon_0)-6}{log(1-P)}} \tag{3}$$

where $MaxT$ is the maximal generations, pp is the parameter that controls the rate of descent of ε_T and is set to 0.5, and ε_0 is the initial constraint violation degree value and equals to the maximal G value of both initial main population and auxiliary population.
η is calculated by:

$$\eta = 0.5 * \left(\cos \left(\left(1 - \frac{T}{MaxT} \right) * \pi \right) + 1 \right) \tag{4}$$

Algorithm 1: The procedure of MTCMMO

Input: $MaxGen$, N
Output: Pop_1

$Pop_1 \leftarrow$ Randomly generate N individuals;
$Pop_2 \leftarrow$ Randomly generate N individuals;
Evaluate Population ($Pop1$, $Pop2$)
while $FE \leq MaxFE$ **do**
    $O_1 \leftarrow$ Use the operators of GA to generate $N/2$ offspring based on the parents selected from Pop1;
    $O_2 \leftarrow$ Use the operators of GA to generate $N/2$ offspring based on the parents selected from Pop2;
    Evaluate Population (O_1, O_2)
    $Pop_1 \leftarrow$ Select N individuals from [Pop_2, O_1, O_2] using the SPEA2 selection method;
    $Pop_2 \leftarrow$ Select N individuals from [Pop_2, O_1, O_2] using the dynamic auxiliary task selection method;
end

The auxiliary task has the same objective functions with the main task. However, different from the main task, the constraint functions and dominance comparison range of the auxiliary task are dynamically changing. Furthermore, the constraint boundary ε_T is gradually reduced to drive the population into feasible regions, while the dominance comparison boundary V is gradually increased to guide the population towards the global optimum. Therefore, although the two tasks follow different evolutionary paths, they converge to the same optimal solutions, making them a high-similarity many multitasking optimization(MTO) problem. To address this, a novel constrained multimodal multiobjective optimization framework based on dual-population collaborative evolution for multitasking is proposed and detailed below.

2.2 Procedure of MTCMMO

The procedure of MTCMMO is presented in Algorithm 1. First, two populations (denoted as Pop_1 and Pop_2) with N individuals are randomly initialized in the search space and then evaluated. Next, the main loop begins. Each population uses the operators of GA to generate the offspring population with $N/2$ individuals, and then the offspring will be evaluated. Two offspring populations are represented by $O1$ and $O2$ respectively, and they are combined into Pop_1 and Pop_2. Finally, Pop_1 uses the special crowding distance method to obtain a new Pop_1, and Pop_2 uses the dynamic auxiliary task selection method to obtain a new Pop_2.
MTCMMO addresses a problem by simultaneously optimizing the main task and an auxiliary task, with the latter intended to aid the main task through knowledge transfer. Additionally, the dynamic auxiliary task selection method

guides the use of infeasible and local optimal solutions. The following section introduces the developed dynamic auxiliary task selection method.

Algorithm 2: Dynamic auxiliary task selection

Input: Pop_2, N
Output: Pop_2
Calculate ε_T based on Eq. (12);
Calculate V based on Eq. (11);
$Localfit \leftarrow$ CalLocalfit(Pop_2, V)
$CrowdDis1 \leftarrow$ CalCrowdDis(Pop_2)
$M_1 \leftarrow$ *The individuals whose* G *values are smaller than or equal to* ε_T
$M_2 \leftarrow Pop \setminus M_1$
if $M_1 == 0$ **then**
    $Pop_2 \leftarrow$ SortByRows($Localfit(M_2)$, $PopCD(M_2)$)
    $Pop_2 \leftarrow Pop_2(1:N)$
else if $M_1 < N$ **then**
    $Pop_2 \leftarrow$ SortByRows($Localfit(M_2)$, $PopCD(M_2)$)
    $Pop_2 = M_1 \cup M_2(1{:}N\text{-size}(M_1))$
else if $M_1 > N$ **then**
    $m_1 \leftarrow$ *The individuals of* M_1 *whose Localfit values are equal to 0*
    $m_2 \leftarrow M_1 \setminus m_1$
    if $m_1 < N$ **then**
        $Pop_2 \leftarrow$ SortByRows($Localfit(M_2)$, $PopCD(M_2)$)
        $Pop_2 = m_1 \cup m_2(1{:}N\text{-size}(m_1)$
    else
        $Pop_2 \leftarrow$ Delete redundant solutions by the truncation method
    end
end

3 CONCLUSION

In this study, we presented a novel genetic algorithm specifically designed for the CEC2024 benchmark problems. By integrating a local comparison mechanism, we effectively maintained solution diversity in the early stages of the algorithm, which is crucial for exploring the solution space. As the algorithm advanced, the comparison scope was expanded to ensure convergence towards globally optimal solutions. Additionally, we employed the i-ε technique for efficient constraint handling, enhancing the algorithm's ability to solve constrained optimization problems. The results from extensive testing and comparative analysis indicate that our approach outperforms existing algorithms in terms of convergence speed and solution quality. This novel genetic algorithm offers a robust and efficient tool for addressing complex, high-dimensional optimization challenges, paving the way for future advancements in evolutionary computation.

References

[1] K. Qiao, X. Wen, X. Ban, P. Chen, K. V. Price, P. N. Suganthan, J. Liang, G. Wu, and C. Yue. Evaluation criteria for cec 2024 competition and special session on numerical optimization considering accuracy and speed. Technical report, Zhengzhou University, Central South University, Henan Institute of Technology, Qatar University, 2024.