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An optimized grey wolf optimizer based on a mutation operator and eliminating-reconstructing mechanism and its application

Key words: Swarm intelligence; Grey wolf optimizer; Optimization; Radial basis function network

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Motivation

1. The new intelligence algorithm, grey wolf optimizer (GWO), can be applied to all walks of life immediately because it is easy to understand, especially in solving problems in electric power systems.

2. There is only one parameter to be adjusted in the iterative process for GWO, that is, $\boldsymbol{a}$. In early iterations, when the value of $\boldsymbol{a}$ is larger, the exploration ability of GWO is stronger. In later iterations, with $\boldsymbol{a}$ gradually decreasing, the exploitation ability is strengthened and the exploration ability is weakened which will increase the risk of being trapped in local optima.

Motivation

3. Moreover, in GWO, the search behavior occurs mainly around the three leader grey wolves α, β, and δ, and if the three leader grey wolves are all in local optima area, it will be hard for the algorithm to jump out of the local optimum.

4. Therefore, for better applications of GWO and a comprehensive improvement of its exploration and exploitation abilities, an improved GWO algorithm is proposed based on the mutation operator and eliminating-restructuring mechanism (MR- GWO).

Method

- **Eliminating-restructuring mechanism**

The first step is to sort the ω wolves, keep the better R_num ones, and then eliminate the inferior ones, which will be reconstructed following Eq. (8) or (9).

$$x_i^k(t+1) = x_{\min} + r_2(x_{\max} - x_{\min}), \tag{8}$$

$$x_i^k(t+1) = X_\alpha^k(t) + \eta r_1(x_{\max} - x_{\min}). \tag{9}$$

- **Mutation operator for excellent search wolves**

The differential mutation operator is introduced to accelerate the algorithm to find the global optimum. The mutation probability means that the mutation will occur only for some excellent ω wolves.

$$x_i^k(t+1) = \begin{cases} x_i^k(t) + F\cdot(x_j^k(t) - x_l^k(t) + X_\alpha^k(t) - x_n^k(t)), \\ \qquad\qquad \mathrm{rand}_i > P_{\mathrm{m}}, \\ x_i^k(t), \quad \mathrm{rand}_i \le P_{\mathrm{m}}. \end{cases} \tag{10}$$

MR-GWO application

◆ Global optimization experiments

Table 6 Error results of the unimodal group of functions

Algorithm	Average mean absolute error	Rank
GWO	3.856 772	4
R-GWO	0.018 835	2
MR-GWO	0.004 229	1
PSO	15.097 13	6
EA	527.8688	8
CGWO1	7.02×10^{8}	9
CGWO2	9.087 390	5
bGWO1	67.123 82	7
bGWO2	3.761 914	3

Table 7 Error results of the multimodal group of functions

Algorithm	Average mean absolute error	Rank
GWO	1058.37	3
R-GWO	0.006 33	2
MR-GWO	0.002 83	1
PSO	1165.456	4
EA	1349.792	6
CGWO1	1.40×10^{7}	9
CGWO2	1253.419	5
bGWO1	1707.751	8
bGWO2	1700.133	7

◆ RBF network approximation

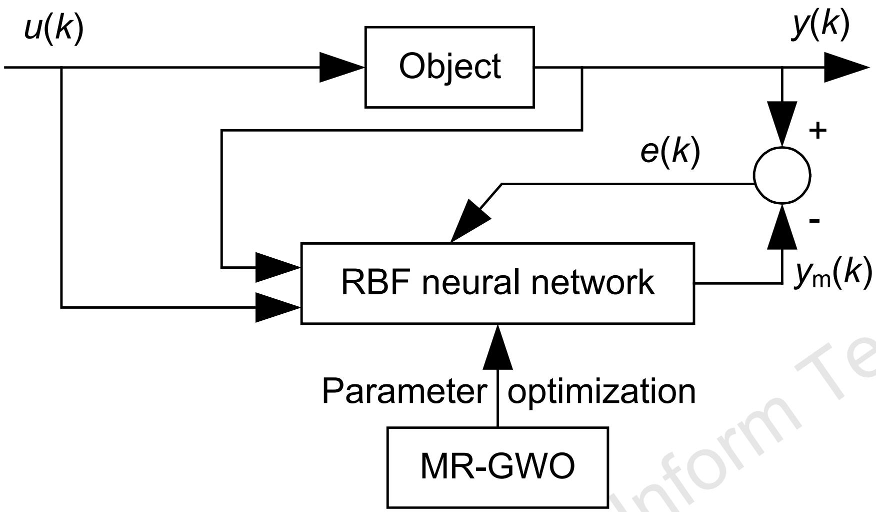

Fig. 8 Structure of RBF network approximation based on MR-GWO

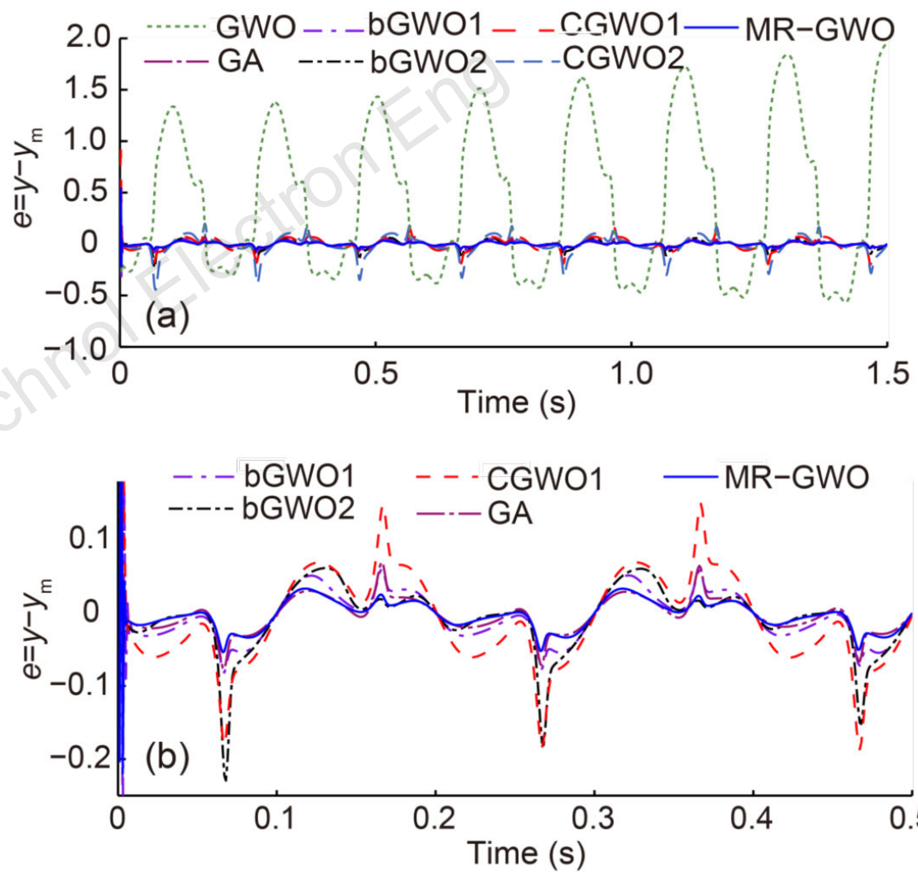

Fig. 10 Errors of RBF network approximation

Major results

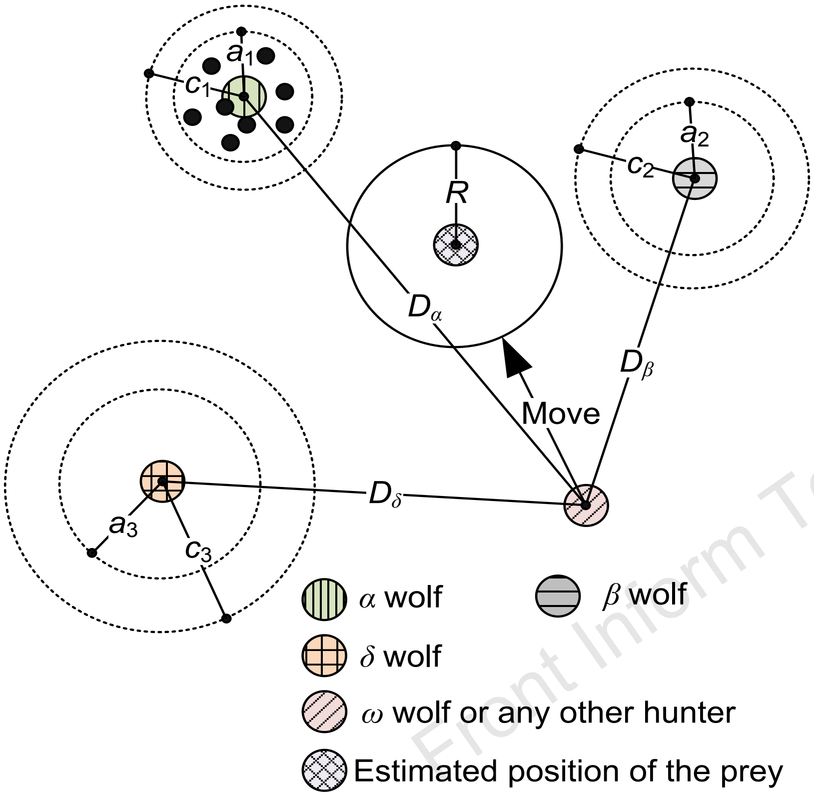

Fig. 4 Position updating in gray wolf optimizer

The performances of MR-GWO are summarized as follows:

1. It has a quick convergence and stable property.

2. It has a good capability for resisting local optima.

3. It has strong exploration and exploitation abilities throughout the iterations.

In addition, the influences of the mutation probability and closing factor are analyzed, and their general scopes are clarified.

Conclusions

According to the analysis of the entire research, it is found that not only in the global optimization experiment, but also in the RBF network approximation experiment, all results of the improved algorithm, MR-GWO, are better, and the improved algorithm is not easily trapped in local optima. This fully confirms that MR-GWO has stronger abilities in dealing with not only unimodal problems but also multimodal problems, and even some parameter optimization problems.