CEC 2024 Competition on Seeking Multiple Optima in Dynamic Environments

Xin Lin[1], Wenjian Luo[2], Changhe Li[3], Shengxiang Yang[4], Yuhui Shi[5]

[1] *Nanjing University of Information Sciences and Technology*

[2] *Harbin Institute of Technology, Shenzhen,*

[3] *China University of Geosciences*

[4] *The De Montfort University*

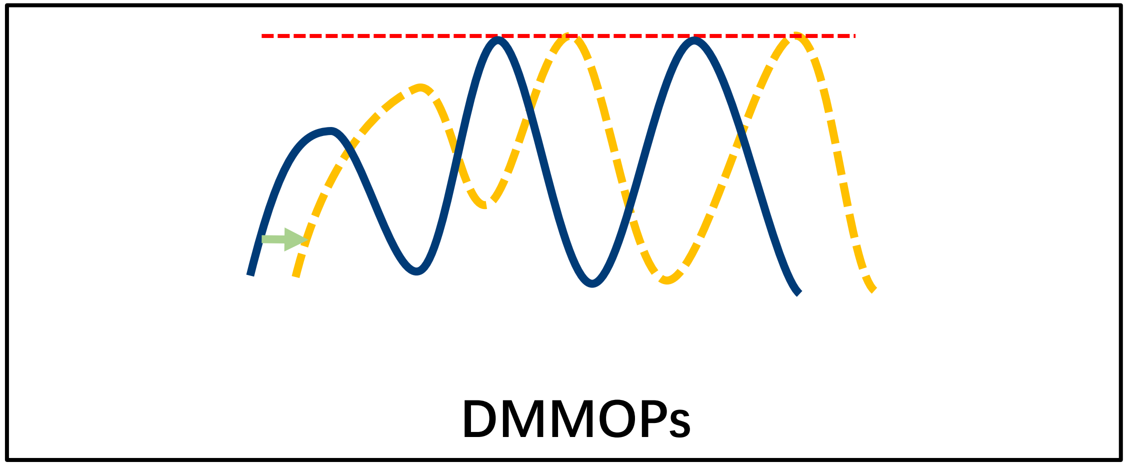
[5] *Southern University of Science and Technology*

Outline

- **Introduction**
- Benchmarks
- Experiment Settings
- Results

Dynamic Multimodal Optimization Problems (DMMOPs)

- Dynamic multimodal optimization problems (DMMOPs) have the dynamic and multimodal natures*.
  - DMMOPs changes from one environment to another.
  - In each environment, there exists multiple global peaks.



* Wenjian Luo, Xin Lin, Tao Zhu, and Peilan Xu. A Clonal Selection Algorithm for Dynamic Multimodal Function Optimization. *Swarm and Evolutionary Computation, 50, 100459, 2019*

Definitions of DMMOPs

- Definitions

$$\begin{pmatrix} \boldsymbol{o}_{11} & \boldsymbol{o}_{12} & \cdots & \boldsymbol{o}_{t1} \\ \boldsymbol{o}_{12} & \boldsymbol{o}_{22} & \cdots & \boldsymbol{o}_{t2} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{o}_{1n_1} & \boldsymbol{o}_{2n_2} & \cdots & \boldsymbol{o}_{tn_t} \end{pmatrix} = arg\max_{\boldsymbol{x}\in\Omega} f(\boldsymbol{x}, t)$$

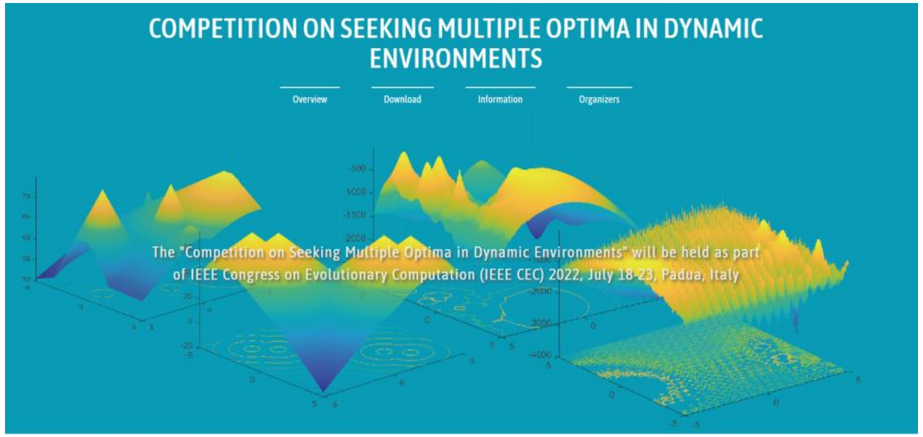
- Problem $f(\boldsymbol{x}, t)$ is a maximized DMMOP.
- $\boldsymbol{o}_{tn_t}$ represents the n_t-th optimal solution in the t-th environment.
- Parameter Ω defines the whole decision space.
- Goal:

  The optimization algorithms solving DMMOPs should find all the optimal solutions in each environment.

Competition on DMMOPs

- The goal of this competition is to test the performance of various optimization algorithms for solving DMMOPs.
  - The benchmark suit contains 24 problems, which are from our previous work*.
- Website of the competition

http://mi.hitsz.edu.cn/activities/2022dmmo_competition.html



ORGANIZERS

- **Wenjian Luo**, Harbin Institute of Technology, Shenzhen, China, Email: luowenjian@hit.com
- **Xin Lin**, University of Science and Technology of China, Hefei, China, Email: iskcal@mail.ustc.edu.cn
- **Changhe Li**, China University of Geosciences, Wuhan, China, Email: change.lw@gmail.com
- **Shengxiang Yang**, the De Montfort University, Leicester LE1 9BH, United Kingdom, Email: syang@dmu.ac.uk
- **Yuhui Shi**, Southern University of Science and Technology, Shenzhen, China, Email: shiyh@sustech.edu.cn

* X. Lin, W. Luo, P. Xu, Y. Qiao, and S. Yang, PopDMMO: A general framework of population-based stochastic search algorithms for dynamic multimodal optimization, *Swarm and Evolutionary Computation*, p. 101011, 2021.

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Multimodal Functions

- Functions 1~4: Simple Multimodal Functions

Constructed by the DF generator*

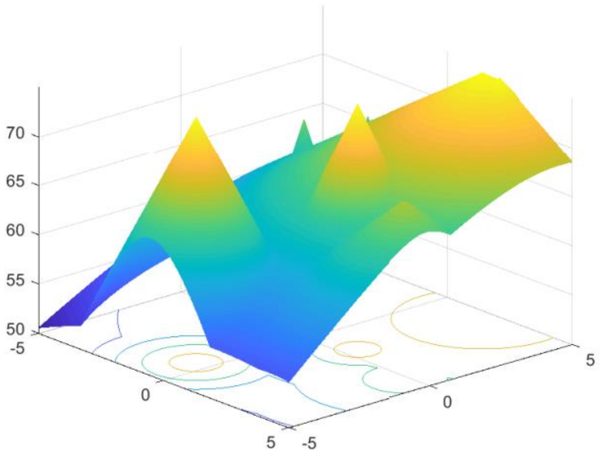
$$f(x) = \max_{\substack{i=1,\dots,G,\\ G+1,\dots,G+L}} \left(H_i - W_i * \sqrt{\sum_{j=1}^{D} (x_j - X_{ij})^2} \right)$$

- H_i, W_i and X_{ij} represent the initial height, width and position of the i-th peak, respectively.
- G and L represent the number of global peaks and the maximum number of local peaks.
- The heights of the global peaks are the same and higher than the local peaks.
- The minimum distance between peaks is no less than 0.1.

* R. W. Morrison and K. A. De Jong, "A test problem generator for non-stationary environments," *Proceedings of the 1999 Congress on Evolutionary Computation*, 1999, pp. 2047-2053 Vol. 3.

Multimodal Functions

- The first four functions simulate the fitness landscapes of benchmarks in CEC2013 competitions for multimodal optimization.



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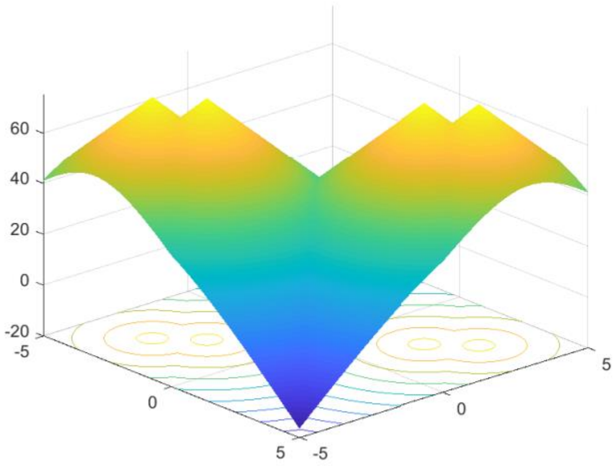

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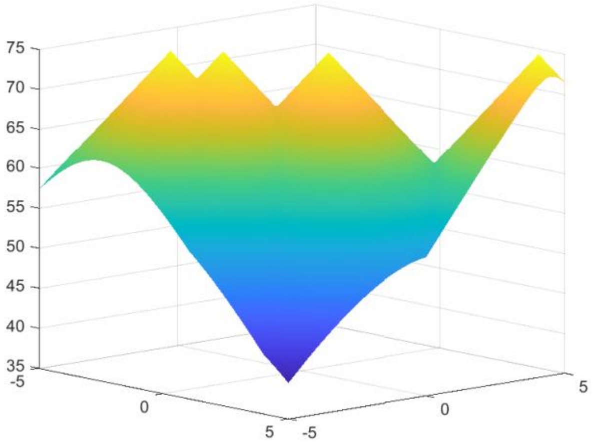

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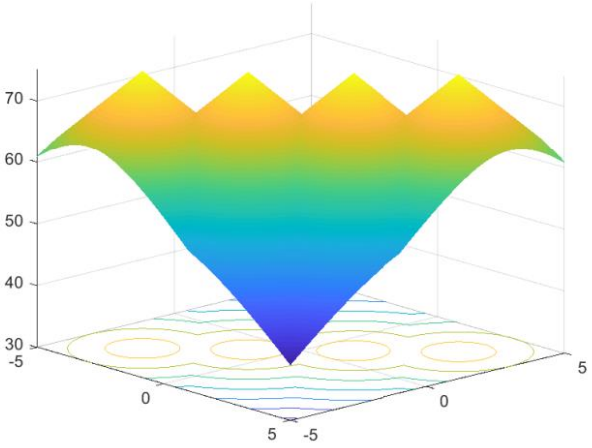

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Multimodal Functions

- Functions 5~8: Complex Multimodal Functions

Constructed by the composition functions in CEC 2013 competition for multimodal optimization*.

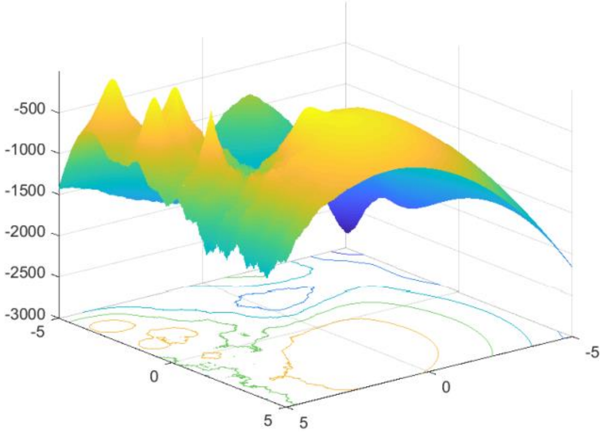
$$f(x) = -\sum_{i=1}^{n} \omega_i(\hat{f}_i(\frac{\boldsymbol{x} - \boldsymbol{o}_i}{\lambda_i} * \boldsymbol{M}_i))$$

- The composition function is composed by n basic functions.
- ω_i is the weight of the *i*-th basic functions, and $\hat{f}_i$ is the normalized version of f_i.
- $\boldsymbol{o}_i$, λ_i and $\boldsymbol{M}_i$ are the global optima, scale and rotation matrix of the *i*-th basic function, respectively.

* Li, X., Engelbrecht, A., & Epitropakis, M. G. Benchmark functions for CEC'2013 special session and competition on niching methods for multimodal function optimization. RMIT University, Evolutionary Computation and Machine Learning Group, Australia, Tech. Rep. 2013

Multimodal Functions

- The last four functions are directly from the composition functions in CEC2013 competitions for multimodal optimization.



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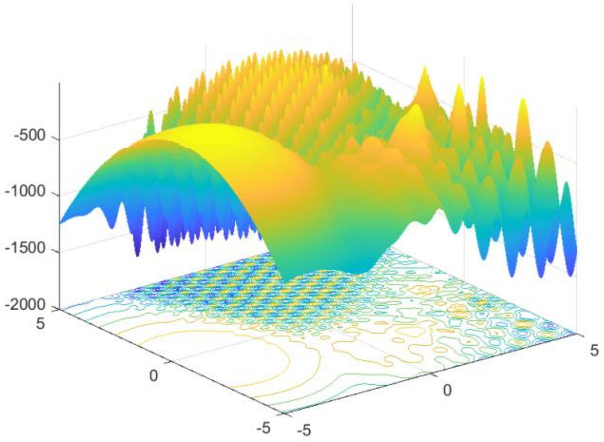

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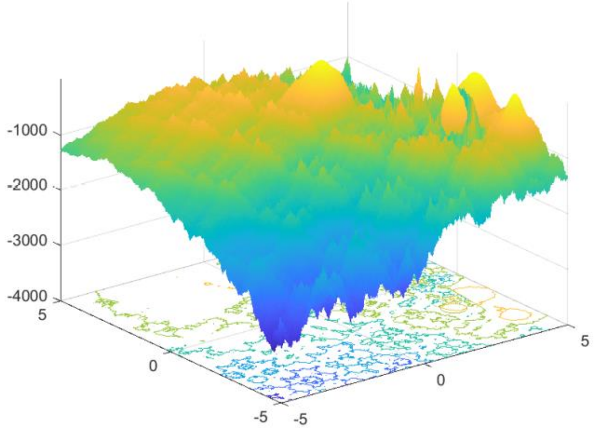

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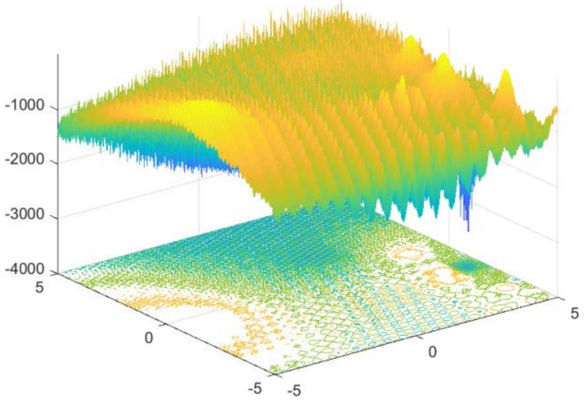


F8

Dynamic Change Modes

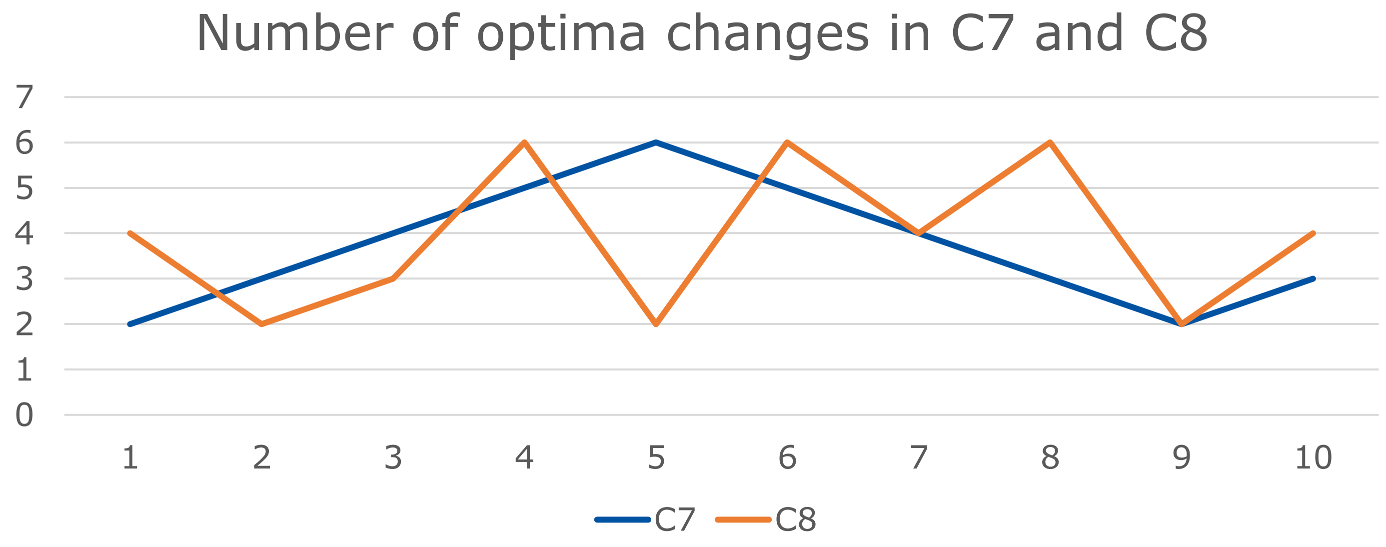
- Modes 1~6: Basic change modes from GDBG*
- .

C1:Small step changes	C2: Large step changes	C3: Random changes
C4: Chaotic changes	C5: Recurrent changes	C6: Recurrent with noisy changes

* Li, C., Yang, S., Nguyen, T. T., Yu, E. L., Yao, X., Jin, Y., Beyer, H., Suganthan, P. N. Benchmark generator for CEC 2009 competition on dynamic optimization. Tech. Rep. 2008.

Dynamic Change Modes

- Modes 7~8: Additional change modes about the number of optima.
  - C7 changes the number of optima linearly.
  - C8 changes the number of optima randomly.
  - Other core parameters changes according to C1.



Others

- Move conditions
  - The nearest distance from the current optimum to the rest optima must be larger than a predefined threshold.
  - If the condition is not satisfied, the current optimum should move multiple times until satisfying the condition.
- Information of DMMOPs
  - 60 environments for each problem
  - 5000*D number of fitness evaluations in each environment

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General Settings

- The 24 benchmarks are divided into 3 groups, i.e., G1, G2 and G3.
  - G1 => Multimodal property (F1~F8)
  - G2 => Dynamic property (C1~C8)
  - G3 => High dimensional property (D = 10)

Table 1: Details of the benchmark problems

Group	Index	Multimodal function	Dynamic Mode	Dimension
G1	P1	F1	C1	5
	P2	F2	C1	5
	P3	F3	C1	5
	P4	F4	C1	5
	P5	F5	C1	5
	P6	F6	C1	5
	P7	F7	C1	5
	P8	F8	C1	5
G2	P9	F8	C1	5
	P10	F8	C2	5
	P11	F8	C3	5
	P12	F8	C4	5
	P13	F8	C5	5
	P14	F8	C6	5
	P15	F8	C7	5
	P16	F8	C8	5
G3	P17	F1	C1	10
	P18	F2	C1	10
	P19	F3	C1	10
	P20	F4	C1	10
	P21	F5	C1	10
	P22	F6	C1	10
	P23	F7	C1	10
	P24	F8	C1	10

General Settings

- Parameters:
  - Runs: 30. Each problem is executed 30 times.
  - Frequency: each environment contains $5000 * D$ fitness evaluations.
  - Number of Environments: 60.
  - Maximum Fitness evaluations: the maximum of fitness evaluations in all environments is set to $5000 * D * 60$.
  - Environmental change condition: there is no fitness evaluation for the current environment.
  - Termination condition: all the fitness evaluations are consumed.

Performance Metric

Peak Ratio (PR) is adopted as the performance metric.

$$PR = \frac{\sum_{i=1}^{Run}\sum_{j=1}^{Env} NPF_{ij}}{\sum_{i=1}^{Run}\sum_{j=1}^{Env} Peaks_{ij}}$$

- *Run*: the total number of the independent runs, i.e., 30.
- *Env*: the number of the environment in a run
- NPF_{ij}: the number of the found optimal solutions in the final population of the *j*-th environment and *i*-th run.
- $Peaks_{ij}$: the total number of global peaks in the corresponding environment and run.

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Algorithms

Name	Authors
DAEA*	Ying Zhu, Jiahao Huang, Tao Yu, Peilan Xu

*Link:https://github.com/EvoNexusX/2023ZhuDAEA

Results

Results at 1e-3			Results at 1e-4			Results at 1e-5		
Group	Problem	DAEA	Group	Problem	DAEA	Group	Problem	DAEA
G1	P1	0.753	G1	P1	0.753	G1	P1	0.753
	P2	1.000		P2	**1.000**		P2	**1.000**
	P3	1.000		P3	**1.000**		P3	**1.000**
	P4	1.000		P4	**1.000**		P4	**1.000**
	P5	0.653		P5	0.653		P5	0.653
	P6	0.337		P6	0.337		P6	0.337
	P7	0.665		P7	0.665		P7	0.665
	P8	0.687		P8	0.687		P8	0.687
G2	P9	0.687	G2	P9	0.687	G2	P9	0.687
	P10	0.636		P10	0.636		P10	0.636
	P11	0.605		P11	0.605		P11	0.605
	P12	0.584		P12	0.584		P12	0.584
	P13	0.645		P13	0.645		P13	0.645
	P14	0.622		P14	0.622		P14	0.622
	P15	0.480		P15	0.480		P15	0.480
	P16	0.584		P16	0.584		P16	0.584
G3	P17	0.649	G3	P17	0.649	G3	P17	0.649
	P18	0.971		P18	0.971		P18	0.971
	P19	0.838		P19	0.838		P19	0.838
	P20	0.951		P20	0.951		P20	0.951
	P21	0.565		P21	0.565		P21	0.565
	P22	0.428		P22	0.428		P22	0.428
	P23	0.602		P23	0.602		P23	0.602
	P24	0.524		P24	0.524		P24	0.524

THANK YOU