Unknown Design Space Exploration using Multi-Agent Bayesian Optimization

Siyu Chen[1], Dr. Alparslan Emrah Bayrak[2], Dr. Zhenghui Sha[1]

1 Walker Department of Mechanical Engineering, The University of Texas at Austin
2 School of Systems and Enterprises, Stevens Institute of Technology

IDETC/CIE 2023 | Location: Boston Park Plaza; Boston MA
Conference Dates: August 20 – 23, 2023

TEXAS The University of Texas at Austin

SIDI Lab

Objective

Develop a **multi-agent system (MAS)** based on **Bayesian optimization (BO)** [1] to model a design team's sequential decision-making in the exploration of complex design spaces.

Research Overview

Design space exploration (DSE) involves finding the optimal solution within a set of requirements by examining various design alternatives [2]. It is a great challenge to explore complex design spaces with many local optima. Therefore, forming a MAS as the design team is crucial for effective DSE.

My research goal is to analyze team **global-local communication** and its impact on exploration performance (convergence speed). There are two key **research questions (RQs)** to address:

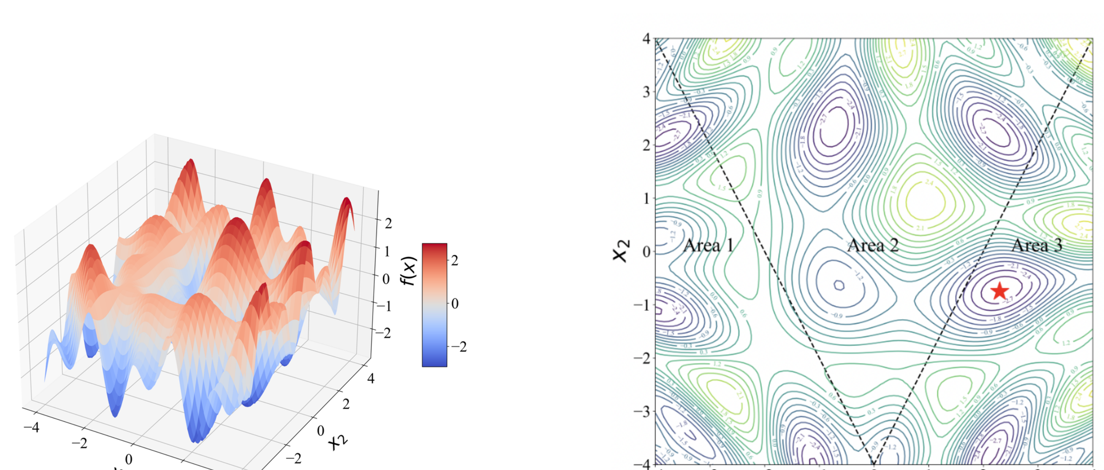
- **RQ1**: What are the guiding principles for a utility-based MAS search strategy that is congruent with the decision-making process of human design teams?
- **RQ2**: In the context of a utility-based MAS search strategy, how can local-global communication influence individual agent behavior?

Problem Formulation

The goal of agent i in a MAS, where $i \in \{1, 2, ..., N\}$ is to find the location of global minimum $\mathbf{x}^*$

$$\mathbf{x}^* = argmin_{\mathbf{x} \in A} f(\mathbf{x}),$$

where $f(\cdot)$ is a black-box objective function and $\mathbf{x} = (x_1, x_2, ..., x_d) \in A$, A is the design space.



(a) Objective function (b) Space division

Figure 1: An example of the objective function

MABO Framework

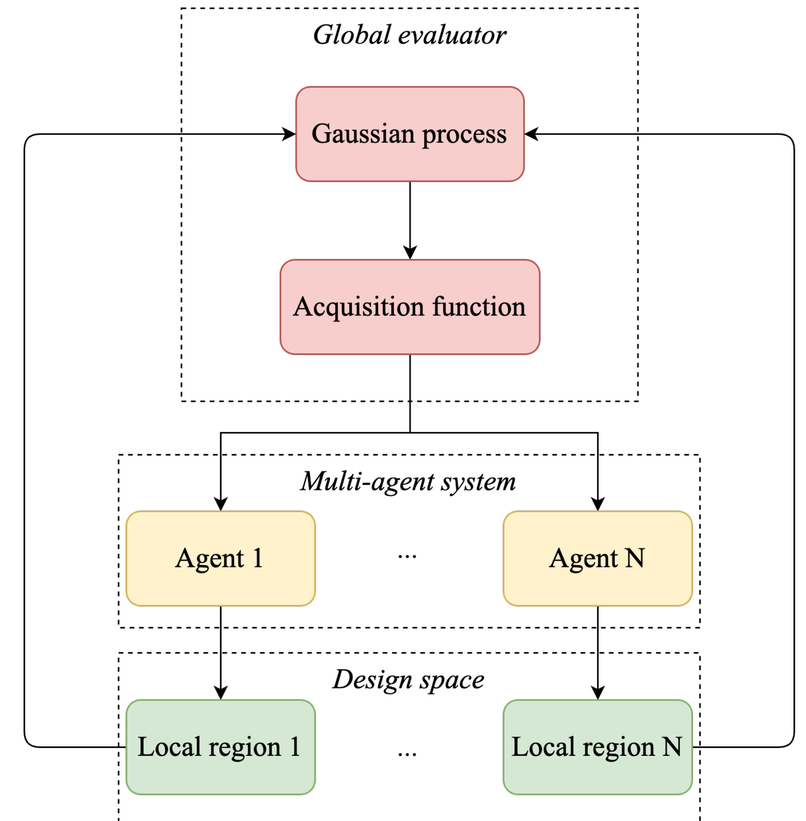
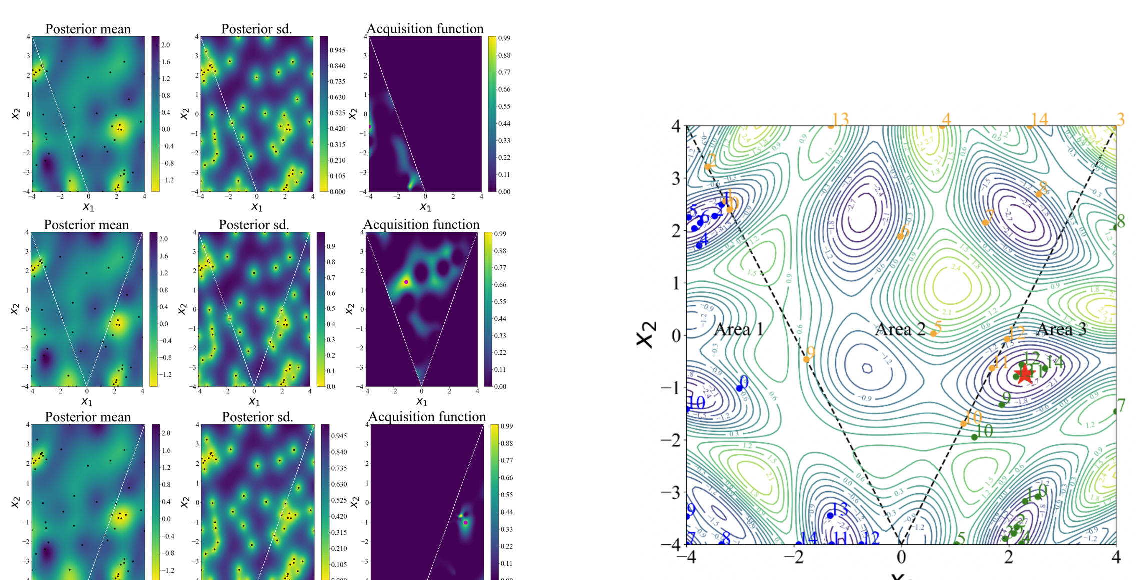


Figure 2: MABO Framework

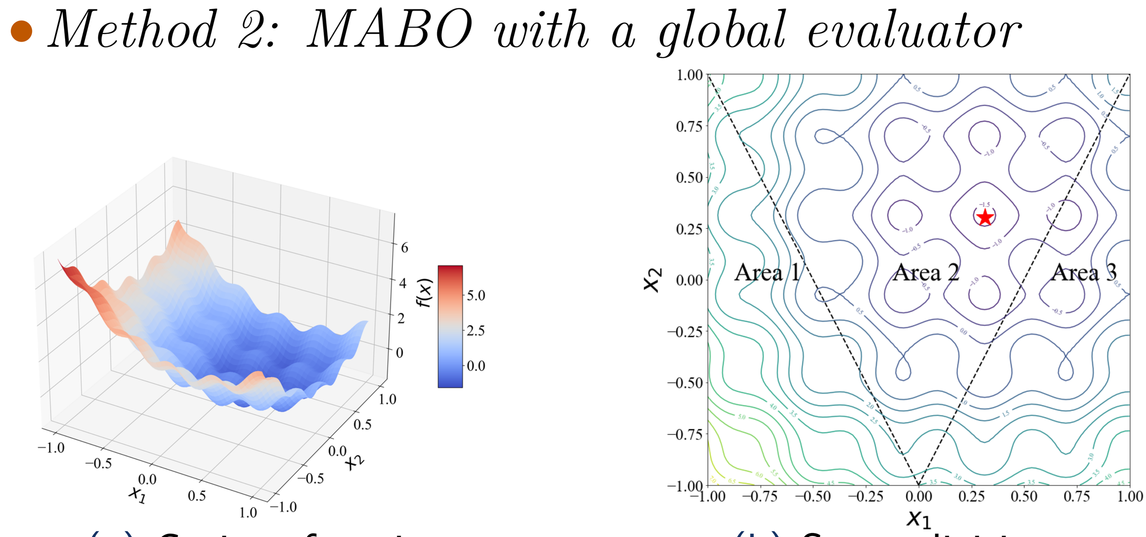


(a) Acquisition function (b) Sampling process

Figure 3: An example of MABO

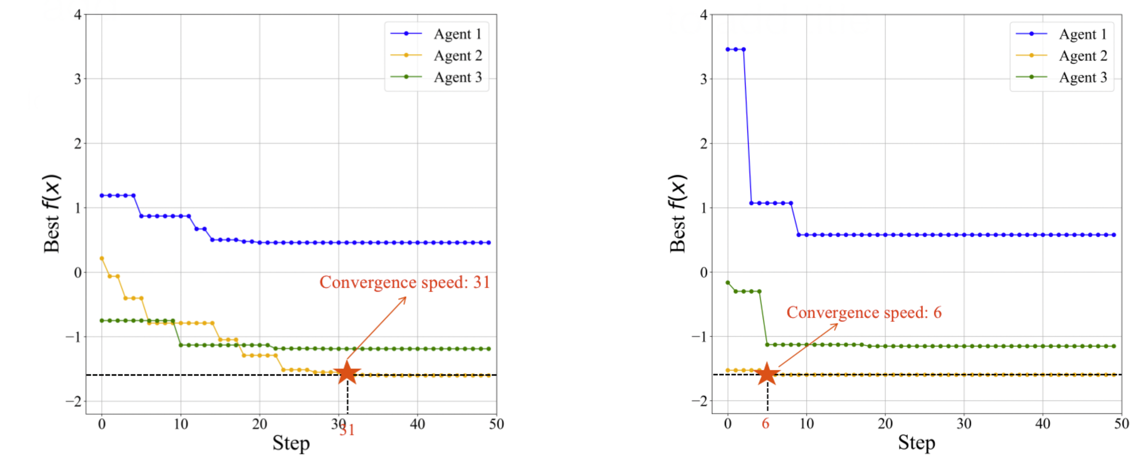
Experimental Results

- *Method 1: MABO without a global evaluator*
- *Method 2: MABO with a global evaluator*



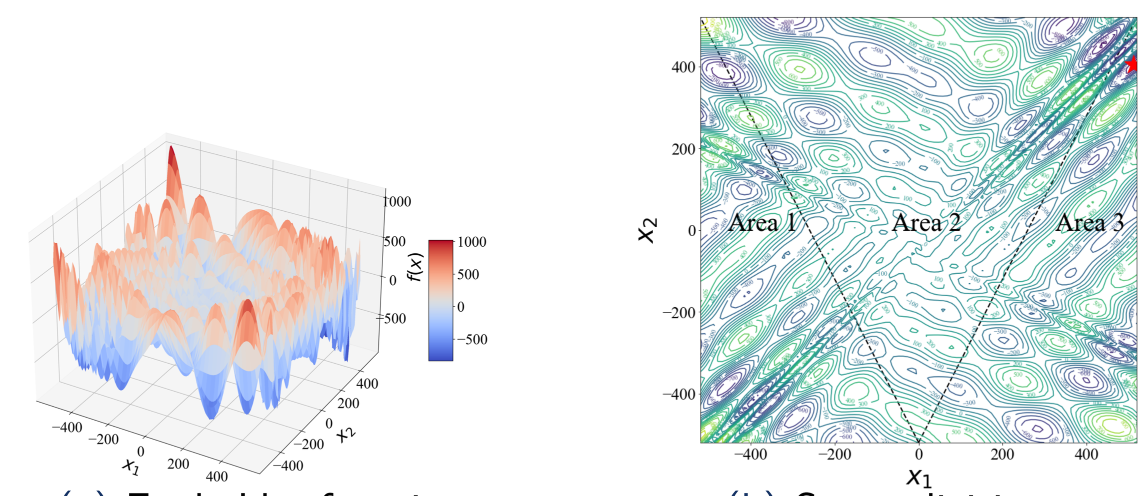
(a) Cosines function (b) Space division

Figure 4: **Cosines function** with a MAS of **three agents**.



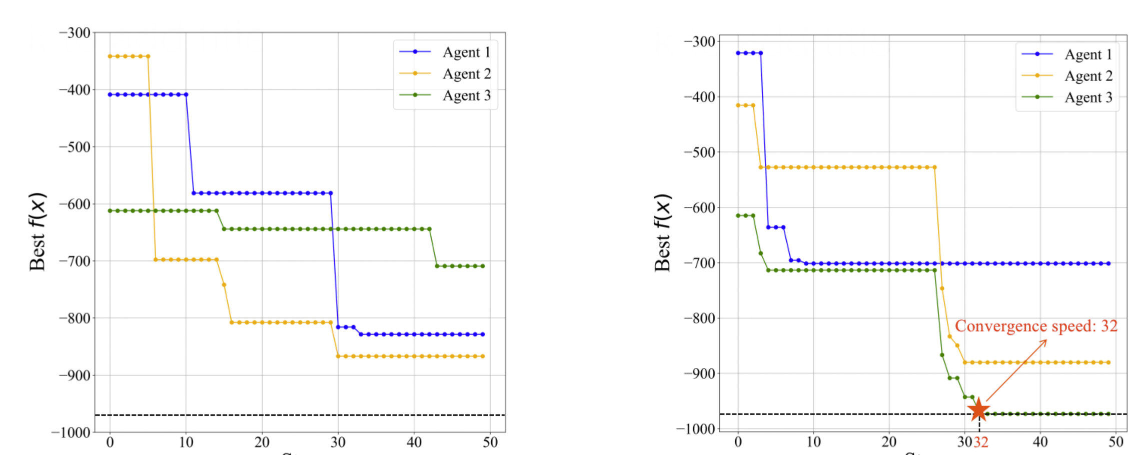
(a) Method 1 (b) Method 2

Figure 5: Faster convergence speed to local and global optima.



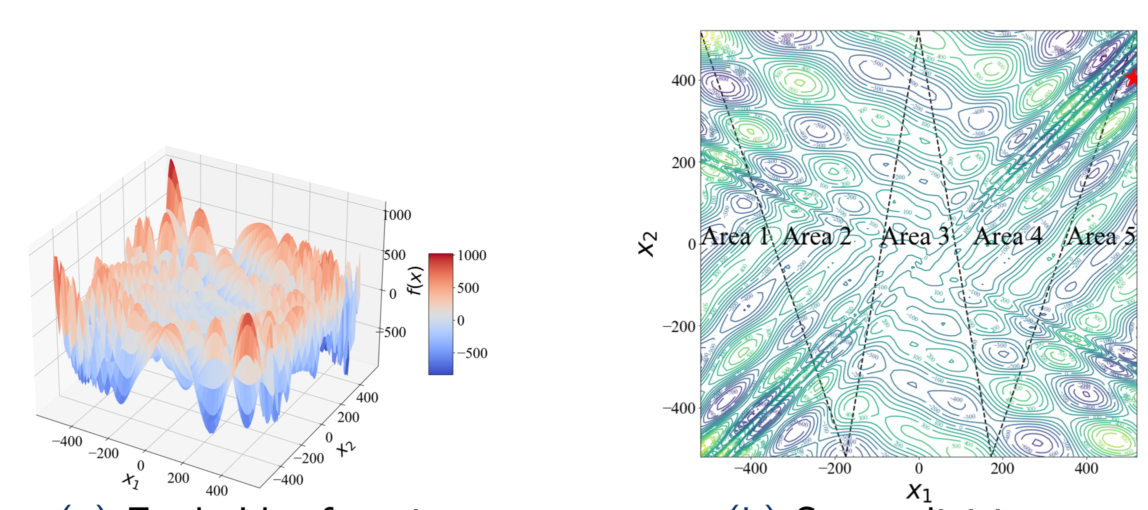
(a) Eggholder function (b) Space division

Figure 6: **Eggholder function** with a MAS of **three agents**.



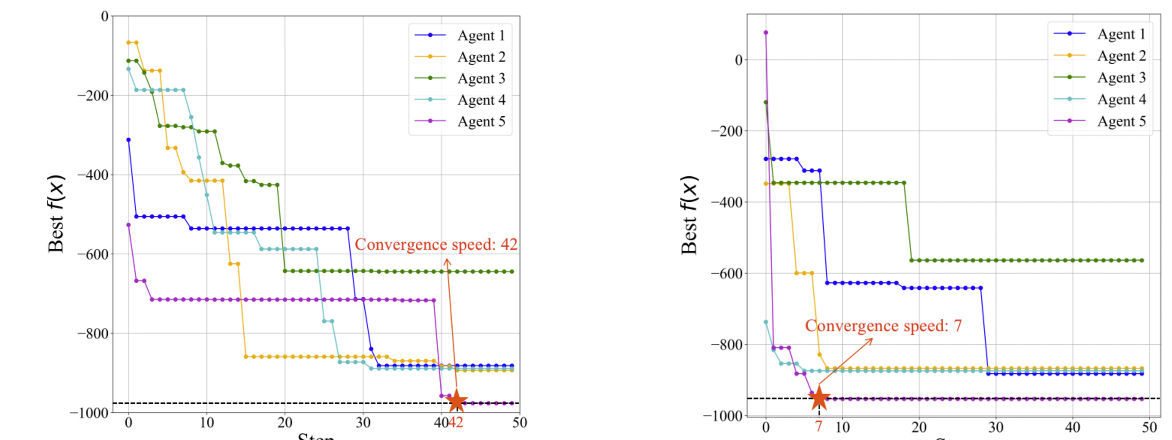
(a) Method 1 (b) Method 2

Figure 7: Faster convergence speed to local and global optima.



(a) Eggholder function (b) Space division

Figure 8: **Eggholder function** with a MAS of **five agents**.



(a) Method 1 (b) Method 2

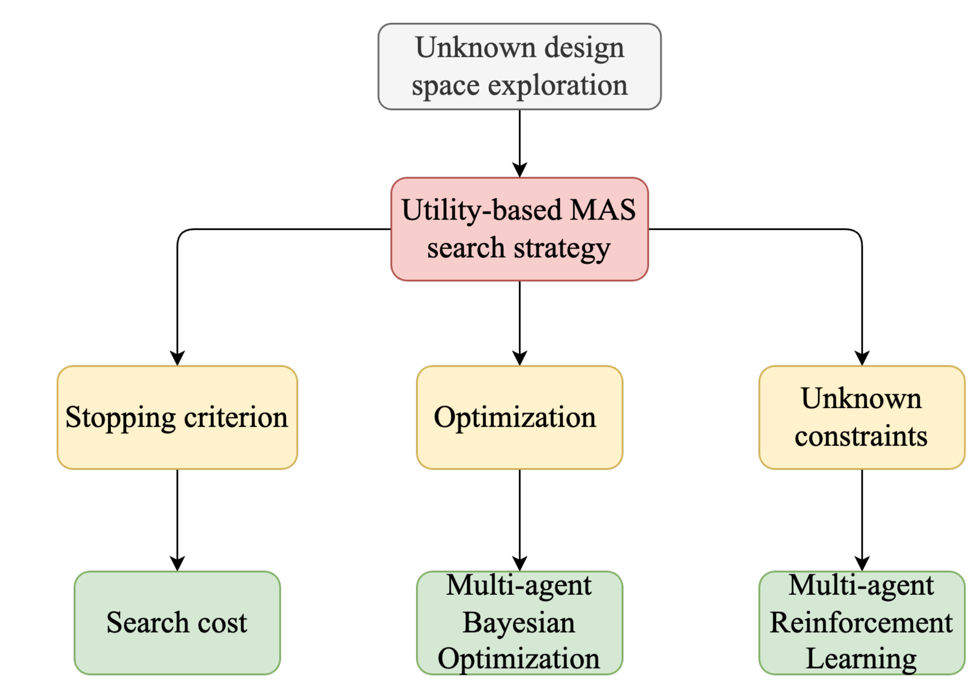
Figure 9: Faster convergence speed to global optima.

Insights and Conclusions

Faster convergence to global optimum but not necessarily to the local optimum for every agent

- Increase **MAS team size** → faster convergence
- Increase **complexity of objective function** → slower convergence

Future Work



References

[1] Bobak Shahriari, Kevin Swersky, Ziyu Wang, Ryan P Adams, and Nando De Freitas. Taking the human out of the loop: A review of bayesian optimization. *Proceedings of the IEEE*, 104(1):148–175, 2015.

[2] Luigi Nardi, David Koeplinger, and Kunle Olukotun. Practical design space exploration. *In 2019 IEEE 27th International Symposium on Modeling, Analysis, and Simulation of Computer and Telecommunication Systems (MASCOTS)*, pages 347–358. IEEE, 2019.

Acknowledgements

The authors would like to express sincere gratitude to ASME Design Theory and Methodology (DTM) for their generous travel support.

CONTACT INFORMATION

For more information, please contact:
Siyu Chen at siyu.chen@utexas.edu