

Sai Wang

Supervisors

Professor: Jianjun Hao (2016 - 2019)
Professor: Yoan Shin (2017 - 2019)
Professor: Yi Gong (2019 - so far)

Other professors

Professor: Wencai Zhao (2012 - 2016)
Professor: Bingsheng He (2020 - 2023)

Coding skill



Scale: 0 (basic skills) - 6 (expert).

Research Experiences

2024	Large Language Model	Efficient AI
	Technologies: pruning, knowledge distillation, quantization, and more for optimizing model size, inference speed, and resource utilization in AI systems.	
2022	Nonlinear convex optimization	Variational analysis
	Solving real-variable and complex-variable convex problems by using the proximal point algorithm, primal-dual method, and ADMM. These methods can achieve an $O(1/t)$ convergence rate.	
2019	Edge-cloud network and federated learning	Task offloading and resource allocation
	Aiming to reduce latency, energy consumption, and training error by optimizing task offloading, transmit power, number of epochs, and data allocation.	
2017	Underwater Wireless sensor network	Clustering algorithm
	In underwater wireless sensor networks, an energy-efficient clustering algorithm based on the Voronoi diagram is proposed for magnetic induction communications.	
2016	Wireless sensor network	Path planning
	Reducing latency and energy consumption by designing the optimal path for UAVs.	

Summary of nonlinear optimization

1. The convex optimization problem with nonlinear inequality constraints:

$$\min \{f(\mathbf{x}) \mid \phi_i(\mathbf{x}) \leq 0, \mathbf{x} \in \mathcal{X}, i = 1, \cdots, m\}, \tag{1}$$

where $\mathcal{X} \in \mathbb{R}^n$ is a nonempty closed convex set, $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $\phi_i : \mathbb{R}^n \rightarrow \mathbb{R}$ ($i = 1, \dots, m$) are proper and closed convex functions, and ϕ_i ($i = 1, \dots, m$) are continuously differentiable.

2. The saddle-point problem with a nonlinear coupling operator:

$$\min_{\mathbf{x} \in \mathcal{X}} \max_{\mathbf{y} \in \mathcal{Y}} \mathcal{L}(\mathbf{x}, \mathbf{y}) := f(\mathbf{x}) + \langle \mathbf{y}, \Phi(\mathbf{x}) \rangle - g(\mathbf{y}), \tag{2}$$

where $\mathcal{X} \subseteq \mathbb{R}^n$ and $\mathcal{Y} \subseteq \mathbb{R}^m$ are two closed convex sets. $f : \mathcal{X} \rightarrow \mathbb{R}$ and $g : \mathcal{Y} \rightarrow \mathbb{R}$ are two proper convex but not necessarily smooth functions. The nonlinear function $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is both convex and continuously differentiable over \mathcal{X} .

3. The convex complex-variable matrix optimization problem:

$$\min \{f(\mathbf{X}) \mid \phi_i(\mathbf{X}) \leq 0, \mathbf{X} \in \mathcal{X}, i = 1, \cdots, p\}, \tag{3}$$

where $\mathcal{X} \subseteq \mathbb{C}^{m \times n}$ is a convex set and objective $f : \mathbb{C}^{m \times n} \rightarrow \mathbb{R}$ is convex. Constraint functions $\phi_i : \mathbb{C}^{m \times n} \rightarrow \mathbb{R}$ ($i = 1, \dots, p$) are convex and differentiable over \mathcal{X} .

4. The separable convex optimization problem with nonlinear inequality constraints:

$$\min \{f(\mathbf{x}) + g(\mathbf{y}) \mid \phi_i(\mathbf{x}) + \psi_i(\mathbf{y}) \leq 0, \mathbf{x} \in \mathcal{X}, \mathbf{y} \in \mathcal{Y}, i = 1, \cdots, p\}, \tag{4}$$

where $\mathcal{X} \in \mathbb{R}^n$ and $\mathcal{Y} \in \mathbb{R}^m$ are two nonempty closed convex set, $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $\phi_i : \mathbb{R}^n \rightarrow \mathbb{R}$ ($i = 1, \dots, p$), $g : \mathbb{R}^m \rightarrow \mathbb{R}$ and $\psi_i : \mathbb{R}^m \rightarrow \mathbb{R}$ ($i = 1, \dots, p$) are proper and closed convex functions, and ϕ_i, ψ_i ($i = 1, \dots, p$) are continuously differentiable.