Black-Box Optimization: from Climate Change to Audio and Robotics

Simple, robust methods when gradients fail

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Slides: https://github.com/TUIlmenauAMS/BlackBoxOptimizerSPcomparison

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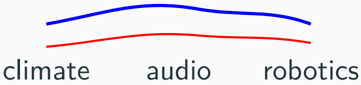
Motivation

- Many engineering objectives are non-convex, noisy, costly to evaluate, and lack usable gradients.
- **Black-box optimization (BBO)** treats the system as an oracle: propose x, observe $f(x)$.
- Today's focus: cross-domain uses in climate/energy and audio, plus robotics.
- Thread through the talk: a lightweight BBO—**Random Directions**.
  (filter banks, blind source separation, RNNs, walking control)



Black-Box Optimization: Basics

- Problem: $\min_x f(x)$, only function evaluations available; evaluations may be noisy/expensive.
- Key trade-offs: *exploration vs. exploitation*, sample efficiency vs. robustness.
- Families of methods:
  - *Direct search / ES (Evolutionary Strategies)*: Nelder–Mead, CMA-ES (Covariance Matrix Adaptation-ES).
  - *Surrogate-based*: Bayesian optimization with Gaussian Processes (GPs)/trees; acquisition functions (EI- (Evolutionary Strategy with Iterated Variance), KG-(Kruglov's inheritance) ES).
  - *Random search heuristics*: coordinate/axis sampling, ARS-like methods.
- Practicalities: parallelism, constraints, noisy objectives, trust regions, restart strategies.

Our Method: Random Directions (RD)

Idea

Sample random directions in parameter space, test small steps in each direction, and keep the best-improving step. Reduce step scale over time; optionally restrict to random subspaces in high dimensions.

Given objective f(θ), initial θ_0, step scale s_0
for t = 0,1,2,...,T:
    draw P random unit directions u_p (optionally in random subspaces)
    evaluate $f(\theta_t + s_t u_p)$ for all u_p
    pick $v_t = argmin_{s_t u_p} f(\theta_t + s_t u_p)$
    if $f(\theta_t + v_t) < f(\theta_t)$:
        line-search along v_t (optional)
        $\theta_{t+1} = \theta_t + v_t$
    else:
        reduce s_t (shrink scale)
return best θ

Why it works in practice

- Few evaluations per iteration, trivially parallel.
- Robust to noise; no gradients/Jacobians required.
- Random subspace restriction scales to high dimensions.
- Works with hardware-in-the-loop.

RD vs. Other BBO Methods (Qualitative)

CMA-ES

- Learns covariance of successful steps; strong on ill-conditioned, non-separable problems.
- Heavier compute per iteration; strong global search.

Bayesian Optimization

- Sample-efficient with expensive objectives; surrogate + acquisition.
- Struggles in very high dimensions or heavy noise without structure.

SPSA [1] / Finite-diff.

- Two-point gradient estimates; good when #params large, evaluations cheap.

Random/ARS[2]-like

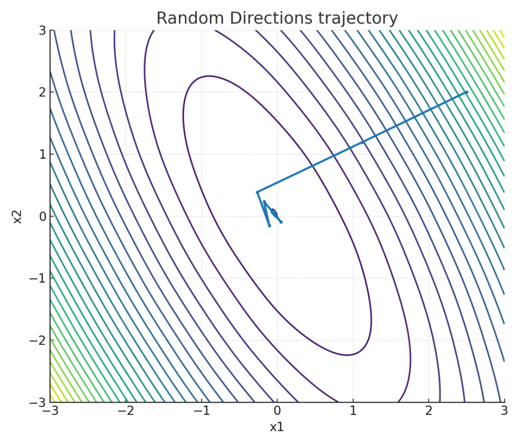
- Policy-space random search competitive for RL control; simple, robust.

RD

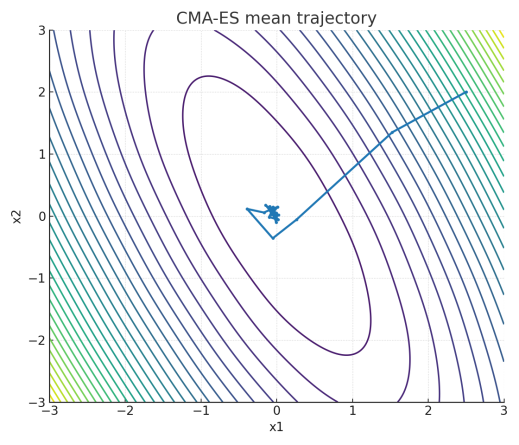
- Sweet spot: simple, parallel, noise-tolerant; easy to hybridize with trust regions or surrogates.

[a] Simul. Perturbation Stochastic Approx.
[b] Adaptive Response Surface

Live Demo: RD vs. CMA-ES



Random Directions trajectory (2D test function)



CMA-ES mean trajectory (same function)

Figures auto-generated by the demo script (`bbo_demo_rd_vs_cmaes.py`). Demo video

Audio Applications

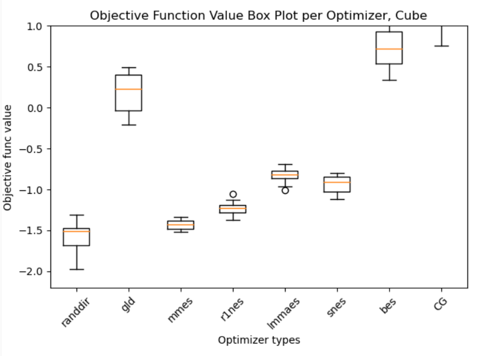
Application: Blind Audio Source Separation (time-domain)

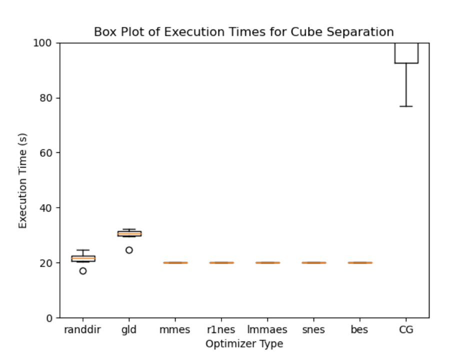
- Optimize an unmixing matrix W on short time frames (low delay), minimizing divergence between outputs.
- Objective examples: KL-divergence between output stats and target priors; SDR proxies with masks.
- RD enables parallel per-frame (or windowed) optimization under tight time budgets.
- Demo/repo: LowDelayMultichannelSourceSeparation_Random-Directions_Demo

$$\text{mix } x \xrightarrow{\text{frames}} \boxed{\text{RD optimizer on } W} \xrightarrow{\text{separated } y}$$

Results: Separation Quality and Runtime (examples)

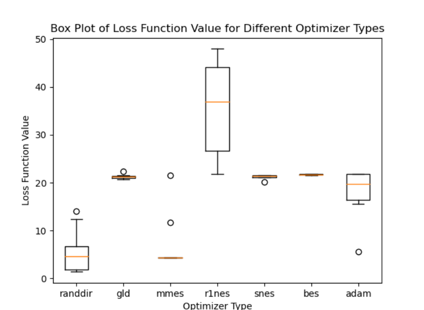
- RD performs among the top methods in objective value while keeping processing time low (stereo and cube arrays).
- Suited for real-time constraints with parallelization.





Application: Optimizing RNNs (derivative-free tuning)

- Train/tune RNN weights or hyperparameters when gradients are unstable (vanishing/exploding) or unavailable.
- Example task: decaying sinusoid (2nd-order IIR) fitting; objective = MSE over long horizon.
- RD evaluates candidate weight perturbations directly on sequence loss; optionally constrain spectral radius. It obtains the best performance:



Robotics

Application: Robotic Walking (policy search)

- Optimize gait policy parameters for stability, speed, energy; evaluation via simulation or on-hardware.
- RD and ARS-like updates in policy parameter space are simple and competitive for locomotion.
- Embedded-friendly: small memory footprint, parallel rollouts.
- Demo: Our robots webpage

Climate/Energy

Climate/Energy: Where BBO Fits

- **Energy storage sizing**: capacity/cycling/lifetime cost trade-offs under uncertainty.
- **EV adoption modeling**: S-curve/Bass diffusion calibration; policy portfolio search.
- **Renewable integration**: wind/solar forecasting models, controller tuning, dispatch.
- **Strategy**: use surrogates (BO) for costly simulators; use RD for scalable parameter sweeps/trust-region steps.

Case Examples (pointers)

- Bayesian-optimized forecasting/control for wind turbines and power prediction.
- Microgrid sizing & EMS: metaheuristics and BO for techno-economic optimization.
- EV diffusion calibration: Bass/Logistic models; sensitivity to incentive parameters.

Practical Tips

1. Start with a coarse RD or ES sweep to map structure; then refine with BO in promising regions.
2. Model noise explicitly; average repeats where variance is large.
3. Parallelize evaluations; cache and resume across runs.

Speech Timbre Disentanglement & Emotion

Timbre Disentanglement → Emotion Recognition (SER)

- Speech factors: *content*, *timbre* (who/voice quality), *prosody* (how/intonation).
- Disentanglement improves robustness/transfer for SER categories: anger, sadness, neutral, happiness.
- BBO role: tune disentanglement losses, fusion layers, thresholds using human-in-the-loop or nondifferential metrics.
- Robotics: adjust dialogue policy/affect generation conditioned on SER; safe exploration via trust regions.

speech > encoder

z_{content} $\quad z_{\text{timbre}}$ $\quad z_{\text{prosody}}$

$\downarrow$ SER $\quad \downarrow$ SER $\quad \downarrow$ SER

Synthesis

Cross-Domain Lessons

- Shared traits: non-convex, noisy, expensive objectives; gradients often unreliable.
- **RD** thrives with: parallel evaluations, high dimension (subspaces), hardware-in-the-loop.
- Hybrid pipelines (RD/ES + BO) deliver both *coverage* and *sample efficiency*.
- Human-in-the-loop metrics (perception, preference, safety) fit naturally into BBO.

Future Directions

- RD + Bayesian surrogates (trust region BO) for faster convergence.
- Constrained BBO: safety, stability, fairness; robust objectives.
- AutoML/Neuroevolution crossovers for audio and robotics.
- Open benchmarks in climate/audio with human ratings or grid simulators.

Conclusion

- Black-box optimization is a practical bridge across climate, audio, and robotics.
- **Random Directions**: simple, robust, and effective under real-world constraints.
- Students: many open problems - from timbre-aware SER to microgrid sizing under uncertainty.

Code pointers: BlackBoxOptimizerSPcomparison & LowDelayMultichannelSourceSeparation_Random-Directions_Demo

References (selected) i

- N. Hansen, “The CMA Evolution Strategy: A Tutorial,” *arXiv:1604.00772*, 2016.
- B. Shahriari et al., “Taking the Human Out of the Loop: A Review of Bayesian Optimization,” *Proc. IEEE*, 2016.
- P. I. Frazier, “A Tutorial on Bayesian Optimization,” *arXiv:1807.02811*, 2018.
- J. C. Spall, “Implementation of SPSA,” *Johns Hopkins APL Technical Digest*, 1998.
- H. Mania, A. Guy, B. Recht, “Simple random search provides a competitive approach to RL,” *arXiv:1803.07055*, 2018.
- M. Tang et al., “Robust MPC of Wind Turbines via Bayesian Optimization,” *Frontiers in Energy Research*, 2023.

References (selected) ii

- G. S. Thirunavukkarasu et al., "Optimization in Microgrid Energy Management: A Review," 2022.
- A. Brdulak et al., "BASS Model Analysis in E-Cars Innovation Diffusion," *Energies*, 2021.
- N. Gengembre et al., "Disentangling prosody and timbre embeddings," *INTERSPEECH*, 2024.
- Z. Peng et al., "EmoTalk: Speech-Driven Emotional Disentanglement for 3D Face Animation," *ICCV*, 2023.

Questions?

Slides/resources