







2022 Optimization Days

Nature et technologies

Escaping unknown discontinuous regions in blackbox optimization

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 Motivation
 Modeling
 Basics
 DiscoMads
 Results
 Conclusion

 An example of discontinuous problem







Source (right picture): Source: Harvey, Ramsden 2000 - ASME Turbo Expo Robert 2011 - Brevet US20110085896 A1

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 An example of discontinuous problem

vibrations of aircraft engine blades







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 Modeling
 Basics
 DiscoMads
 Results
 Conclusion

 Problem characterization



▶ *f* and *c* : given by a **blackbox**, possibly **discontinuous functions**

 Modeling
 Basics
 DiscoMads
 Results
 Conclusion

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f and *c* : given by a blackbox, possibly discontinuous functions
 d : infinite constraint

 Modeling
 Basics
 DiscoMads
 Results
 Conclusion

 Problem characterization

$$\min_{x \in X} \quad f(x)$$
s.t. $c(x) \le 0$
 $d(x) \le 0 \implies x$ "far away" from discontinuities of f or c

f and *c* : given by a blackbox, possibly discontinuous functions
 d : infinite constraint

Objective : treat constraint d in a blackbox optimization context with the Mesh Adaptive Direct Search

Motivation	Modeling	Basics	DiscoMads	Results	Conclusion
Outline					



2 Basics on direct search methods

B DiscoMads

4 Numerical results

5 Conclusion





 $\Omega = \{ x \in X : c(x) \le 0 \}$



► region of weak discontinuities D (=): slope of f or c_j between two points at distance at most r_d exceeds a limit slope τ



 $D = \{ y \in X : \exists j \in J, \exists z \in X \cap B_{r_{d}}(y), |c_{j}(y) - c_{j}(z)| > \tau ||y - z|| \}$

Motivation Modeling Basics DiscoMads Results Conclusion Problem modeling

► region of weak discontinuities D (\blacksquare): slope of f or c_j between two points at distance at most r_d exceeds a limit slope τ

▶ safety margin M (■ \cup ■): region of radius r_e around D



 $M = X \cap \left(\cup_{x \in D} B_{r_{e}}(x) \right)$

Motivation Modeling Basics DiscoMads Results Conclusion Problem modeling

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 $M = X \cap \left(\cup_{x \in D} B_{r_{e}}(x) \right)$

 $x \notin M \iff d(x) \leq 0$

Motivation	Modeling	Basics	DiscoMads	Results	Conclusion
Outline					

1 Modeling

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B DiscoMads

4 Numerical results

5 Conclusion



► example: $\min_{x \in \mathbb{R}^2} f(x)$



¹E. Fermi and N. Metropolis. Numerical solution of a minimum problem. Los Alamos Unclassified Report LA–1492. Los Alamos, USA: Los Alamos National Laboratory, 1952.



► example: $\min_{x \in \mathbb{R}^2} f(x)$



poll at iteration 0

•
$$f(x^0) \leq f(t^1)$$

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• example: $\min_{x \in \mathbb{R}^2} f(x)$



poll at iteration 0

- $f(x^0) \leq f(t^1)$
- $f(x^0) \leq f(t^2)$
- $f(x^0) > f(t^3)$

 \Rightarrow successful

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• example: $\min_{x \in \mathbb{R}^2} f(x)$



poll at iteration 1

- $f(x^1) \leq f(t^4)$
- $f(x^1) \leq f(t^5)$
- $f(x^1) \leq f(t^6)$

 \Rightarrow unsuccessful

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► example: $\min_{x \in \mathbb{R}^2} f(x)$



▶ poll at iteration 2 ...

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²C. Audet and J.E. Dennis, Jr. "Mesh Adaptive Direct Search Algorithms for Constrained Optimization". *SIAM Journal on Optimization* 17.1 (2006), pages 188–217. URL: http://dx.doi.org/doi:10.1137/040603371.



1 search step : user-defined points on the mesh

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- 1 search step : user-defined points on the mesh
- **2** poll step : poll parameter $\Delta^k \Rightarrow$ diversified poll directions \Rightarrow stronger convergence results

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- ${f S}$ update of mesh size δ^k and poll parameter Δ^k

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- a Mads iteration
 - 1 search step : user-defined points on the mesh
 - ② poll step : poll parameter Δ^k ⇒ diversified poll directions ⇒ stronger convergence results
 - **③** update of mesh size δ^k and poll parameter Δ^k
- ► can solve constrained problems : $\min_{x \in X \subseteq \mathbb{R}^n} \{f(x) : c(x) \leq 0\}$
 - progressive barrier approach

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 - progressive barrier approach
 - constraint violation function

$$h(x) = \begin{cases} \sum_{j=1}^{m} (\max(c_j(x), 0))^2 & \text{if } x \in X, \\ \infty & \text{otherwise} \end{cases}$$

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 Key algorithmic mechanisms: example on Cs





1 revelation (radius r_d and limit slope τ)





() revelation (radius r_d and limit slope τ)





() revelation (radius r_d and limit slope τ)



 $|f(t^6) - f(x^1)| > \tau ||t^6 - x^1|| \implies t^6 \text{ and } x^1 \text{ are revealing points} \in D$



- **1** revelation (radius r_d and limit slope τ)
- **2** exclusion (radius $r_{\rm e}$)



 t^6 and x^1 are revealing points \implies exclusion constraint



• set of revealing points D^k at iteration k



- **•** set of revealing points D^k at iteration k
- exclusion constraint d^k at iteration k

$$d^{k}(x) = \begin{cases} 1 - \frac{\operatorname{dist}(x, D^{k})}{r_{e}} & \text{if } D^{k} \cap B_{r_{e}}(x) \neq \emptyset, \\ 0 & \text{otherwise.} \end{cases}$$

Motivation Modeling Basics DiscoMads Results Conclusion Exclusion mechanism

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• constraint violation function h^k

$$h^{k}(x) = \begin{cases} \sum_{j=1}^{m} \max(c_{j}(x), 0)^{2} + \max(d^{k}(x), 0)^{2} & \text{if } x \in X \\ \infty & \text{otherwise} \end{cases}$$

Motivation Modeling Basics DiscoMads Results Conclusion
Exclusion mechanism

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problem solved at iteration k:

$$\begin{array}{ll} \min_{x \in X} & f(x) \\ \text{s.t.} & c(x) \leqslant 0 \\ \text{and} & d^k(x) \leqslant 0 \end{array}$$



- Mads iteration :
- search step
- poll step

S parameters update depending on iteration type



- DiscoMads iteration : try to reveal discontinuity after each evaluation
- 1 search step
- 2 poll step

B parameters update depending on iteration type



- DiscoMads iteration : try to reveal discontinuity after each evaluation
- search step
- 2 poll step
 - revealing poll : n_{alea} random points in $B_{r_s}(x^k)$ with $r_s > r_d + r_e$
 - usual Mads poll
- B parameters update depending on iteration type



- DiscoMads iteration : try to reveal discontinuity after each evaluation
- search step
- 2 poll step
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 - usual Mads poll
- B parameters update depending on iteration type
 - revealing iteration
 - otherwise usual iteration types from Mads



1 mesh gets infinitely fine when $k \to \infty$



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- Prefining point analysis





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 - case A $\implies f^{\circ}(\hat{x}, p) \ge 0$ (from Mads)





- 1 mesh gets infinitely fine when $k \to \infty$
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 - case A \implies $f^{\circ}(\hat{x}, p) \ge 0$ (from Mads)
 - case B $\implies \hat{h}^{\circ}(\hat{x}, p) \ge 0$ (from Mads)





- 1 mesh gets infinitely fine when $k \to \infty$
- Prefining point analysis
 - case A \implies $f^{\circ}(\hat{x}, p) \ge 0$ (from Mads)
 - case B $\implies \hat{h}^{\circ}(\hat{x}, p) \ge 0$ (from Mads)
 - case $C \implies \hat{x}$ is a local minimizer of \hat{h} on X

from revealing poll + piecewise continuity assumption



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• magnitude of vibration $u(s, \omega)$











▶ styrene production problem³ \implies styrene blackbox⁴

- 8 variables (between 0 and 100), 11 constraints
- simulation fails for some $x \implies$ hidden constraints

³C. Audet, V. Béchard, and S. Le Digabel. "Nonsmooth optimization through Mesh Adaptive Direct Search and Variable Neighborhood Search". J. Global Optim. 41.2 (2008), pages 299–318.

⁴https://github.com/bbopt/styrene



• styrene production problem³ \implies STYRENE blackbox⁴

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DiscoMads to escape regions of hidden constraints

• failures $\implies f = 10^{20} \implies$ weak discontinuities of f

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how do we know if d is satisfied at x?

• evaluation of severity of hidden constraints around *x*:

 $H(x,\sigma) := \#\{y^i \in B_{\sigma}(x), i \in \{1, ..., 1000\}, \text{ evaluation at } y \text{ fails}\}$

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- ▶ problem
 - x^0 : one of the best known solutions $f(x^0) = -33709000$
 - \rightarrow $H(x^0, 15) = 435 \implies x^0$ in hidden constraints regions

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$$r_{\rm d} = 5, \, \tau = 10^{15}, \, r_{\rm e} = 10^{15}$$

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Motivation	Modeling	Basics	DiscoMads	Results	Conclusion
Outline					

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Basics on direct search methods

B DiscoMads

4 Numerical results

5 Conclusion



▶ DiscoMads⁵ to escape unknown discontinuous regions

- relies on Mads \Rightarrow preserves convergence properties
- validated on low-dimensional numerical problems

⁵C. Audet, A. Batailly, and S. Kojtych. "Escaping unknown discontinuous regions in blackbox optimization". SIAM Journal on Optimization (2022). recently accepted.



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perspectives

- improvements \Rightarrow revealing poll, scaling of variables, surrogates...
- other problems \Rightarrow complex blade design, crash simulations...
- other infinite constraints?

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Thank you for attention !