

Stochastic Tunneling and Time Series Analysis for Global Optimization Techniques

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Preview

- ▶ Motivation – Heuristics, Randomized Algorithms
- ▶ Test Functions
 - ▶ 1D
 - ▶ Spin Glasses
- ▶ Metropolis-based Search
 - ▶ Simulated Annealing
 - ▶ Stochastic Tunneling
- ▶ Search as a Stochastic Process
 - ▶ Analysis: Detrended Fluctuation Analysis (DFA)
 - ▶ Guidance via DFA
- ▶ Application: Protein Structure Prediction of GvpA

Test Functions

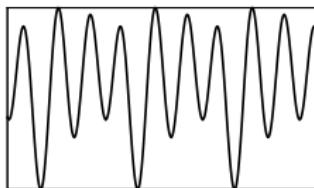
Ideas for Algorithms?

Need to Evaluate Performance

→ test functions

- ▶ known minima
- ▶ combinatorial vs. continuous problems
- ▶ “tune-able” parameters
- ▶ not too hard **but** also not too easy

Test Functions – 1D



Problem!

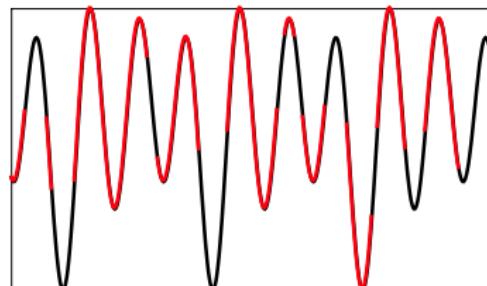
Stochastic Search → Sampling

for general dynamics:

density of bins visited $\rho_s \sim n^\alpha$ for
single walker with $\alpha < 1$

what happens, if

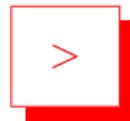
- ▶ we place m many walkers randomly
- ▶ and let them run each n/m many steps?



Test Functions – 1D

density of bins covered $\rho_m(n)$ (success rate), for small m :

$$\begin{aligned}\rho_m(n) &= m \cdot \rho_1\left(\frac{n}{m}\right) \\ &= \frac{1}{N} \cdot m \cdot \langle\delta\rangle \cdot \left(\frac{n}{m}\right)^\alpha \\ &= \frac{1}{N} \cdot \langle\delta\rangle \underbrace{m^{1-\alpha}}_{>1} \cdot n^\alpha\end{aligned}$$



$$\frac{1}{N} \cdot \langle\delta\rangle \cdot n^\alpha = \rho_1(n) = \rho_s$$

N : no. of bins

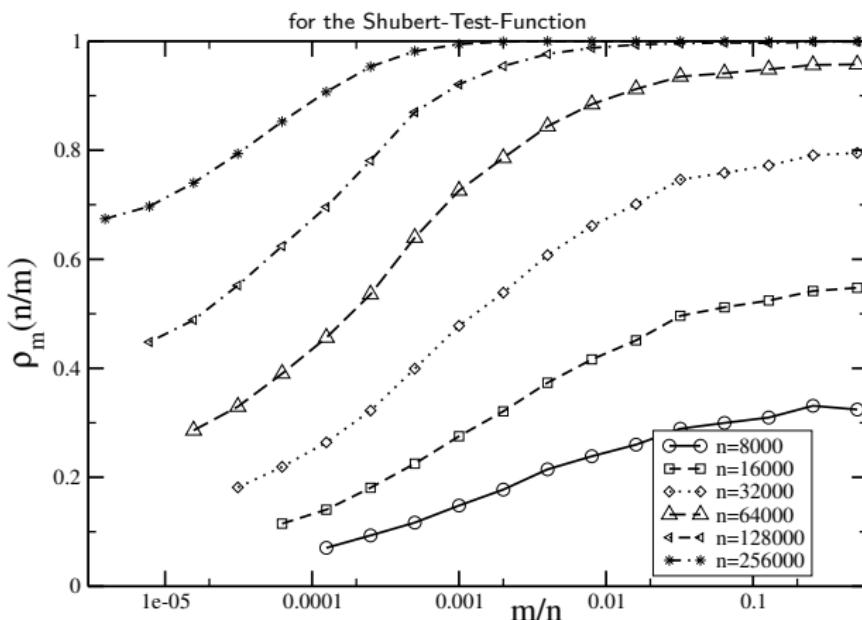
ρ_s : success rate of a single walk
 $\langle\delta\rangle$ expected jump length

for larger m

$$\Rightarrow \rho_n(1) = 1 - \gamma^n$$

with $\gamma := 1 - 1/N$

Test Functions – 1D



K. Hamacher. *On Stochastic Global Optimization of one-dimensional functions*. Physica A 354:547-557, 2005.

⇒ 1D test functions are useless

Test Functions – Spin Glasses

Combinatorial problem in discrete variables $\hat{s}_i \in [-1; +1]$

$$H = \frac{1}{2} \sum_{\langle i,j \rangle} J_{ij} \hat{s}_i \hat{s}_j$$

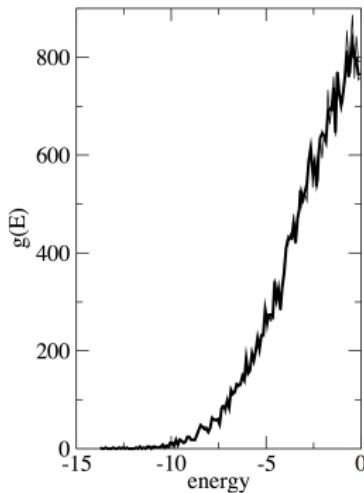
and $J_{ij} \in \mathcal{N}(0, 1)$

reference ground states from

<http://www.informatik.uni-koeln.de/spinglass>

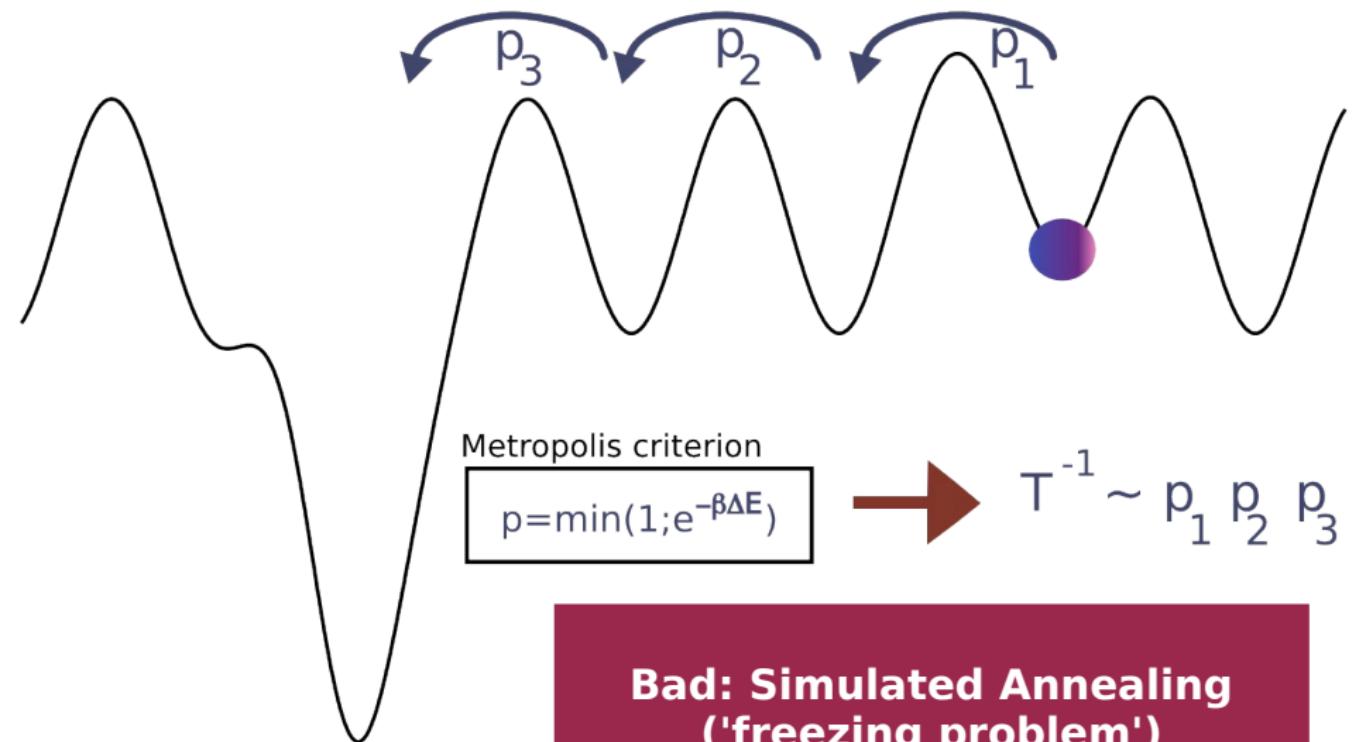


Density of State:



Heilmann, Hoffmann. Europhys. Lett. 70(2005):155

Sampling a PES (Potential Energy Surface) by Monte-Carlo



Bad: Simulated Annealing ('freezing problem')

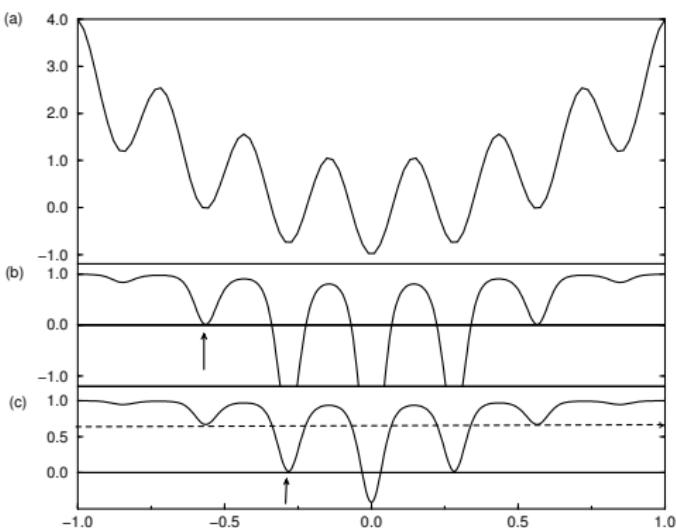
Metropolis-based Search – Stochastic Tunneling

Idea:

do not care about
“high” regions

$$f_{\text{STUN}}(\vec{x}) := 1 - e^{-\gamma \cdot (f(\vec{x}) - f_{\text{best}})}$$

where f_{best} is the best value encountered so far



Metropolis-based Search – Stochastic Tunneling – It works!

Application to a spin model

Wenzel, Hamacher.
Phys. Rev. Lett.
82(15):3003-3007, 1999

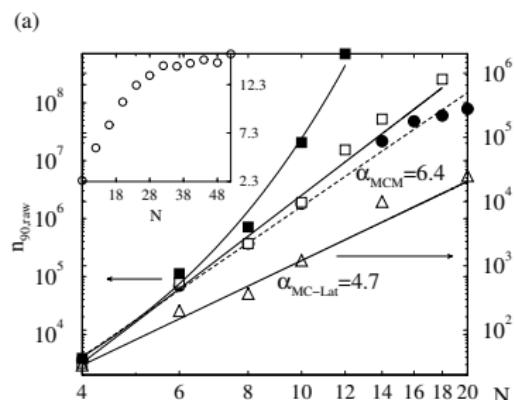
$n_{\text{iter}}/10^3$	SA	STUN
N = 49		
10	212.48 / 176	185.12 / 136
50	196.64 / 164	168.72 / 136
100	191.68 / 144	161.60 / 136
500	177.68 / 136	151.76 / 136
1,000	175.52 / 136	139.44 / 136
N = 101		
10	987.44 / 914	918.08 / 810
50	946.44 / 854	880.08 / 790
100	927.84 / 846	865.76 / 766
500	894.32 / 822	
1,000	891.68 / 818	

Average and best ground state

Metropolis-based Search – Stochastic Tunneling – It works!

Application to a “demixing”
Lennard-Jones model
(toy model for protein folding)

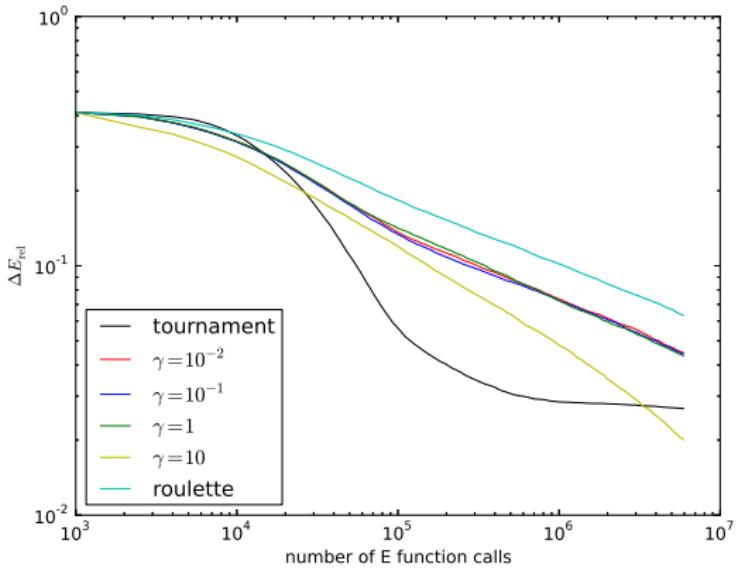
Hamacher, Wenzel.
Phys. Rev. E
59(1):938-941, 1999



Stochastic Tunneling – It even works for GAs!

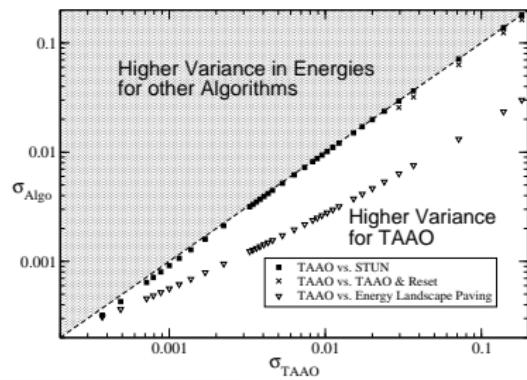
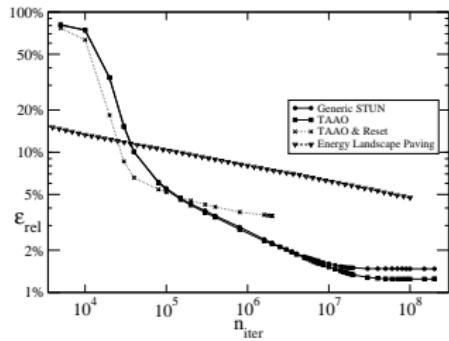
Based on a GA, we
solve spin glasses, again

Mayer,
Hamacher.
GECCO'14
accepted, 2014



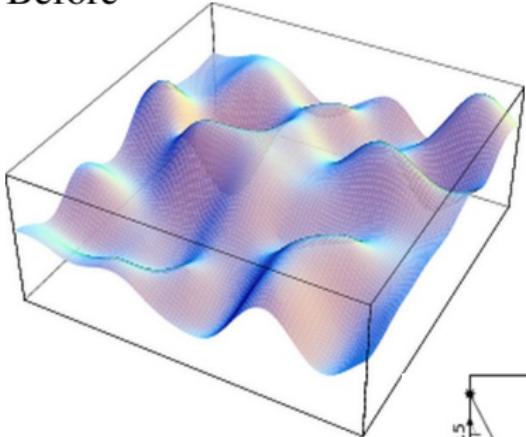
Stochastic Tunneling – Combined with Energy-Landscape-Paving

$$f_{\text{TAAO}}(\vec{x}) := \underbrace{1 - e^{-\gamma \cdot (f(\vec{x}) - f_{\text{best}})}}_{\text{STUN}} + \underbrace{\kappa \cdot H(q)}_{\text{ELP}}$$

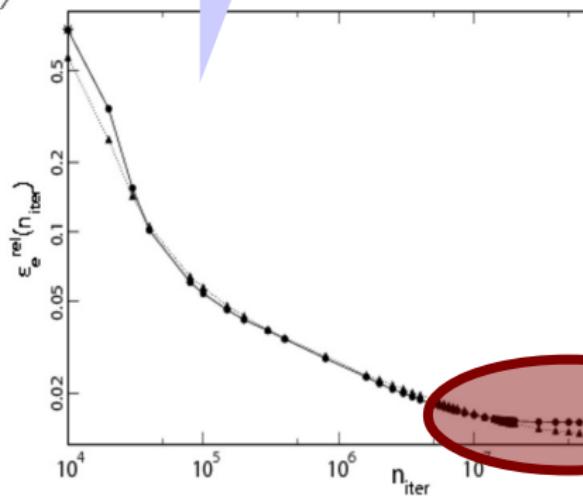
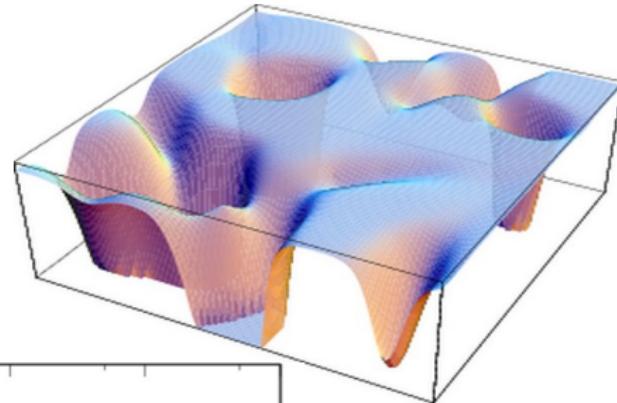


What happens under an STUN-Transformation?

Before



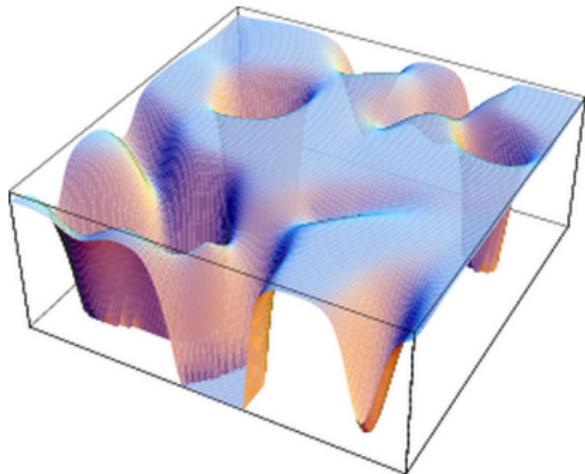
After



Saturation

Search as a Stochastic Process

- ▶ can regard the iterative process as search dynamics evolving in time t
- ▶ visited objective function values E_t becomes time series
- ▶ can apply powerful methods of time series analysis



“forgotten too much”

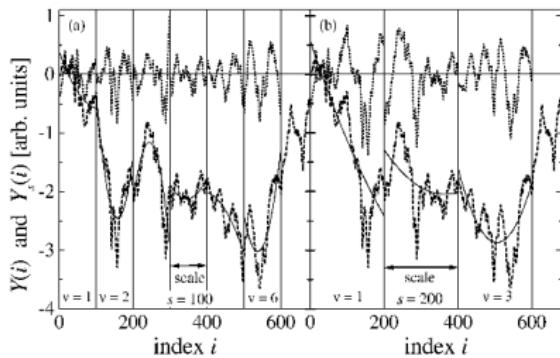
E_t is a random walk in original
 E -values, aka “wild guessing”

Random-Walk of E_t is indicator of poor performance!

Time Series Analysis

Detrended Fluctuation Analysis

- ▶ within time windows τ
delete (polynomial) trend
 $\rightarrow E_t^{(\tau)}$
- ▶ determine fluctuations
 $F^2(\tau)$ in $E_t^{(\tau)}$
- ▶ find scaling law
 $F^2(\tau) \sim \tau^{2-\gamma}$
- ▶ but auto-correlation function
 $C(\tau) \sim \tau^{-\gamma}$
- ▶ $\gamma \approx 1 \implies$ Random-Walk !
- ▶ γ is an online signal



Kantelhardt et al.
295(2001)441

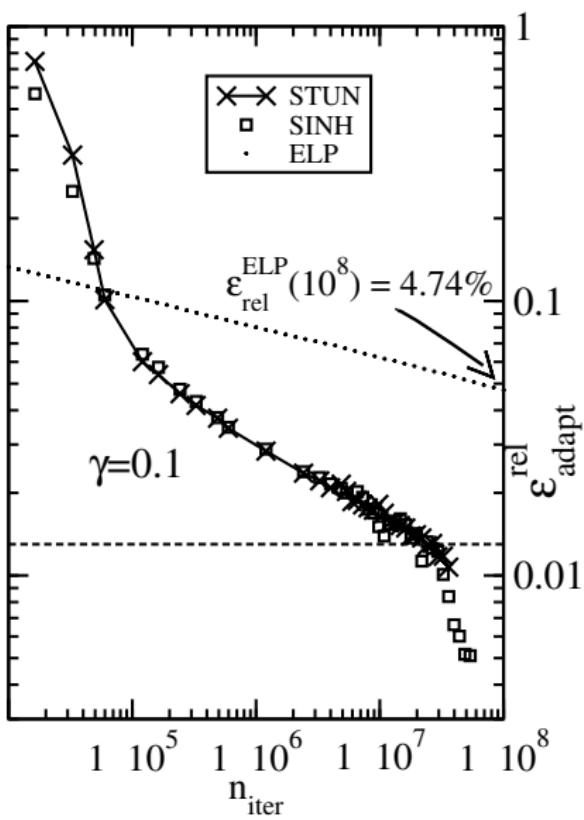
Physica A

DFA & STUN – Steering the Search

Idea:

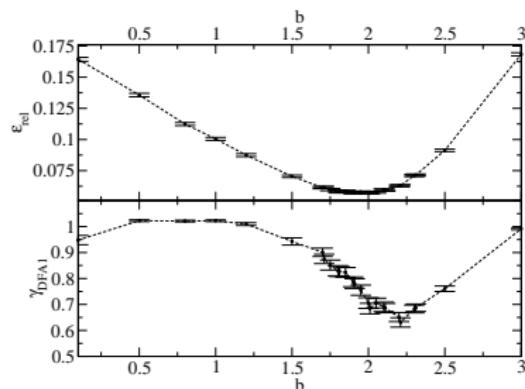
- ▶ whenever γ approaches 1 \rightarrow saturation begins
- ▶ eventually, RW in E_t
- ▶ just start from scratch (keep f_{best})

Hamacher. Europhys. Lett. 74:944–950, 2006

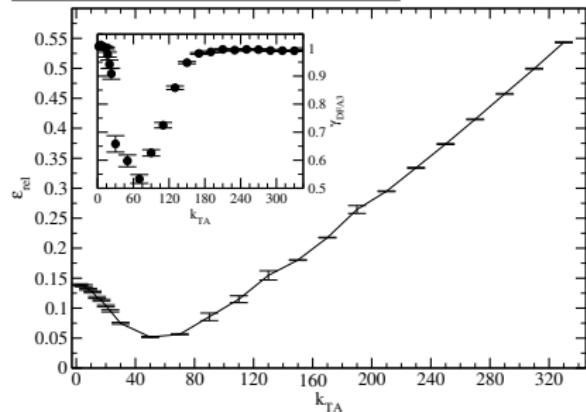


DFA & Other Stochastic Optimization Methods

Basin Hopping



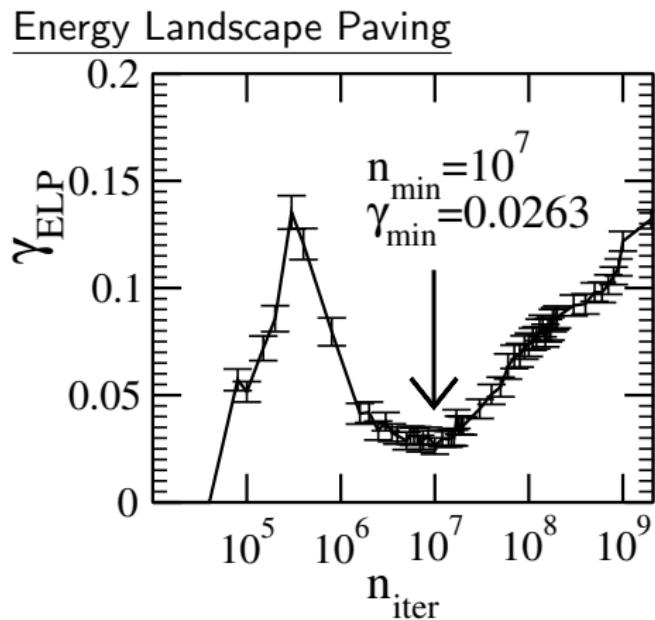
Extremal Optimization



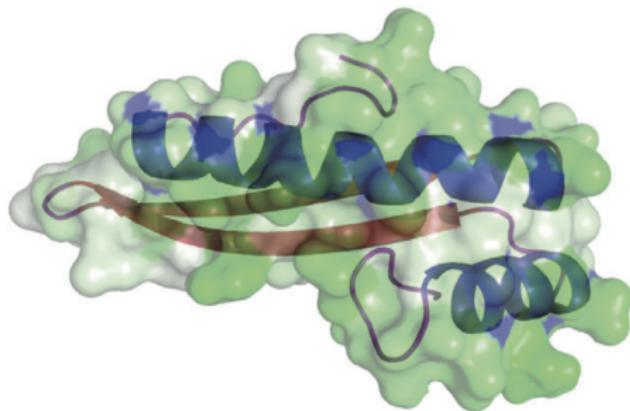
Hamacher. Lecture Notes in Computer Science (LNCS 8457) accepted, 2014

Hamacher. J. Comp. Phys. 227:1500-1509, 2007

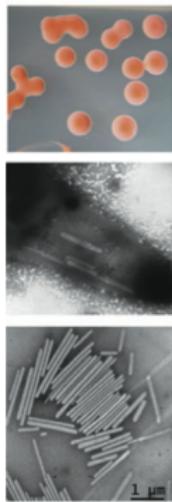
DFA & Other Stochastic Optimization Methods



Application : Protein Structure Prediction



I34M



Strunk, Hamacher, et al. Mol. Microbiol. 1500-1509, 2007

Summary

- ▶ Heuristics solve *pragmatically* GO problems
- ▶ traditional approaches (like SA) suffer from problems
- ▶ STUN one way to address these issues → other problems
- ▶ Time Series Analysis, DFA in particular, leads to insight and thus *empirical algorithm design*
- ▶ Real world problems can be addressed

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