

**ABSTRACT**

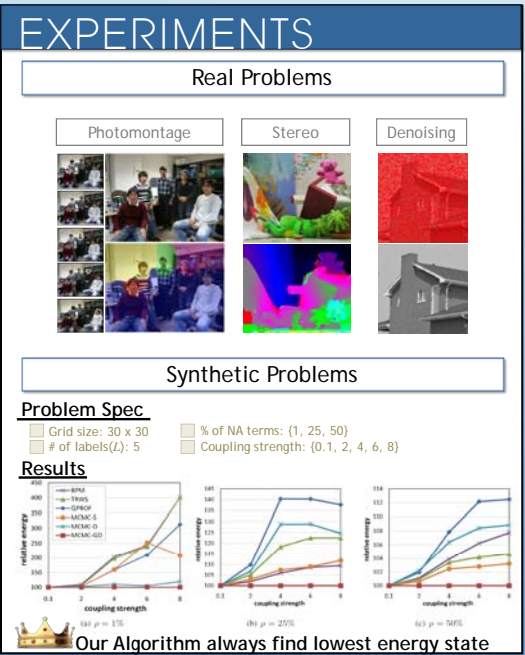
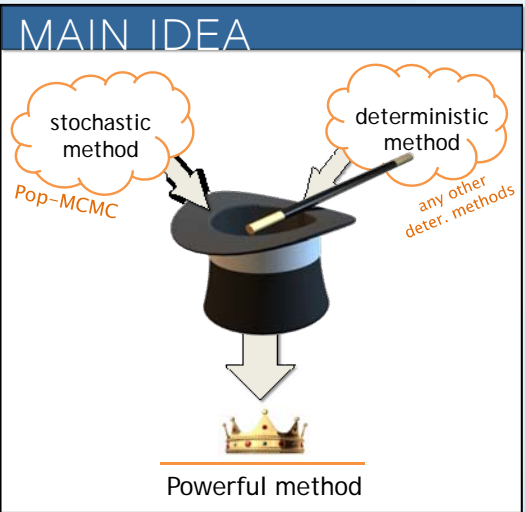
Many computer vision applications have been formulated as optimization problems. Since most of them are NP-hard, all the existing methods end up with approximated solutions. To achieve better solutions, we propose a new hybrid algorithm which elegantly combines the stochastic sampling and deterministic algorithms. By combining those two different approaches in a unified framework, we can utilize the advantages from both approaches.

**MOTIVATION**

**Energy Minimization**  
Many vision problems have been formulated as energy minimization problems

**NP-Hardness**  
In general, we cannot obtain the exact solution

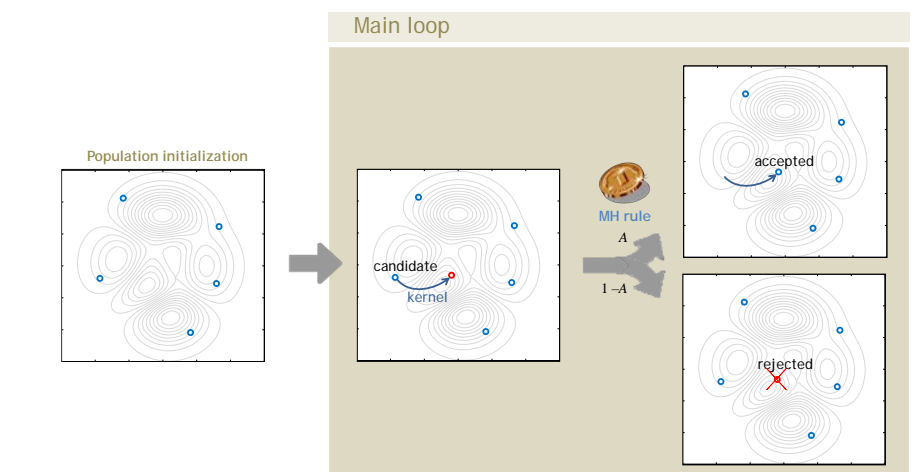
**Goal** to develop a more efficient optimization method



**ALGORITHM**

**Population-based MCMC** previous work

**Main loop**



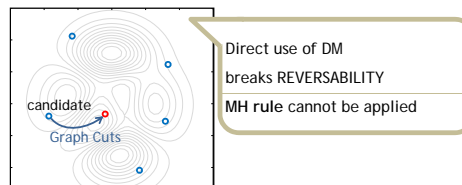
**Metropolis-Hastings rule**

$$A = \min \left( 1, \frac{\exp \{-E(x_{next})\} K(x_{next}, x_{current})}{\exp \{-E(x_{current})\} K(x_{current}, x_{next})} \right)$$

It guarantees sample to converge to the optimal point

**We propose MCMC kernels using DMs**

**Naïve(BAD) Example**  
of using deterministic methods for kernels



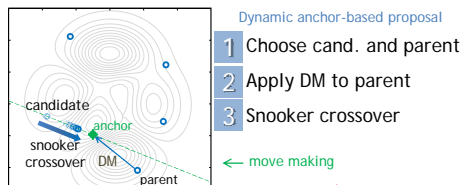
Direct use of DM breaks REVERSABILITY  
MH rule cannot be applied

**Proposed(GOOD) Kernel**

Dynamic anchor-based proposal

- 1 Choose cand. and parent
- 2 Apply DM to parent
- 3 Snooker crossover

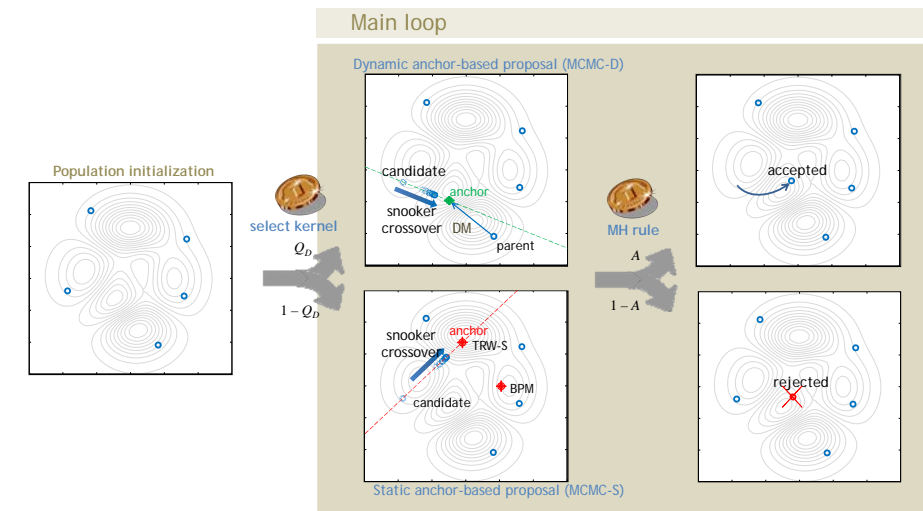
← move making  
↓ message passing



**Proposed Method**

**Main loop**

Dynamic anchor-based proposal (MCMC-D)



Static anchor-based proposal (MCMC-S)