Autonomous Learning of Ball Passing by Four-legged Robots and Trial Reduction by Thinning-out and Surrogate Functions

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Contents

Background

- For robots to function in the real world, **learning** abilities are essential
  - To adapt to unknown environments
- Legged robots must learn many basic skills
  - E.g., walking, running, pushing, pulling, jumping, catching, kicking, hitting, …

Instance

Learning of ball passing skills by AIBO

RoboCup soccer

Competition for autonomous robots that play soccer

Small size league

Standard platform league
(four-legged robot league)

Middle size league

Simulation league

https://www.robocup.org/

Humanoid league

Experimental costs using real robots

- Trial
  - Human intervention
  - Time consuming
  - Motor failure

Ex. Learning process of goal saving skills

Initial phase

https://youtu.be/9oHA-GH9JT8

Later phase

https://youtu.be/3Pluuk20xqs

Our result: reduction of the experimental costs

- Autonomous learning method of passing skills
  - For reducing human intervention
  - Application of the idea of autonomous learning of ball trapping skills [Kobayashi et al. 2006]
- Hybrid method for trial reduction
  - For reducing all costs of each trial
  - Improvement of thinning-out [Kobayashi et al. 2007] utilizing surrogate functions

Contents

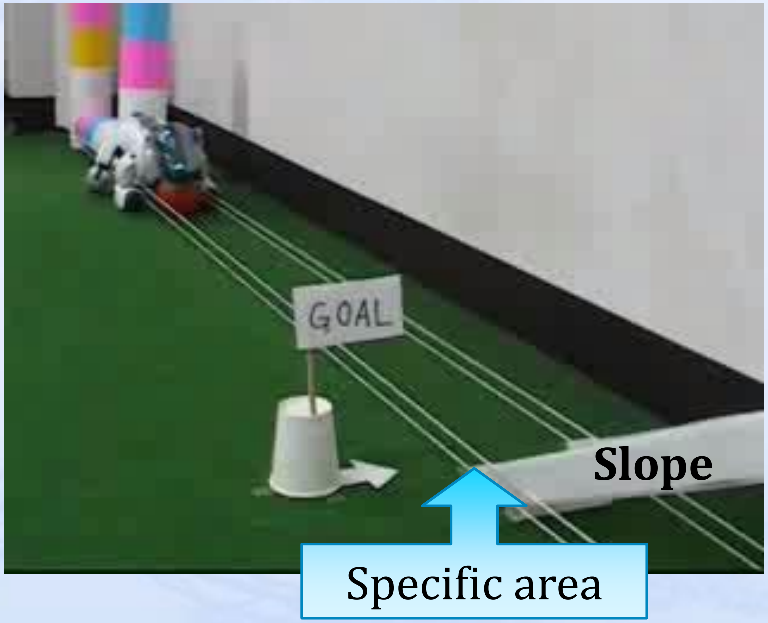
Ball passing skills

- Accurate shooting motions that move and stop a ball to a specific area
  - Neither too strong nor too weak
- Shooting motions
  - Generated by key-frames (seq. of joint angles)

Ex. Forward shooting motion pushing a ball with its chest

Autonomous learning method of ball passing skills

- Robots can acquire passing skills on their own



Hazard Deluxe Putting Mat©JEF World Of Golf

Related work

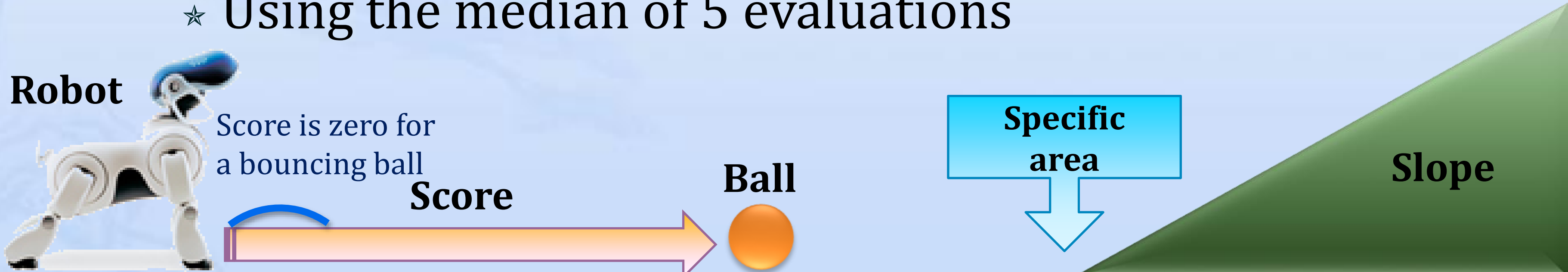
- Learning of walking skills [Kim and Uther 2003][Kohl and Stone 2004] [Hornby et al. 2005][Saggar et al. 2007]
- Learning of ball acquiring skills [Fidelman and Stone 2004][Fidelman and Stone 2007]
- Learning of ball trapping skills [Kobayashi et al. 2007]

Problem formulation

- Maximization of the following score function

Each key-frame is indicated by 8 joint angles
(= head 2 + fore leg 3 + rear leg 3) using symmetry

- Score function f: $X \rightarrow \mathbf{R}$ on $X \subseteq \mathbf{R}^{8K}$ (K=#key-frames)
  - Generate a motion from $x \in X$
  - Make the robot kick the ball using the motion
  - Return the distance to the kicked ball
    - Using the median of 5 evaluations



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- Background
- Autonomous learning of ball passing skills
- Hybrid method for trial reduction
- Experimental results
  - Minimization of test functions
  - Learning of ball passing skills
- Conclusions

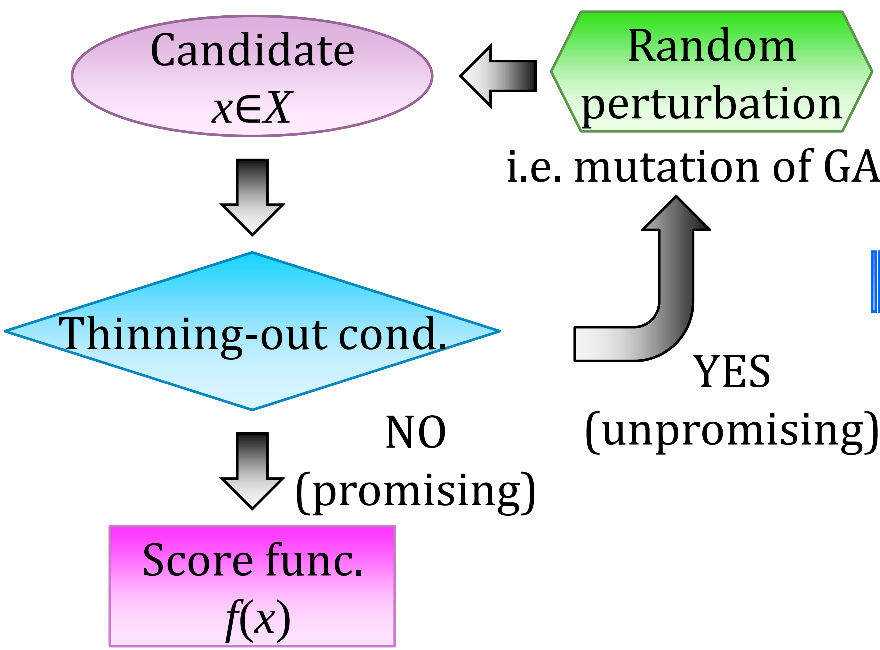
Meta-heuristics

- Heuristic algorithms that are independent of problems
  - Genetic Algorithm
  - Simulated Annealing
  - Policy Gradient
  - Hill Climbing
  - …
- We choose Genetic Algorithm (GA)

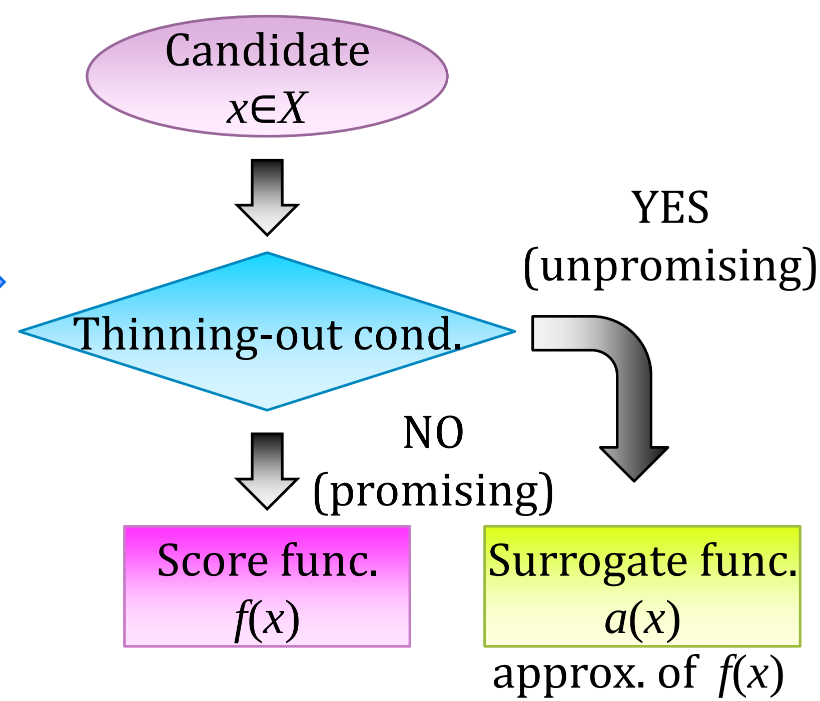
Hybrid method for trial reduction

Idea : Make the resampling process of new candidates more efficient using meta-heuristics instead of random perturbation

Thinning-out [Kobayashi et al. 2007]
To skip over the evaluation of unpromising candidates selected by meta-heuristics



Our hybrid method combining **thinning-out** and **surrogate functions**



Thinning-out
[Kobayashi et al. 2007]

- To reduce unpromising trials
  - The same concept as "pruning" in search trees
- Based on the assumption
  - The score function is *g*-Lipschitz continuous

- Memory-based learning
  - Memory-based fitness evaluation GA [Sano et al. 2000]
  - Locally weighted regression [Schaal and Atkeson 1994]
  - Acceleration by function approximation [Ratle 1998]

We can easily combine the other methods with thinning-out

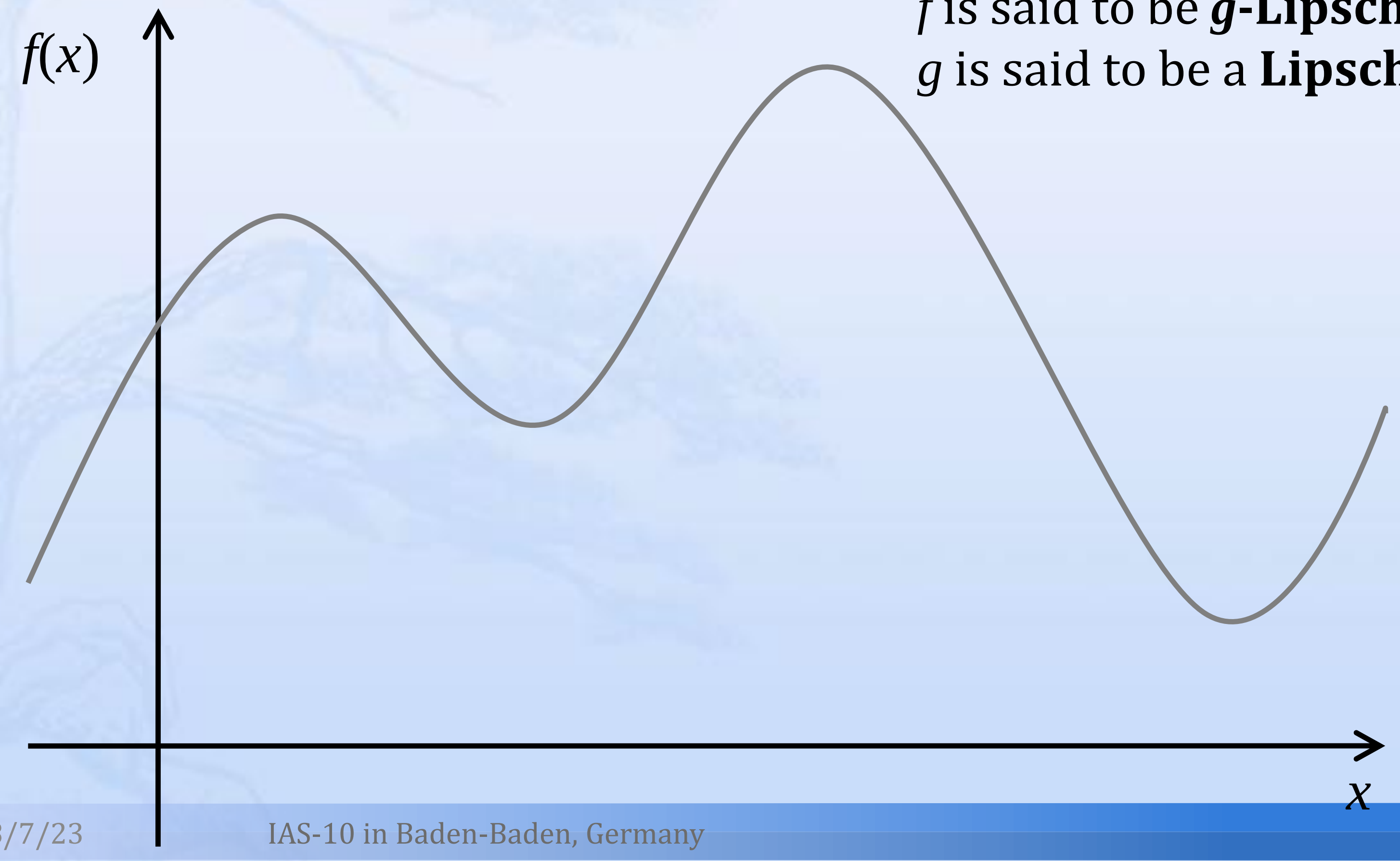
Lipschitz condition

X: Search space
f: Score function
d: Metric of X

Lipschitz condition

$$\exists g : \mathbf{R} \to \mathbf{R}\ \forall x_1, x_2 \in X \left| f(x_1) - f(x_2) \right| \le g\big(d(x_1, x_2)\big)$$

f is said to be ***g*-Lipschitz continuous**
g is said to be a **Lipschitz function**



$$f(x_1) - g(d(x_1, x_2)) \leq f(x_2) \leq f(x_1) + g(d(x_1, x_2))$$

X: Search space
f: Score function
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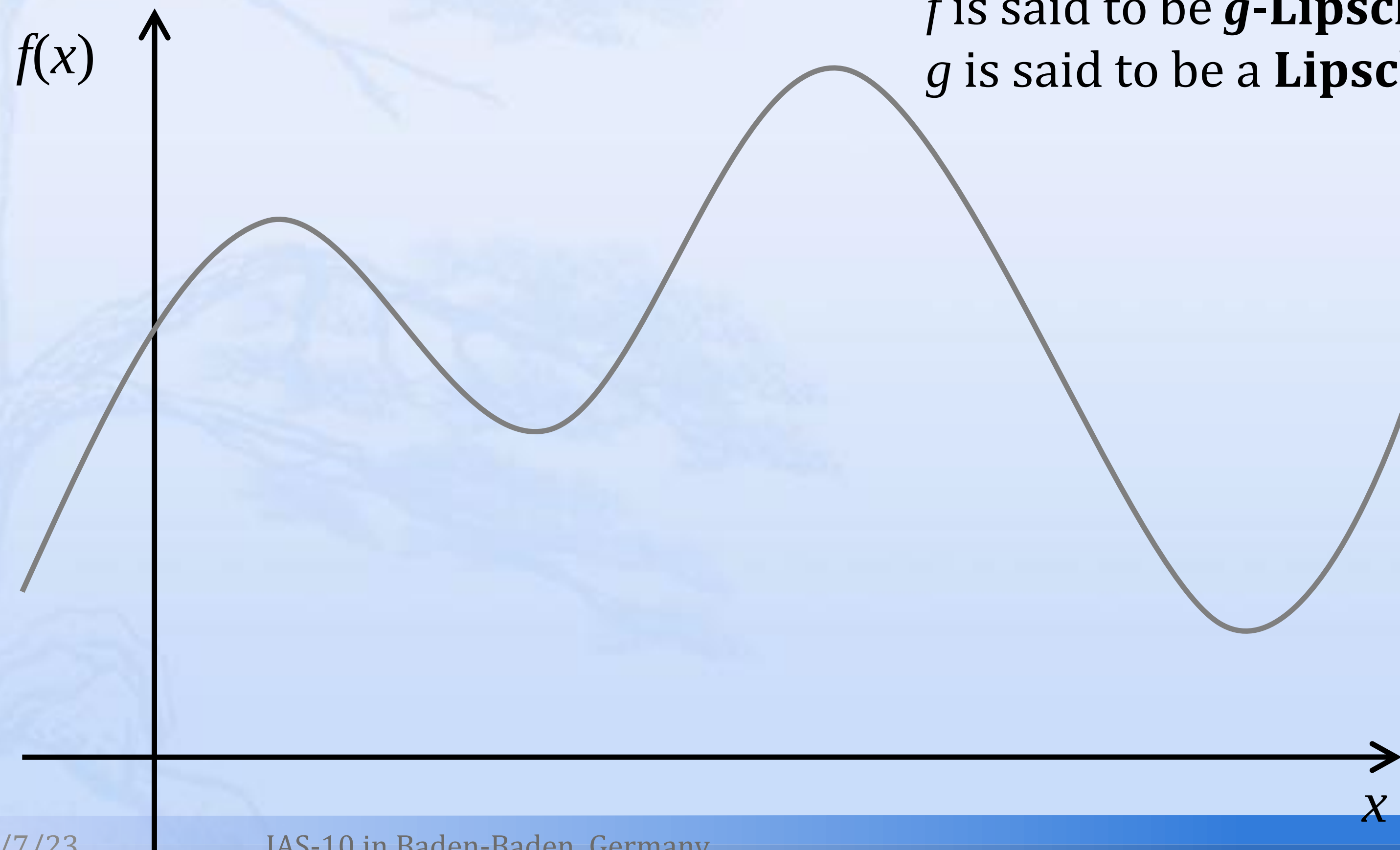

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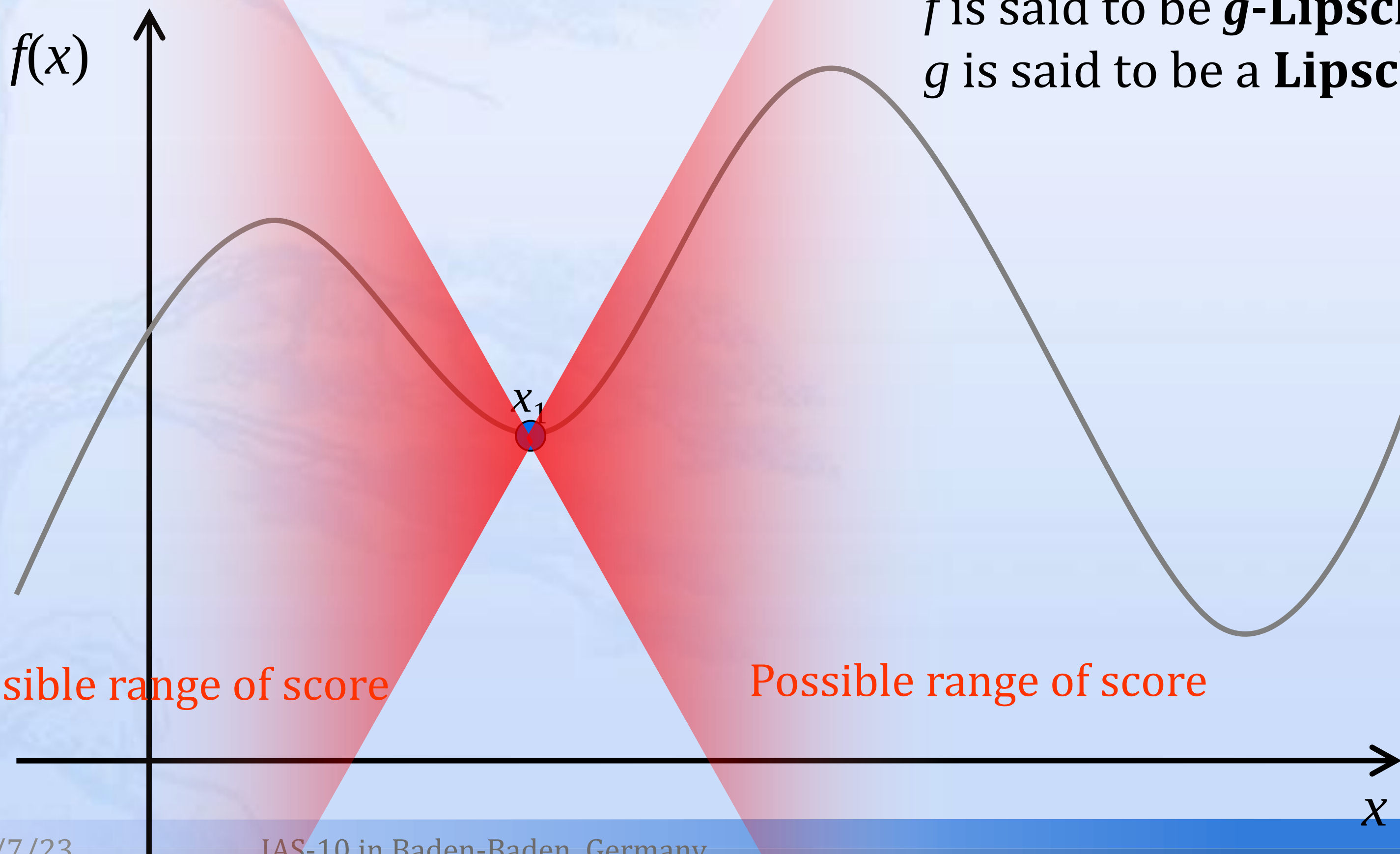

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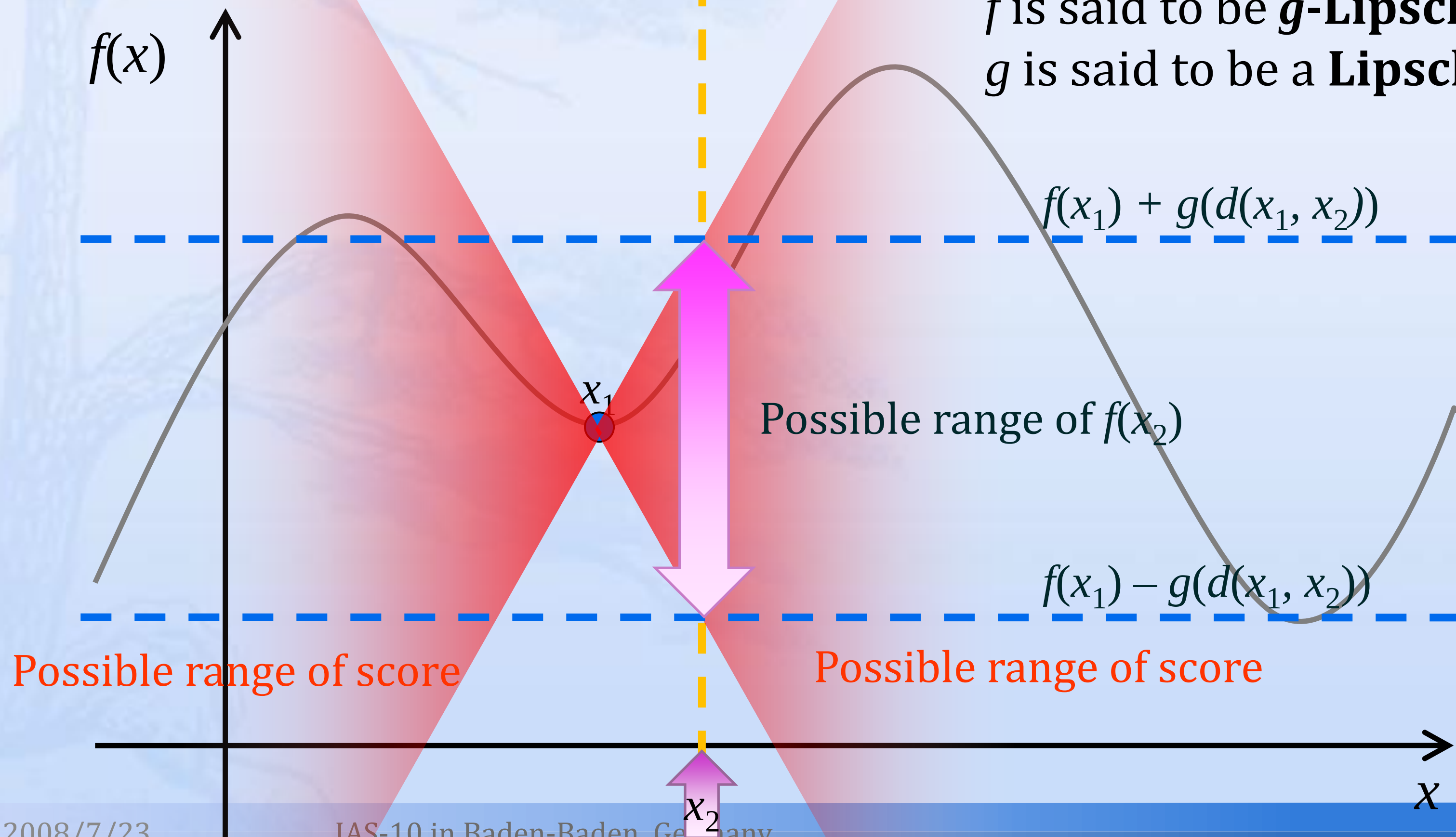


Thinning-out condition

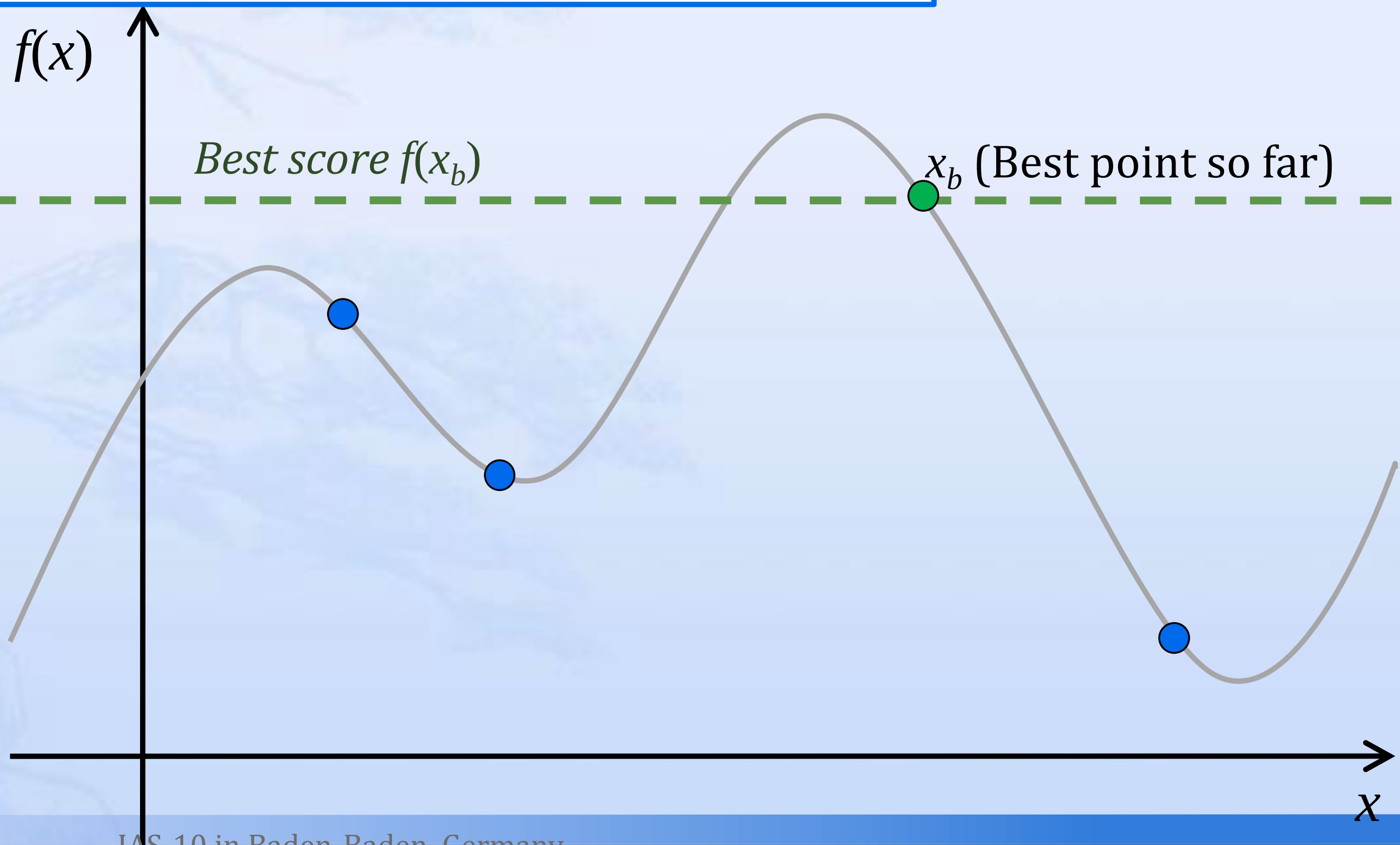
Thinning-out condition

$$f(x_n) + g(d(x_c, x_n)) \le f(x_b)$$

The upperbound of the score range of x_c

$$\left(\Rightarrow f(x_c) \le f(x_b)\right)$$

X: Search space
f: Score function, g-Lipschitz continuous
d: Metric of X



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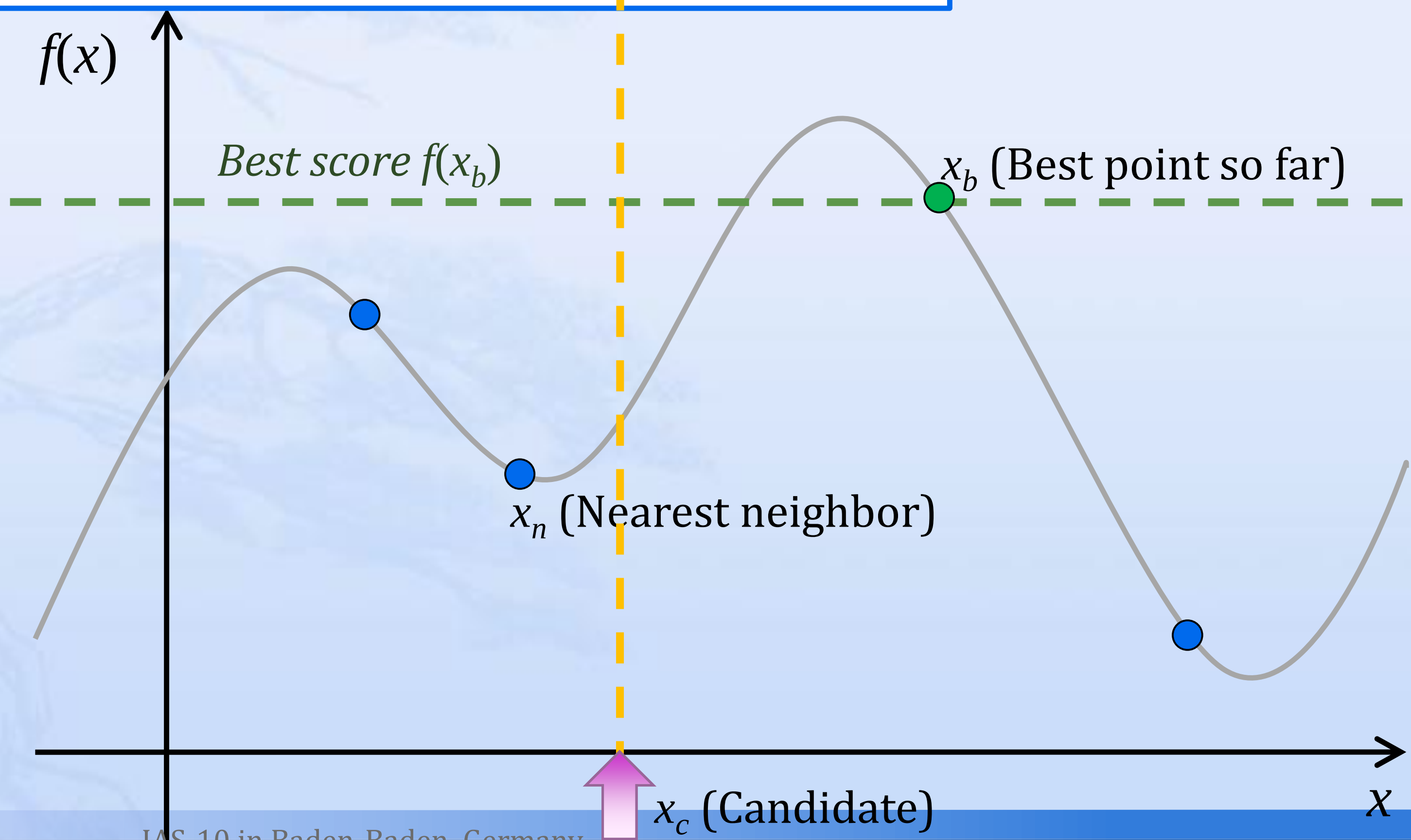

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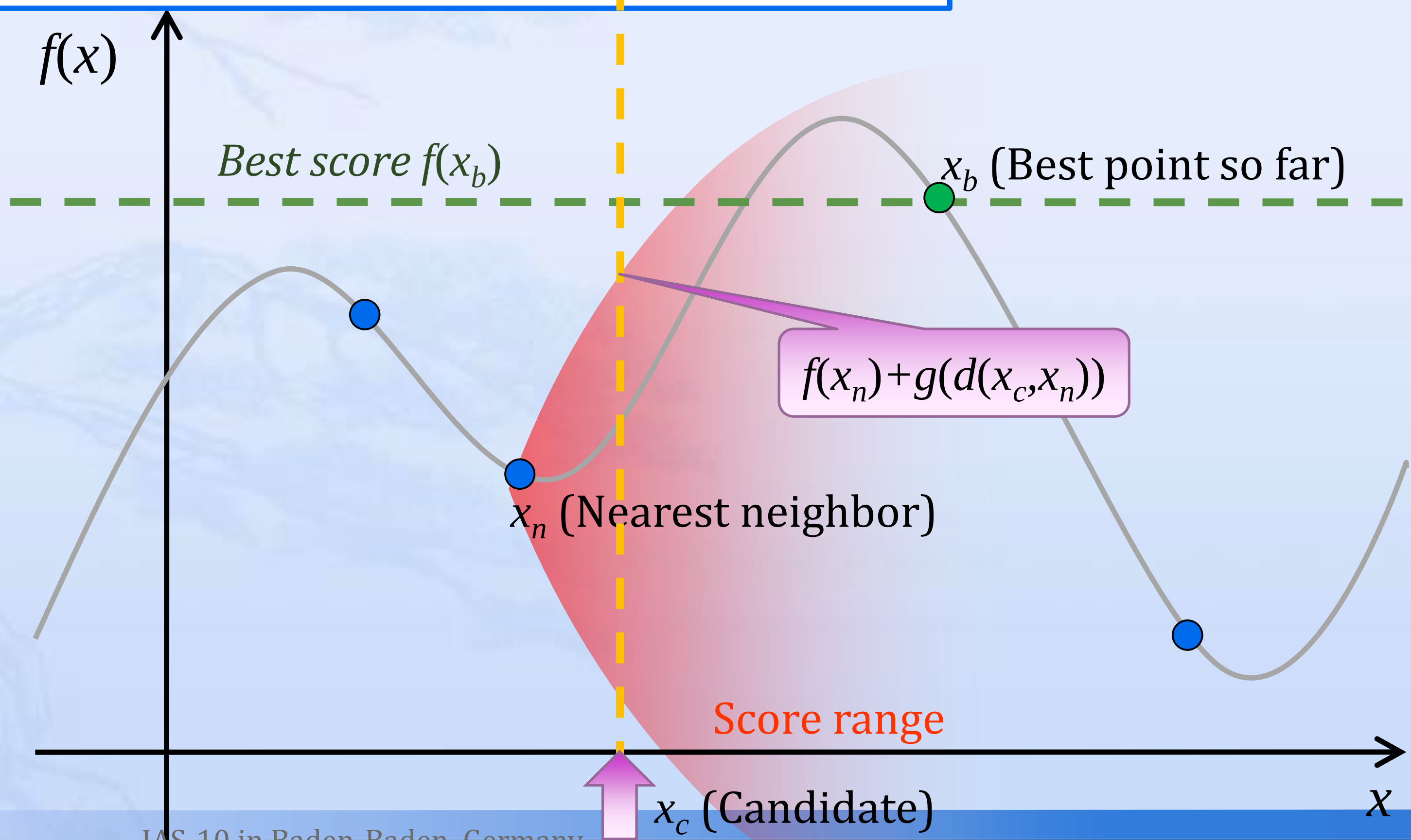

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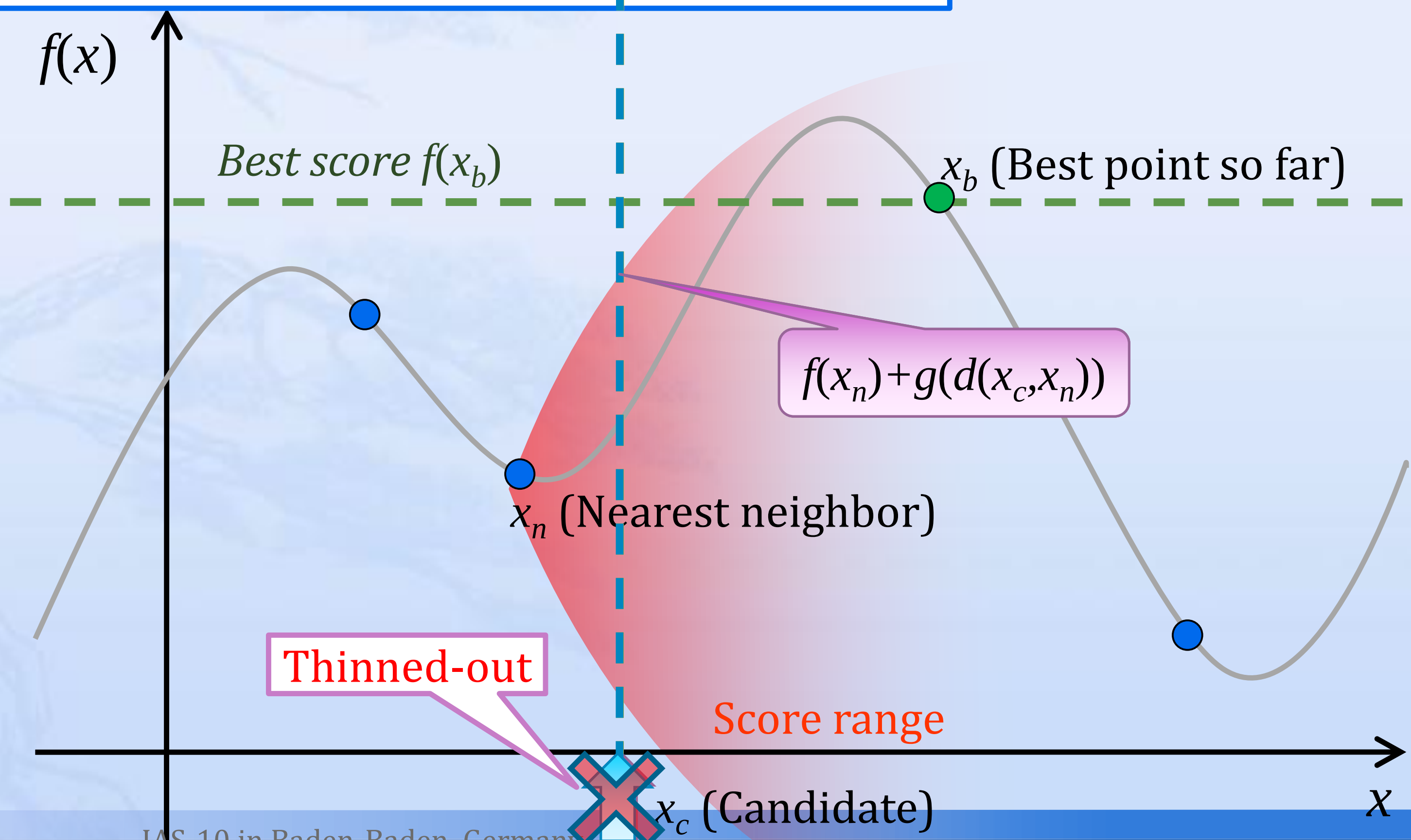

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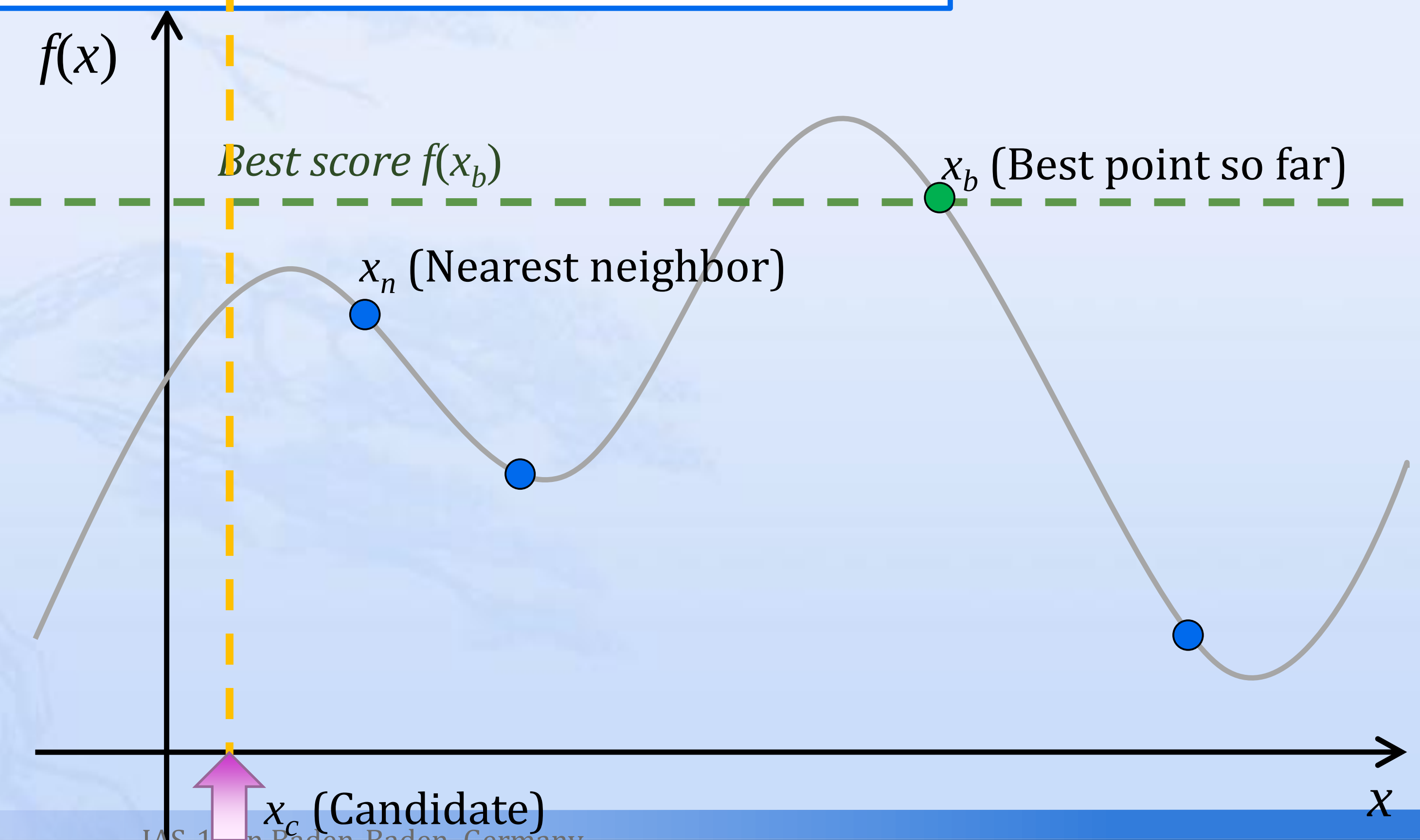

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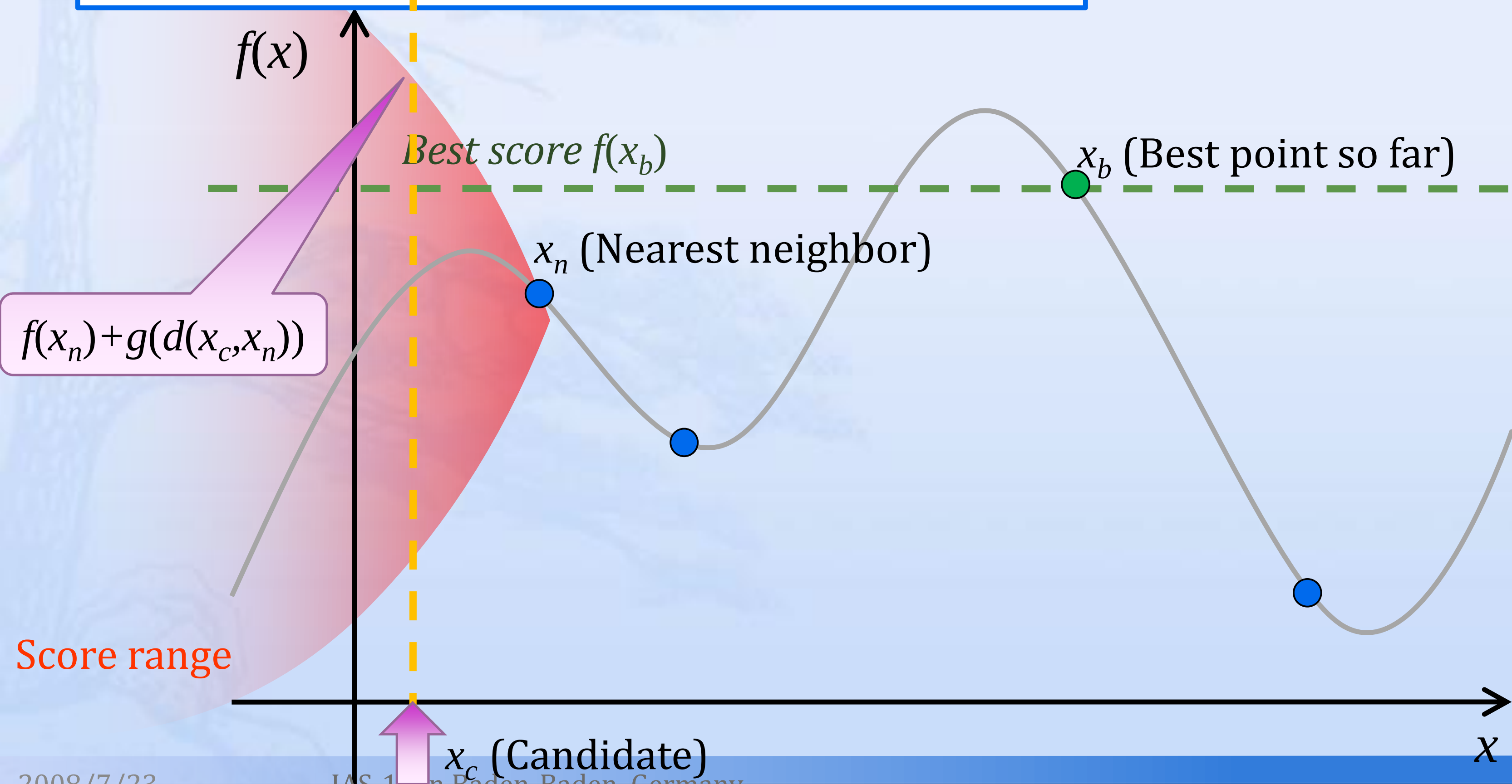

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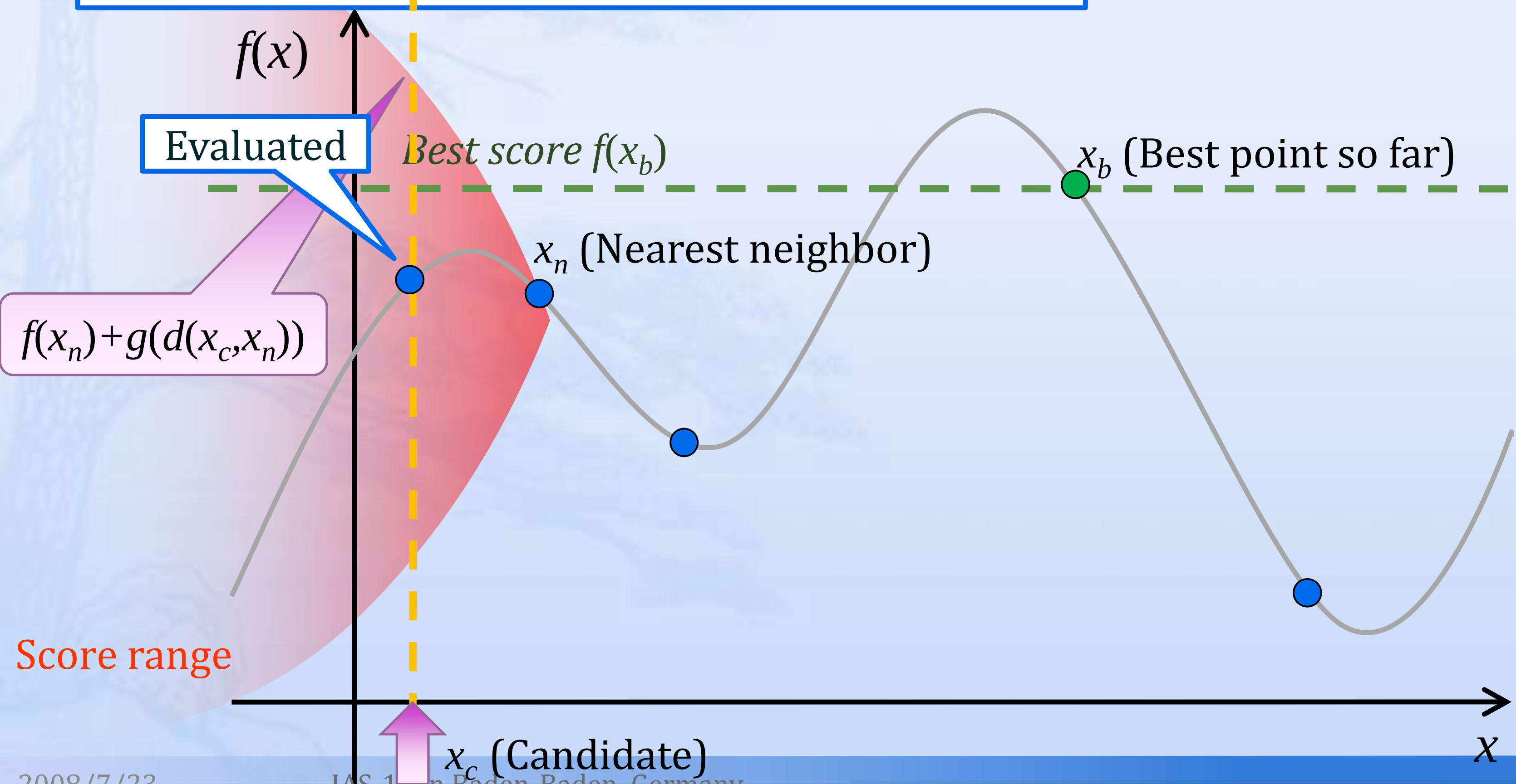
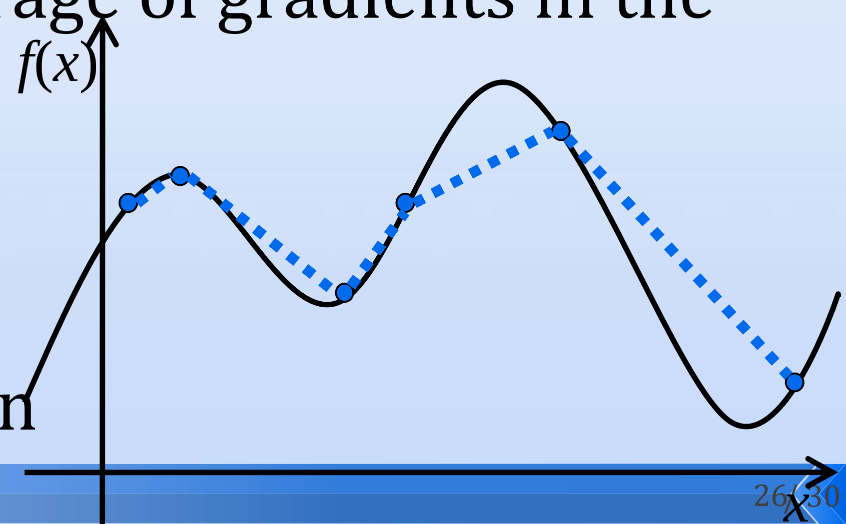


Inferring methods of Lipschitz functions

- Max Gradient method (MG)
  - Using the max gradient in the history
  - Naïve method
  - Thin-out correctly
- Gathering Differences method (GD)
  - Using the weighted average of gradients in the history
  - Heuristic method
  - Thin-out a lot
  - Useful in high dimension



Kriging interpolation as surrogate functions

- Function interpolation method [Matheron 1963]
  - Initially developed in geostatistics
  - Recently used as surrogate functions
- Ordinary kriging
  - Most common type of kriging
  - Related studies used as surrogate functions
    - [Martin and Simpson 2003]
    - [Jouhaud et al. 2007]
    - [Glaz et al. 2008]

Ordinary kriging

Interpolated value of x^* is represented by

$$\hat{f}(x^*) = \sum_{i=1}^{n} w_i f(x_i)$$

weighted linear combination

$f(x_i)$: observed score of $x_i \in X$

w_i: weight of $f(x_i)$

The weights for x* are calculated by minimizing the error variance

$$V_e = Var\left[\ \hat{f}(x^*) - f(x^*)\ \right]$$

subject to

$$\sum_{i=1}^{n} w_i = 1$$

Given by the unbiased condition and second-order stationarity

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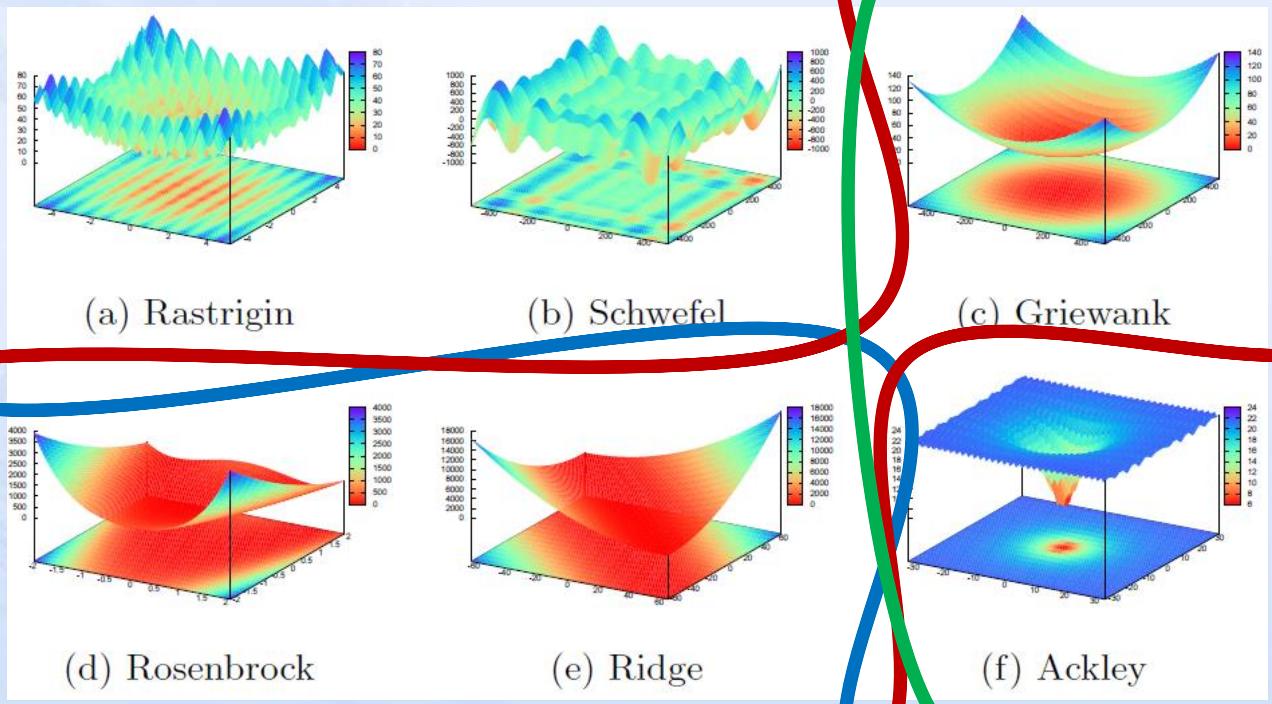
Minimization problems of test functions

Multiple peaks

Single peak with a global view



The shape of test functions in 2 dimensions

Dependency of variables

(Sano et al. (2000) also utilized these test functions for evaluating distributed GA)

Comparison of trial rates and error rates

Trial rates and error rates in 100 candidates (lower = better)

Function in 10 dim.	**GAT [Kobayashi et al. 2007]**		**GATS (this work)**	
	Trial rate (%)	Error rate (%)	Trial rate (%)	Error rate (%)
Rastrigin	54.20	0.80	38.67	0.40
Schwefel	62.84	0.87	42.63	0.17
Griewank	48.24	0.09	35.81	0.00
Rosenbrock	54.75	0.06	39.34	0.00
Ridge	55.42	0.04	38.58	0.00
Ackley	60.37	0.92	43.26	0.05

(Each value is the average over 100 experiments)

$$\text{Trial rate} = \frac{\#(\text{tried candidates})}{\#(\text{all candidates})} \times 100$$

$$\text{Error rate} = \frac{\#(\text{wrongly thinned out candidates})}{\#(\text{thinned out candidates})} \times 100$$

SGA: Simple GA
GAT: SGA with Thinning-out
GATS: GAT with Surrogate func.

The trial rate of SGA is always 100%

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Comparison of minimum scores

Minimum scores in 100 trials (lower = better)

Function in 10 dim.	SGA	GAT [Kobayashi et al. 2007]	GATS (this work)
Rastrigin	260	165	152
Schwefel	3583	1817	1305
Griewank	621	211	112
Rosenbrock	17472	3326	2265
Ridge	5.7e9	6.4e8	2.3e8
Ackley	21	21	21

SGA > GAT > GATS

(Each value is the average over 100 experiments)

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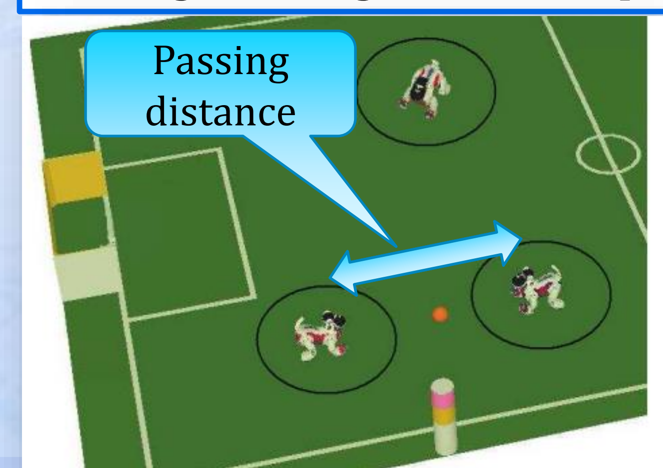
Learning of Passing skills

- Initial motion: Forward chest shooting
  - Search space: 48 dim. (=8 joints × 6 key-frames)
  - Shooting distance: 1500 mm
- Distance to the objective: 800 mm
  - Min. of passing distances in the passing challenge

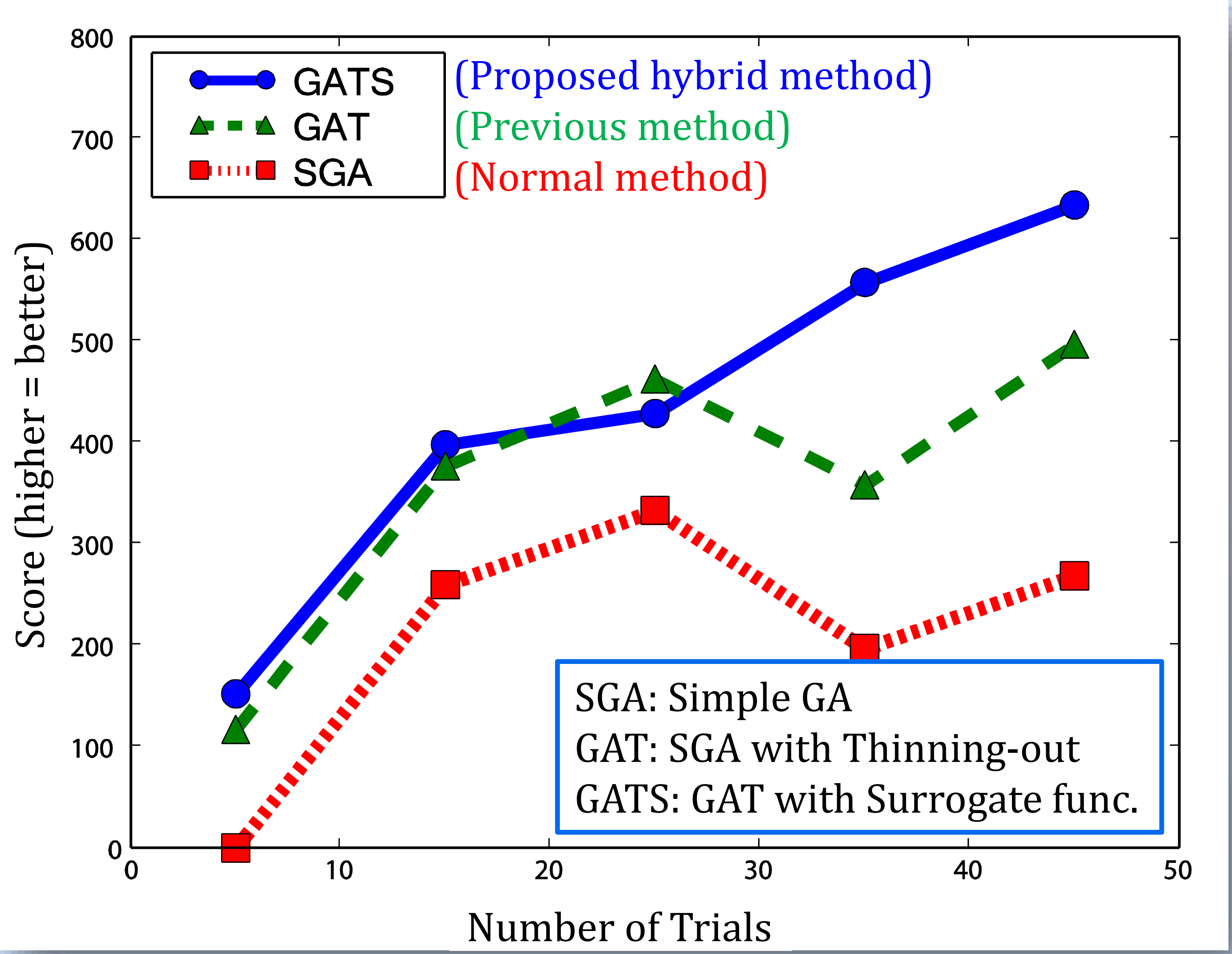
Passing challenge in RoboCup



Initial phase of the experiment

https://youtu.be/QKuRUwwTUbo

Learning results



Learned passing skills

Later phase of the experiment
(accuracy of about 3 cm)
https://youtu.be/WiDadAzfasg

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Conclusions and future work

- Autonomous learning of ball passing skills
- Hybrid method for trial reduction combining thinning-out and surrogate functions
- The first application of thinning-out in the real world

Future work

- Extension to two-dimensions
- Adaptation to arbitrary distances

Thank you for your attention