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A Hybrid Genetic Swarm Algorithm for Interactive Inverse Kinematics

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Master Thesis
Colloquium

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Contents

Introduction and Motivation

Problem Statement

How to adjust a set of joints in order to move an end effector to reach a Cartesian configuration of position and/or orientation?

Kinematics

„Kinema" = „Movement / Motion"

→ Field of classical mechanics

→ Motion of rigid bodies by position, velocity, acceleration

→ **No** consideration of physical dynamics (mass, force, torque, ...)

Introduction and Motivation

Applications

Robotics

→ Grasping and Object Manipulation

→ Bi-Pedal and Multi-Pedal Walking

→ Human Interaction

→ Manufacturing

Games Industry

→ Believable characters

→ Realistic motion

→ Dynamic and flexible animations

Film Industry

→ Motion Tracking

Introduction and Motivation

Challenges

→ Zero up to infinite solutions

→ Geometric complexity

→ High dimensionality

→ Suboptimal extrema and singularities

→ Joint constraints and types

→ Solution quality

→ *Accuracy* versus *Computation Time*

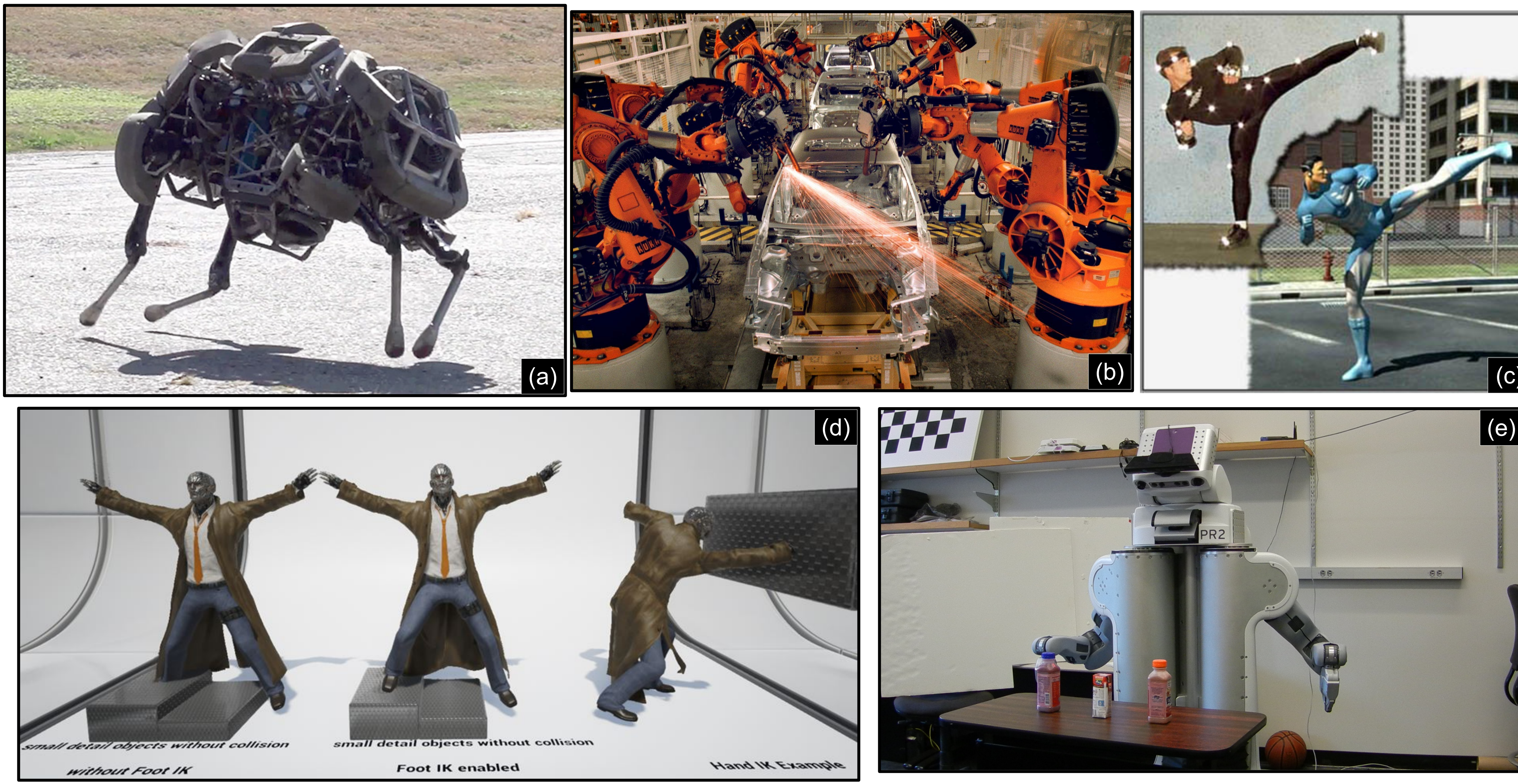
→ *Robustness* and *Reliability*

→ Displacement between solutions

→ Self-Collision

...

Introduction and Motivation



Introduction and Motivation

Major goals of this thesis

A universal IK solver for arbitrary kinematic chains

- Real-time capability for interactive frame rates
- High accuracy for both position and orientation
- Flexible, few parameters and easy-to-use

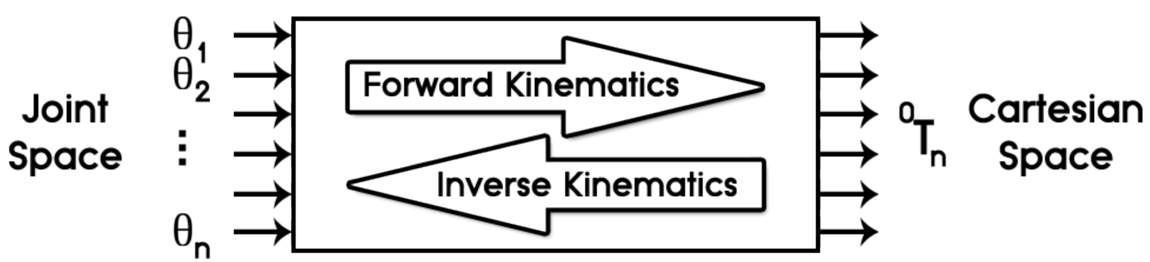
Novel algorithmic improvements for biologically-inspired optimization strategies

- Modular extensions applicable for various problems
- Higher adaptivity in exploitation and exploration
- Biologically-plausible evolutionary concepts

Problem Formalization

X → *Cartesian configuration of position and/or orientation*
θ → *Joint variable configuration*

Forward Kinematics (FK)	*Inverse Kinematics (IK)*
$$\mathcal{X} = f(\theta)$$	$$\theta = f^{-1}(\mathcal{X})$$
→ *Straightforward computation*	→ *Highly non-trivial*
→ *Unique solution*	→ *Complexity scales rapidly*
→ *Only requires kinematic specifications and joint values*	→ *Analytical versus Numerical*



Problem Formalization

Algorithmic Methodology

Analytical		**Numerical**
Extremely fast and exact	⟷	Slower computation and only approximative
Solution is always found	⟷	Solution may not always be found
Not generally available	⟷	Applicable to various kinematic models
Only derivable for simple and specific kinematic geometry	⟷	Only requires knowledge of the FK equations

Problem Formalization

Y → Cartesian target of position and/or orientation
μΘ → Weighted joint variable change

Numerical IK Update

$$\theta' = \theta + \mu\Theta \qquad d(f(\theta'), \mathcal{Y}) < d(f(\theta), \mathcal{Y})$$

Pose Distance

$$d_p = w_t \hat{d}_t + w_r d_r$$

(Rebalanced) Translational Distance

$$\hat{d}_t = \frac{\pi d_t}{\sqrt{l\Delta}} \qquad d_t = ||p_1 - p_2||$$

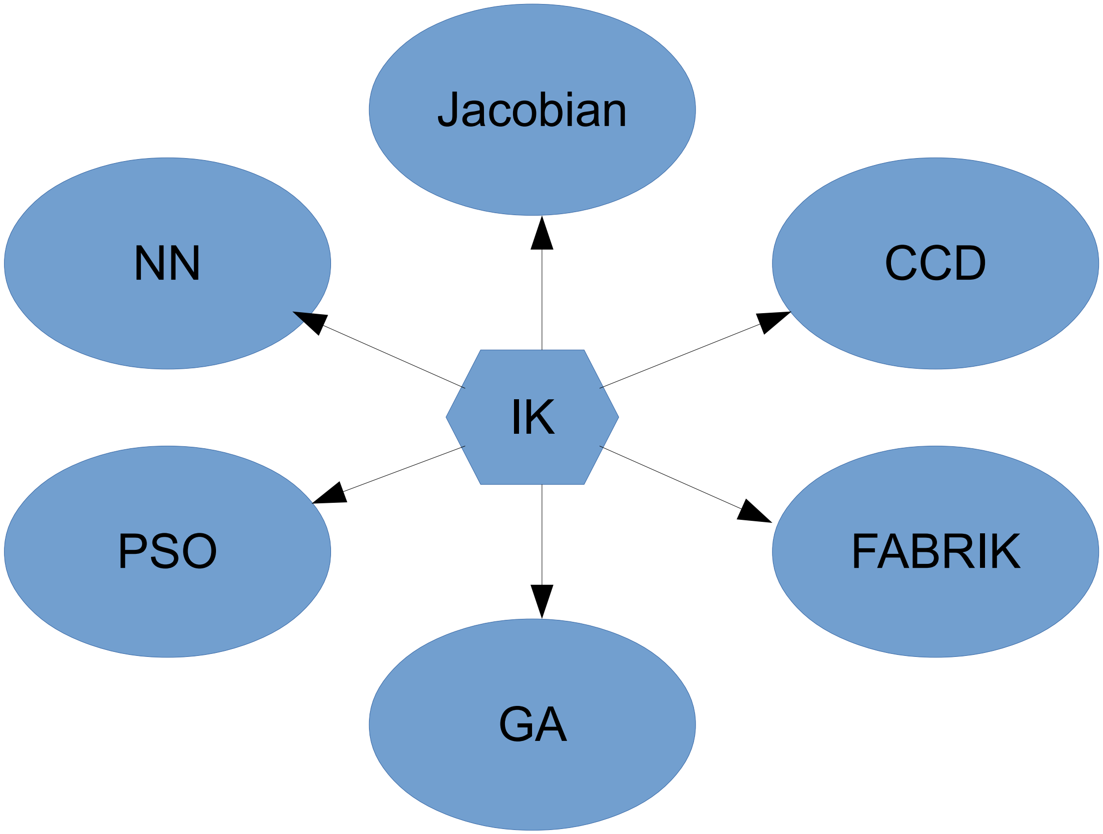
Rotational Distance

$$d_r = q_1 \cdot q_2$$

l → Length of the kinematic chain
Δ → Distance from base to end effector

Related Work

→ IK researched over decades
→ Very many different approaches with focus on numerical



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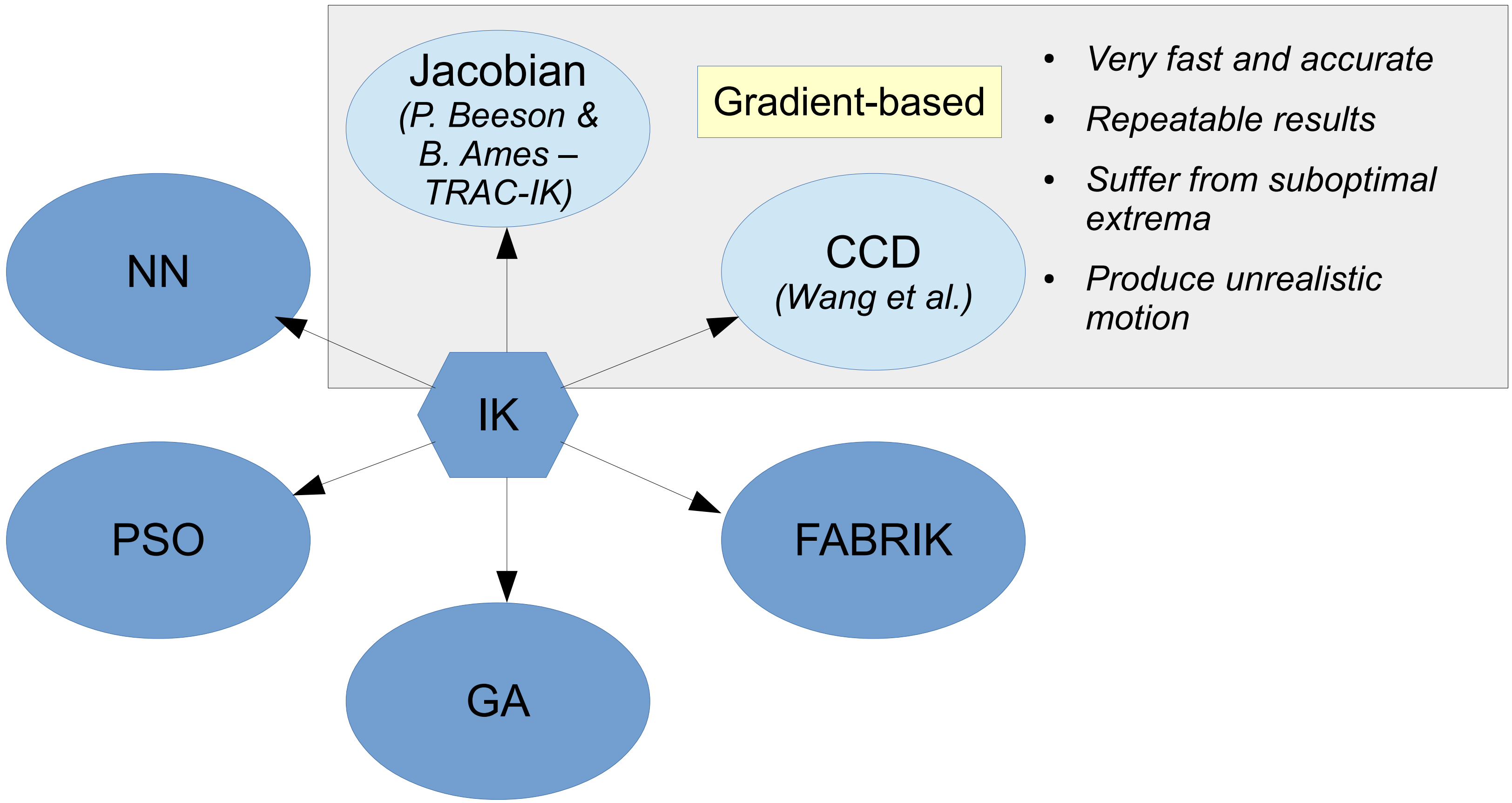

Related Work

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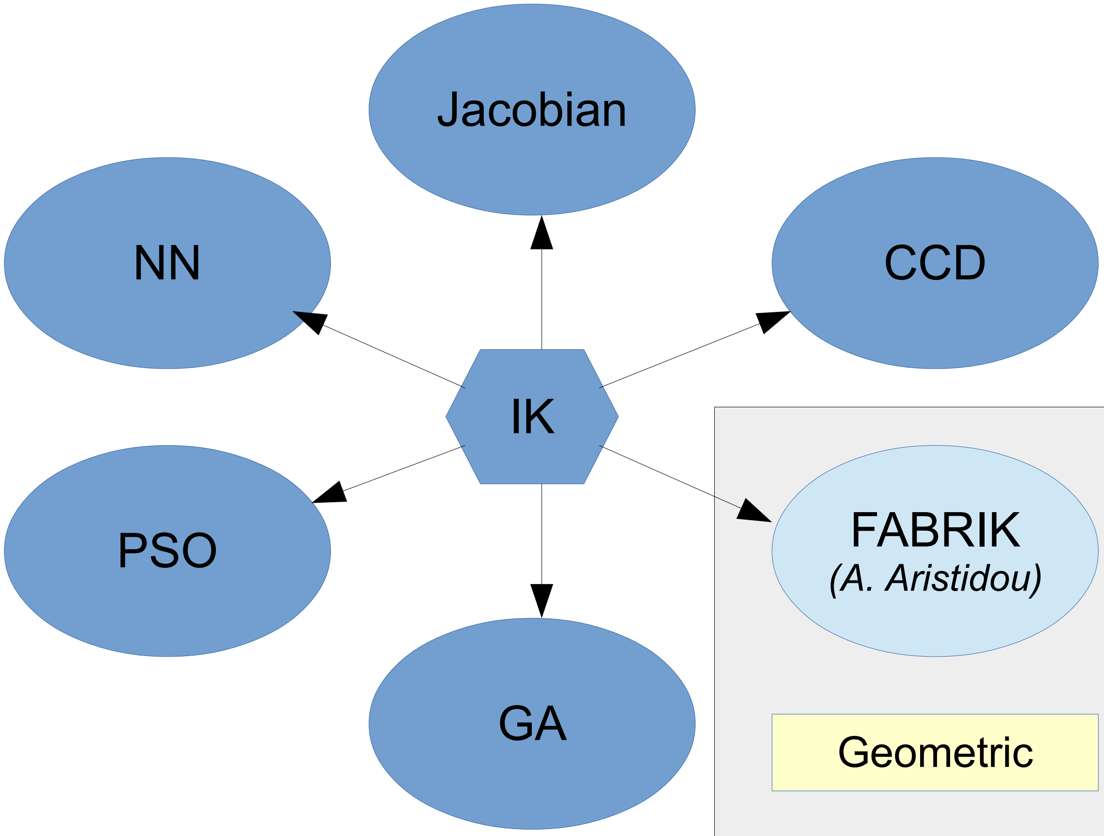
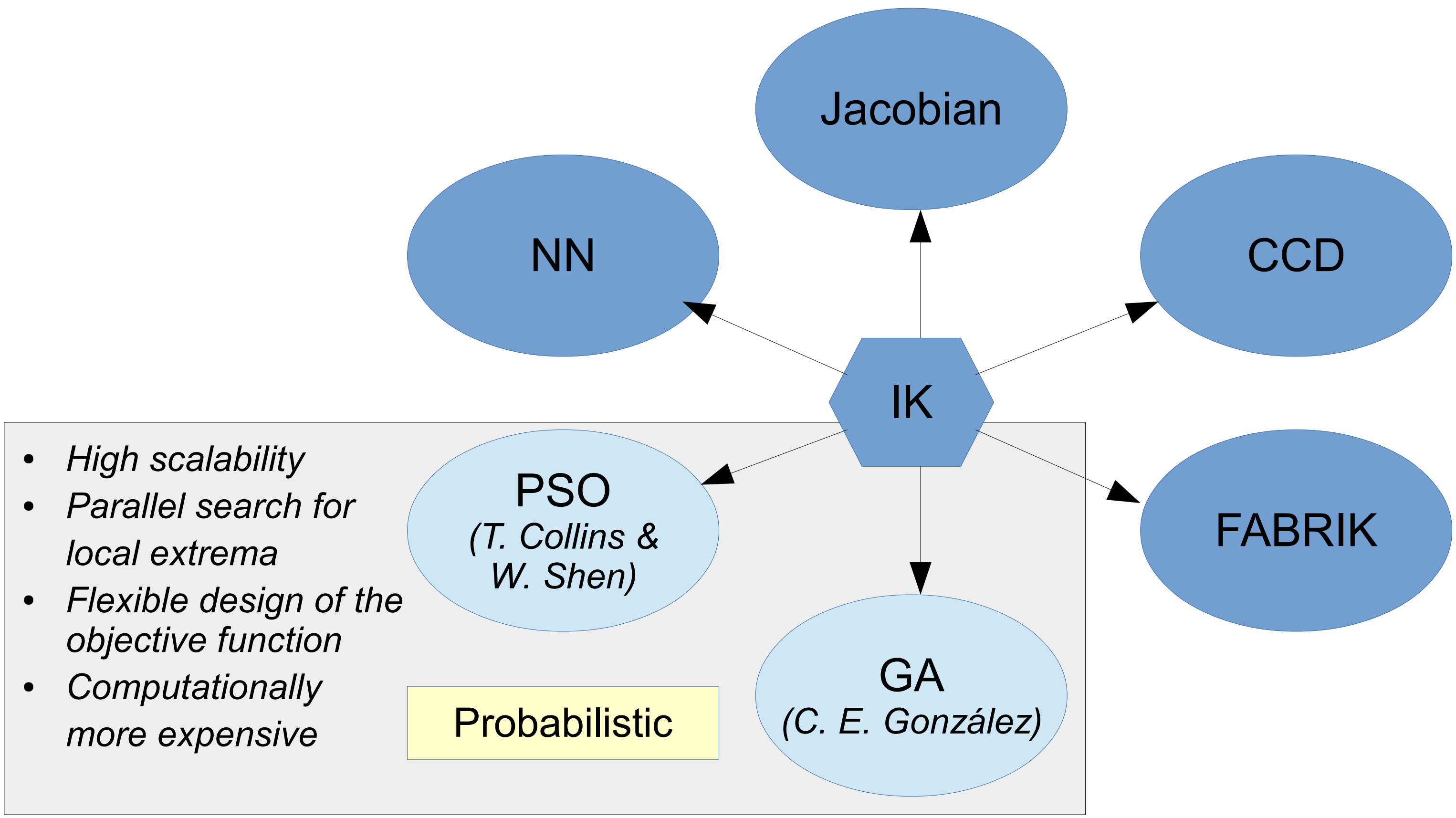


- *„Forward and Backward Reaching IK“*
- *Specifically designed for character animation and motion tracking*
- *Does not operate in joint space*
- *Predominantly rotational movement*

Related Work

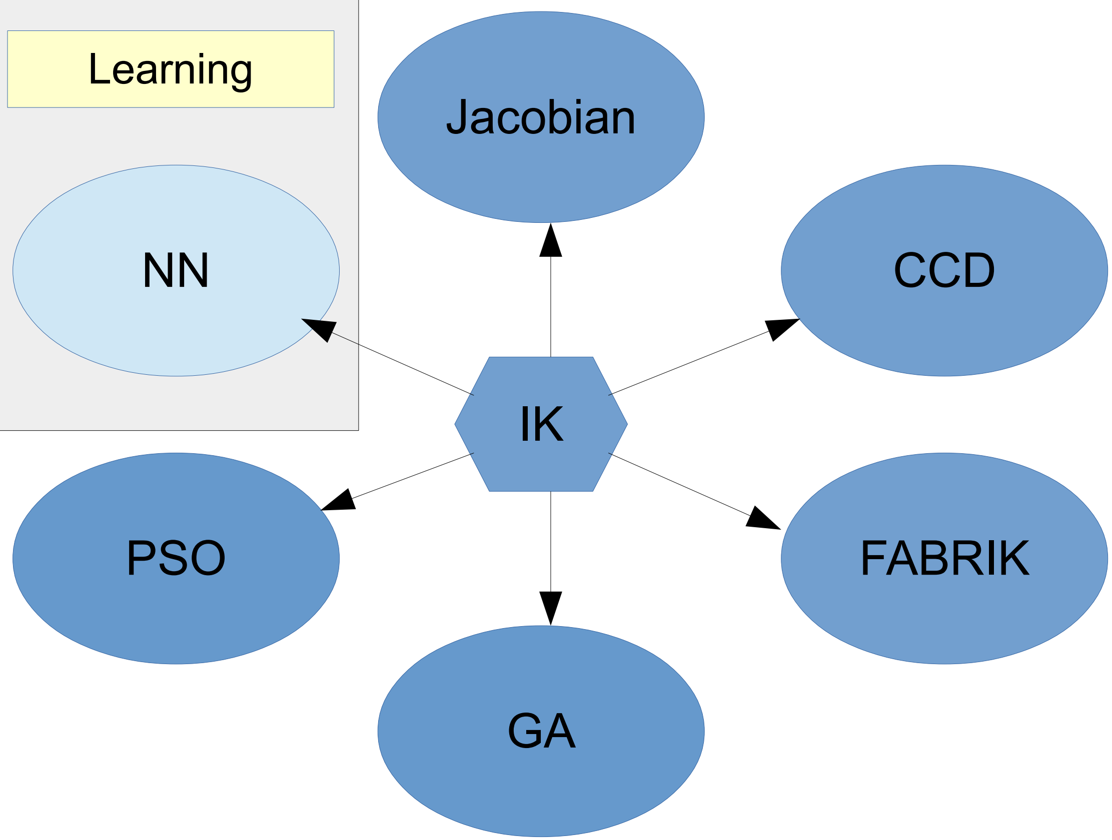
→ IK researched over decades
→ Very many different approaches with focus on numerical



Related Work

→ IK researched over decades
→ Very many different approaches with focus on numerical

- *Low accuracy*
- *Struggle with full posture objectives*
- *Only for low degree of freedom*
- *Choice of training samples remains very difficult*

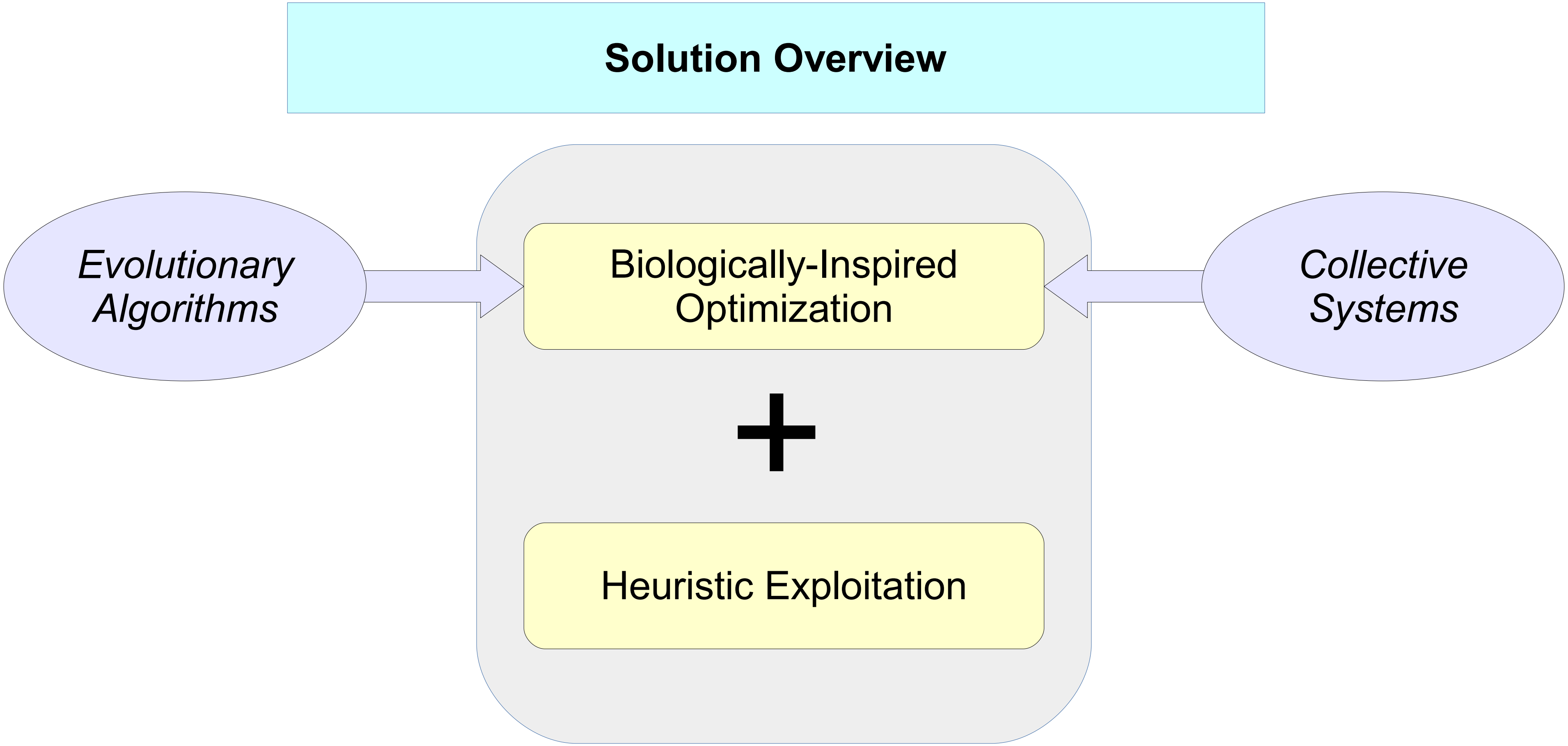


Algorithmic Approach

Design Objectives

Success	*A solution that is existent shall be found.*
Accuracy	*The solution shall be as precise as possible.* *→ approximately or less than 1mm*
Time	*The solution shall be found as fast as possible.* *→ few ms*
Displacement	*The distance between consecutive solutions shall be as minimal as possible.*
Flexibility	*The algorithm maintains high robustness, scalability and convergency even for greatly varying kinematic structure.*

Algorithmic Approach



Algorithmic Approach

Genetic Algorithms

- Developed by *J. F. Holland*
- Inspired by the theory of **natural evolution** as formulated by *C. Darwin*
- *„Survival of the fittest“* and *„Diversity drives change“*
- Group of individuals within a population that evolves over many generations
- **Selection**, **Recombination** and **Mutation**

Particle Swarm Optimization

- Developed by *J. Kennedy and R. Eberhart*
- Inspired by social emerging behaviour of **bird flocks** and **schools of fish**
- Rather simple organisms („particles“) collectively solve a complex problem
- **Velocity** and **direction** update according to success of **neighbouring** particles

Similarities

→ Search space exploration by a **group of organisms**

→ Solution quality determined by **fitness function**

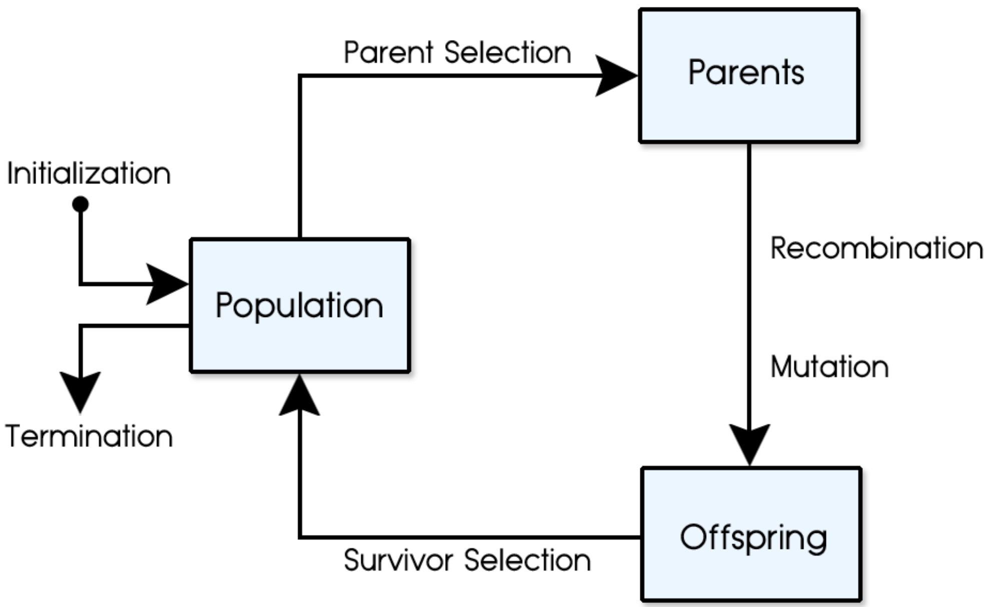
→ **Simultaneous search** for multiple local extrema

→ High **robustness** and **scalability** as well as effectiveness for **multi-objective optimization**

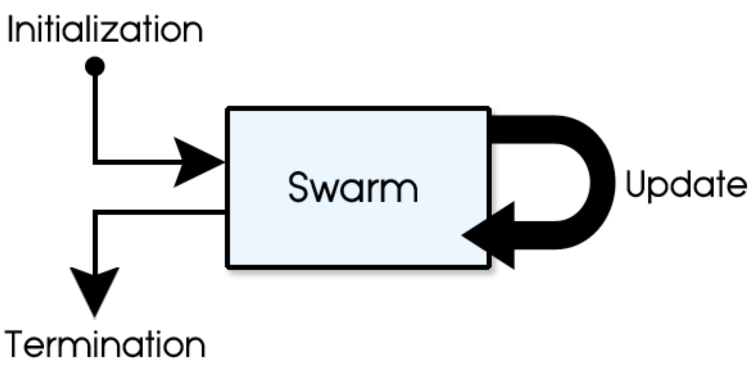
A.E. Eiben and J. E. Smith – *Introduction to Evolutionary Computing*, Springer, 2003
D. Floreano and C. Mattiussi – Bio-Inspired Artificial Intelligence, MIT Press, 2008

Algorithmic Approach

Genetic Algorithms

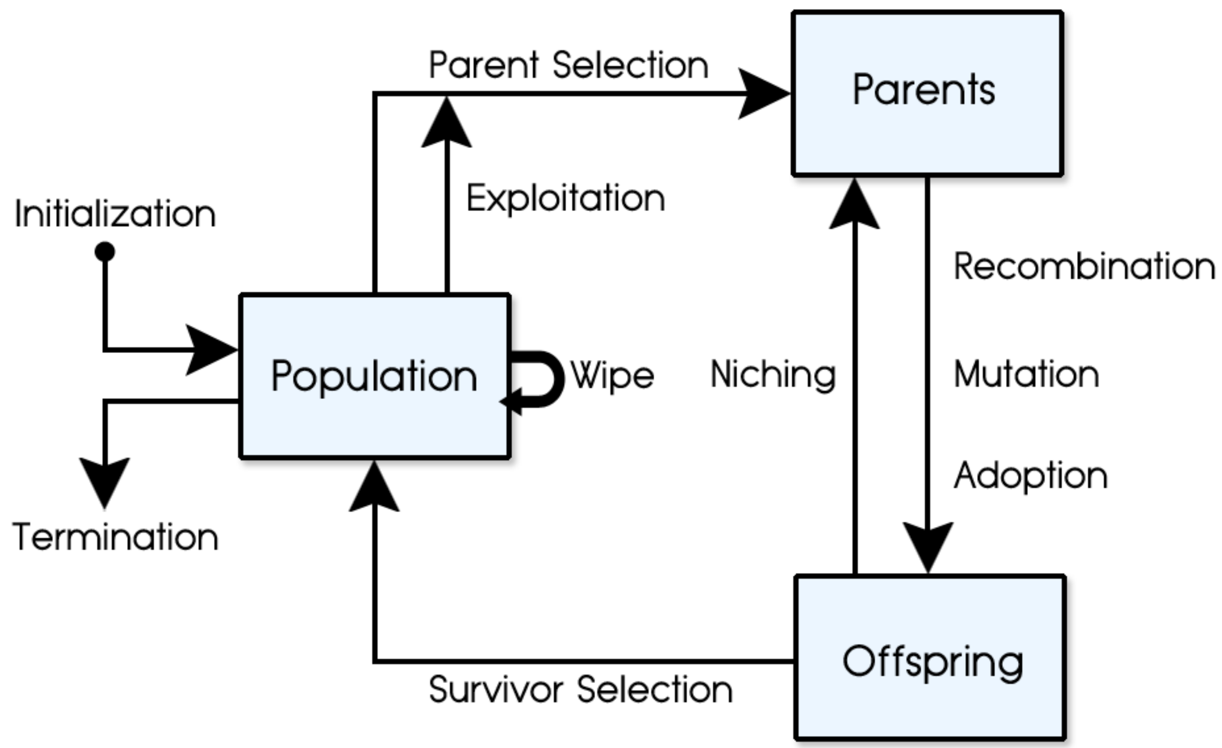


Particle Swarm Optimization



Algorithmic Approach

Hybrid Genetic Swarm Algorithm



Algorithmic Approach

Encoding

Genotype *x* → n-dimensional joint variable configuration

$$x = \left(x_1 \mid x_2 \mid x_3 \mid \ldots \mid x_{n-1} \mid x_n \right)$$

→ Independent of joint types (revolute, prismatic, ...)
→ Joint limits directly incorporated (clipping)
→ Allows algebraic vector calculations

Algorithmic Approach

Fitness Function

Idea

Use randomized weight *w* for multi-objective optimization

→ Models **dynamic environment**
→ Determines individuals that are ***„most responsive to change“***
→ Biologically plausible

Phenotype *X* → Cartesian configuration obtained by forward kinematics function *f*

$$\mathcal{X} = f(x)$$

Fitness function Ω measures fitness π under evolutionary target *Y*

$$\pi = \Omega(\mathcal{X}) \qquad \Omega : \begin{cases} d_t(\mathcal{X}, \mathcal{Y}) & Position \\ d_r(\mathcal{X}, \mathcal{Y}) & Orientation \\ w\hat{d}_t(\mathcal{X}, \mathcal{Y}) + (1-w) d_r(\mathcal{X}, \mathcal{Y}) & Pose \end{cases}$$

Algorithmic Approach

Parent Selection

Rank-based parent selection from mating pool Γ

$$\mathcal{S}_{\mathcal{P}} : \mathcal{P}_{\{1,2\}} \leftarrow p(\Gamma_i) = \frac{\gamma - i + 1}{\sum_{i=1}^{\gamma} i}$$

→ Independent of fitness value distribution
→ Sensitive to local extrema
→ Scales well with population size
→ No parameters required

Algorithmic Approach

Recombination

Idea

Let offspring dive a little deeper into the direction that caused improvement within their parents

→ *Heuristic evolutionary gradients for continuous evolution dynamics*

→ ***Evolutionary gradient*** = *amount of change during* ***mutation*** *and* ***adoption*** *(see later)*

$$\mathcal{R} : x_i = \underbrace{w_i x_i^{\mathcal{P}_1} + (1 - w_i) x_i^{\mathcal{P}_2}} + \underbrace{r_{\mathcal{P}_1} g_i^{\mathcal{P}_1} + r_{\mathcal{P}_2} g_i^{\mathcal{P}_2}} \qquad \underbrace{\mathcal{R}_r = 1.0}$$

Randomly interpolated genotype of parent chromosomes

Randomly weighted swarm dynamics from evolutionary gradient *g*

Constant recombination rate

Algorithmic Approach

Mutation

Motivation

Fixed mutation rate and strength not suitable for arbitrary kinematic models

Idea

→ Let the population itself determine the required amount of **exploitation** and **exploration** by an **extinction rate** that **controls mutation** independent from the problem dimensionality

$$\mathcal{M} : x_i \leftarrow x_i + w_i \mathcal{M}_\beta \qquad \mathcal{M}_r = \mathcal{M}_\alpha \frac{1}{n} \qquad \xi^{\Psi_i} = \frac{\pi_i + \pi_{min}(\frac{i-1}{\psi-1} - 1)}{\pi_{max}}$$

Mutation Strength

- Can grow arbitrarily small to exploit
- Exploration limited to the domain of the search space dimension

$$\mathcal{M}_\beta = \xi^{\mathcal{P}_\varnothing} \Delta n_i$$

Mutation Rate

- Normalized between [1/n; 1.0]
- Adaptive to arbitrary dimensionality

$$\mathcal{M}_\alpha = \xi^{\mathcal{P}_\varnothing}(n-1) + 1$$

Extinction Factor

- Normalized between [0.0; 1.0]
- Measures relative quality of an individual within population
- Controls whole mutation

Algorithmic Approach

Adoption

Idea

Let offspring **adopt characteristics** of
parents and most successful performing prototypes

→ Natural behaviour over lifetime
→ Dynamic search space exploration
→ Very similar to PSO

$$\mathcal{A} : x_i \leftarrow x_i + \underbrace{w_i r_{\mathcal{P}} \left(\frac{x_i^{\mathcal{P}_1} + x_i^{\mathcal{P}_2}}{2} - x_i \right)}_{\text{Averaged gradient to parents}} + \underbrace{(1 - w_i) r_* (x_i^* - x_i)}_{\text{Gradient to best individual}}$$

Averaged gradient to parents

Gradient to best individual

Randomly interpolated

Algorithmic Approach

Niching

Pre-Selection

→ Immediately remove any parent whose fitness is worse than its offspring

Goals

→ Encourages to keep track of multiple local extrema
→ Avoid premature convergency

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Algorithmic Approach

Survivor Selection

Age-based with elitism

→ Merge all elites and newly generated offspring

Goals

→ Let the fittest individuals *(elites)* survive in order not to lose the current evolutionary progress

Algorithmic Approach

Exploitation

Motivation

Increase convergency by further improvement of already good solutions

Approach

Iterative cyclic exploitation of **elite** individual genotypes

1. *Randomly modify each gene by current fitness value into both domain directions*
2. *Take modification that scored improvement*
3. *Calculate averaged fitness value*

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Algorithmic Approach

Initialization

Biased population

1 individual → currently assigned joint variable configuration

All others → randomly generated chromosomes

Termination

Determine whether desired accuracy in

position and **orientation**

is satisfied by the solution

Wipe

Problem

- Many local extrema within search space
- Escape from dead-end paths in good extrema might take too long
- Restart might be more efficient

Approach

- Perform wipe *(restart)* of population if solution

→ could not be improved within last generation
and
→ can not be improved by exploitation

Algorithmic Approach

Solution Filtering

Motivation

Real-time interactive applications → best solution so far is required

Problem

Randomized weights might replace elites by constant dynamics

Solution

Determine joint variable solution by equally weighted objective function

→ Remember best solution in history
→ Let evolution continue approximation underneath

Experiments and Results

Environmental Setup

Laptop – ASUS G751JY

Intel Core i7-4720HQ (2.6 – 3.4 GHz)

(Code running at single core implementation)

unity + **URDF Importer** + **Kinematic Joint** + **IK Solver**

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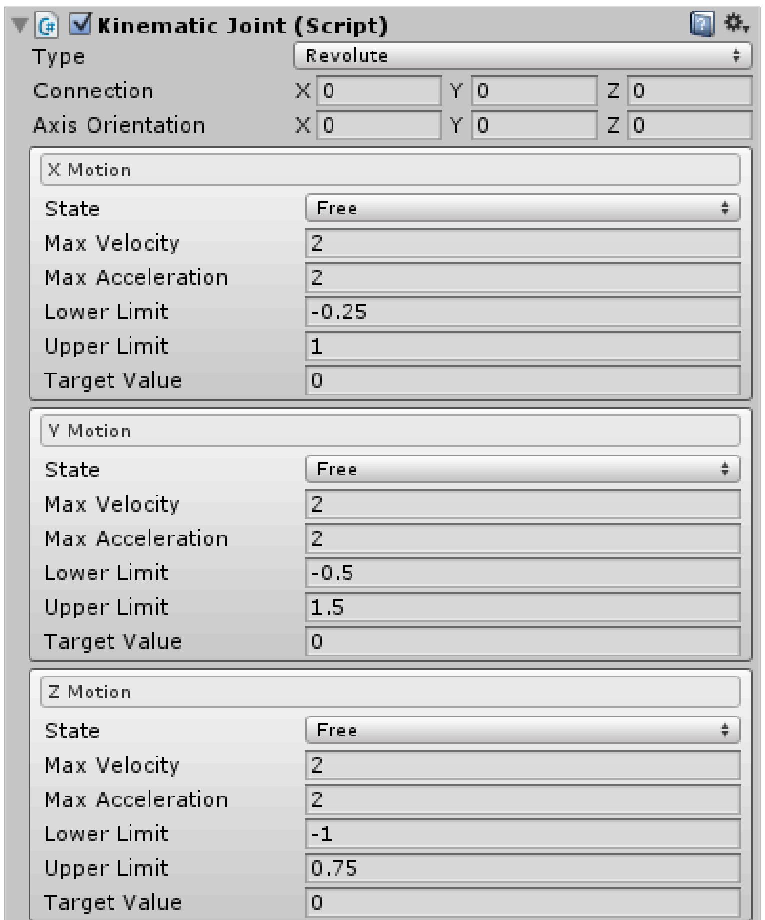
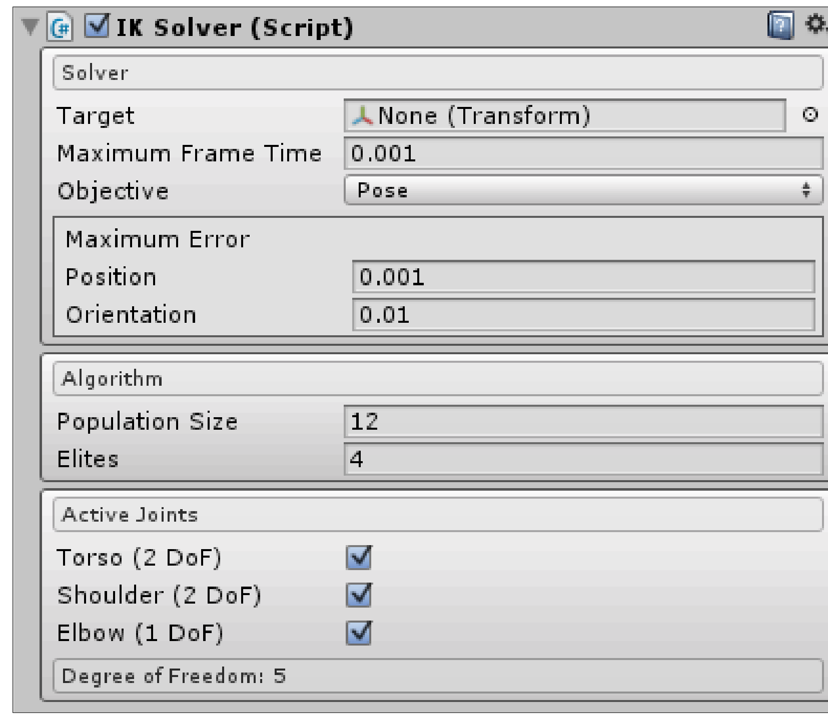
Experiments and Results

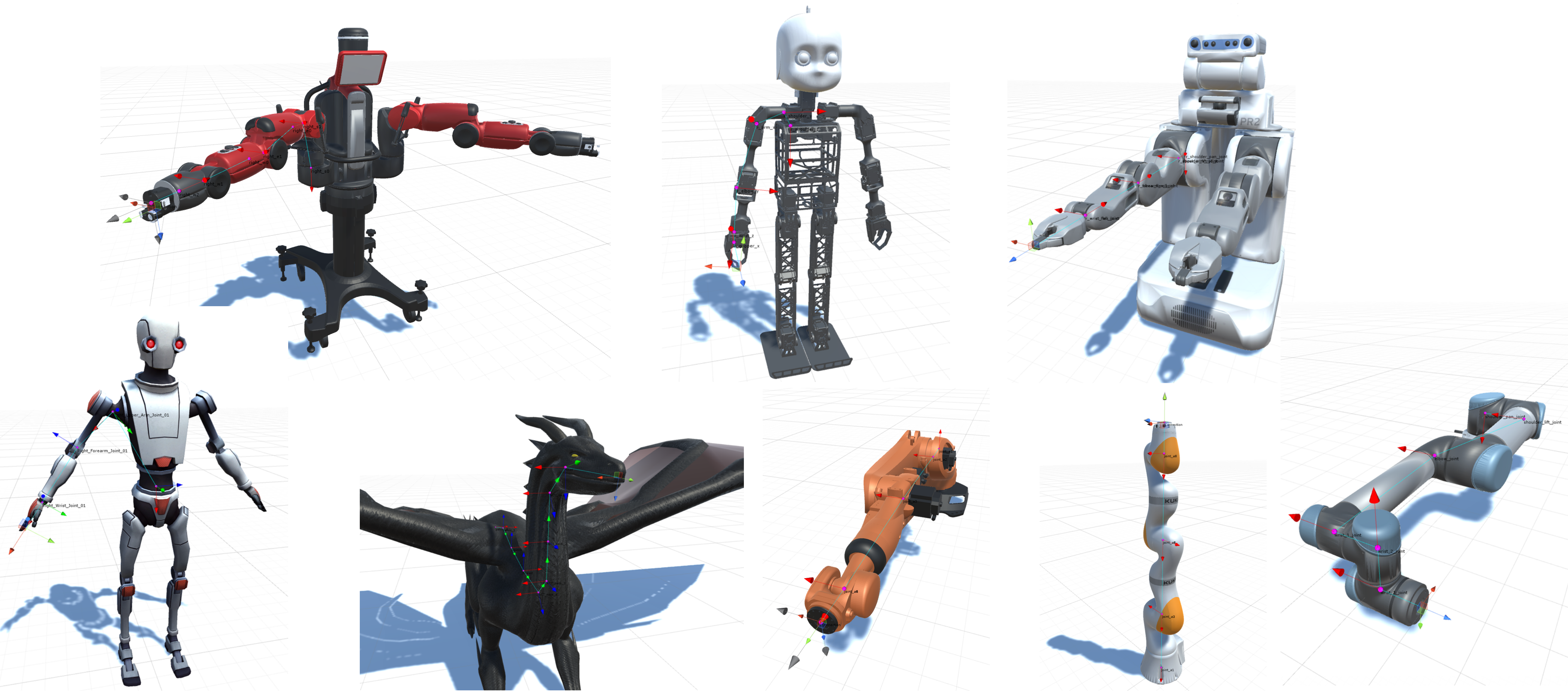
Environmental Setup





Experiments and Results

Environmental Setup



Experiments and Results

– Live Demos in Unity –

1 - https://www.youtube.com/watch?v=dRCY848mSLI
2 - https://www.youtube.com/watch?v=DZFeU_WZlhI
3 - https://www.youtube.com/watch?v=8-kw7RsuD6A
4 - https://www.youtube.com/watch?v=OXtGbrl7qUQ
5 - https://www.youtube.com/watch?v=Gu0CBf18Zf0
6 - https://www.youtube.com/watch?v=a9QPXud-j0Q

Experiments and Results

1. Parameters

→ *Balancing of population size and elites*

→ *UR5 Arm*

2. Selective Study

→ *All versus Nothing*

→ *Selectively taking away improvements*

→ *UR5 Arm*

3. Performance Study

→ *Success, Accuracy, Time, Displacement, Flexibility*

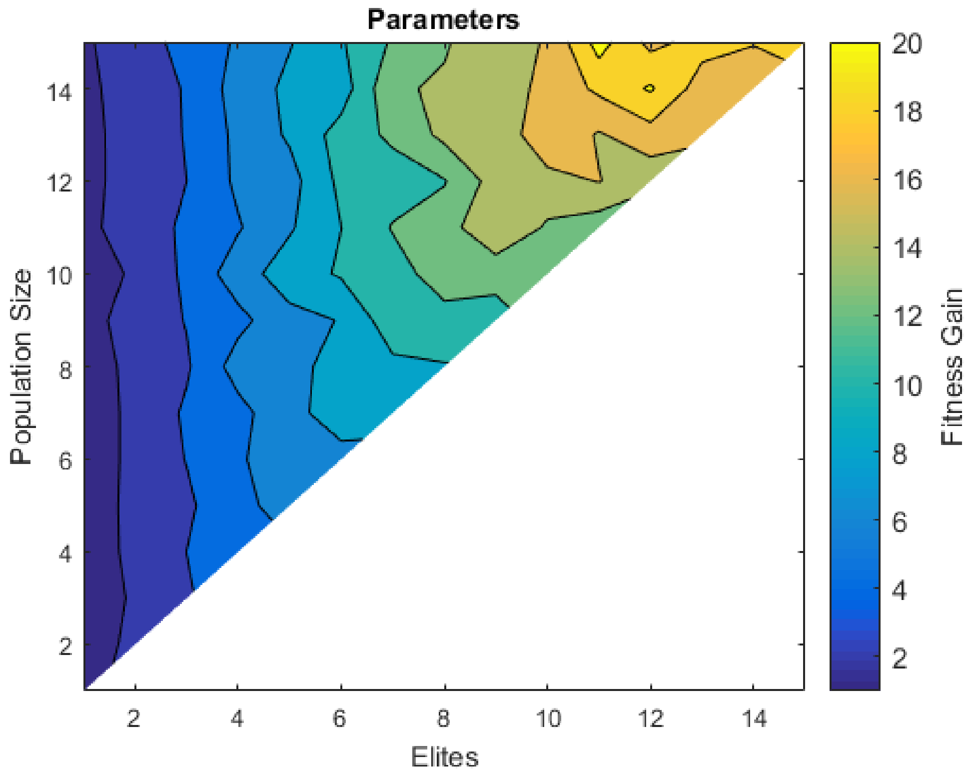
→ *8 Models + 3 high dimensional chains*

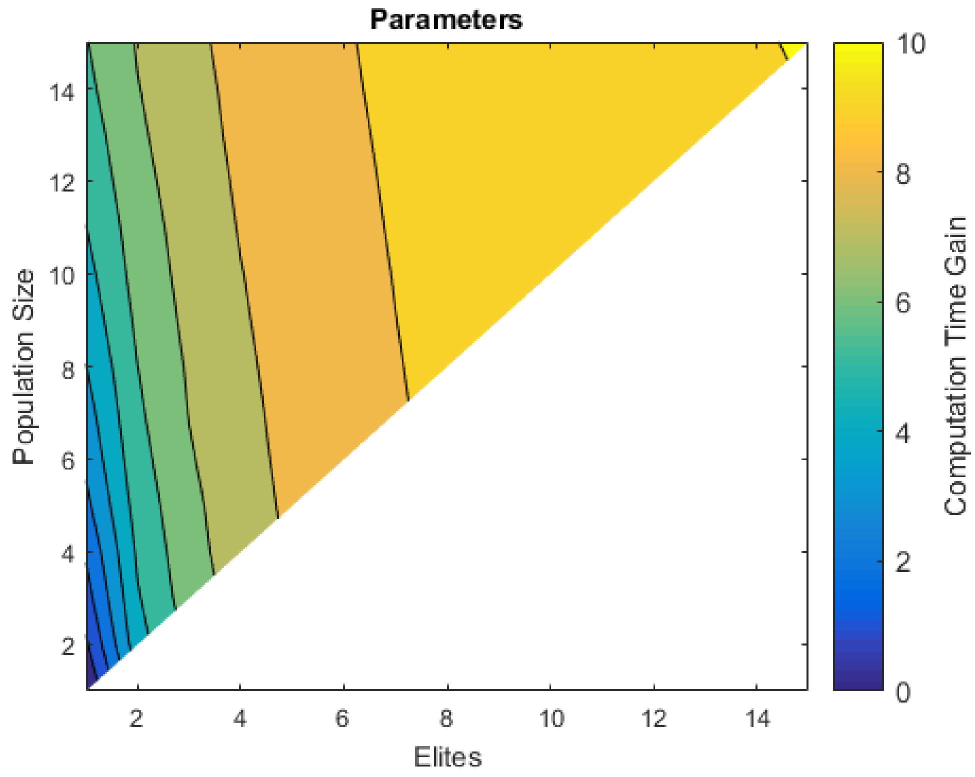
4. Data Comparison

All samples generated as **random poses** or **continual trajectories** of joint space configurations

Experiments and Results

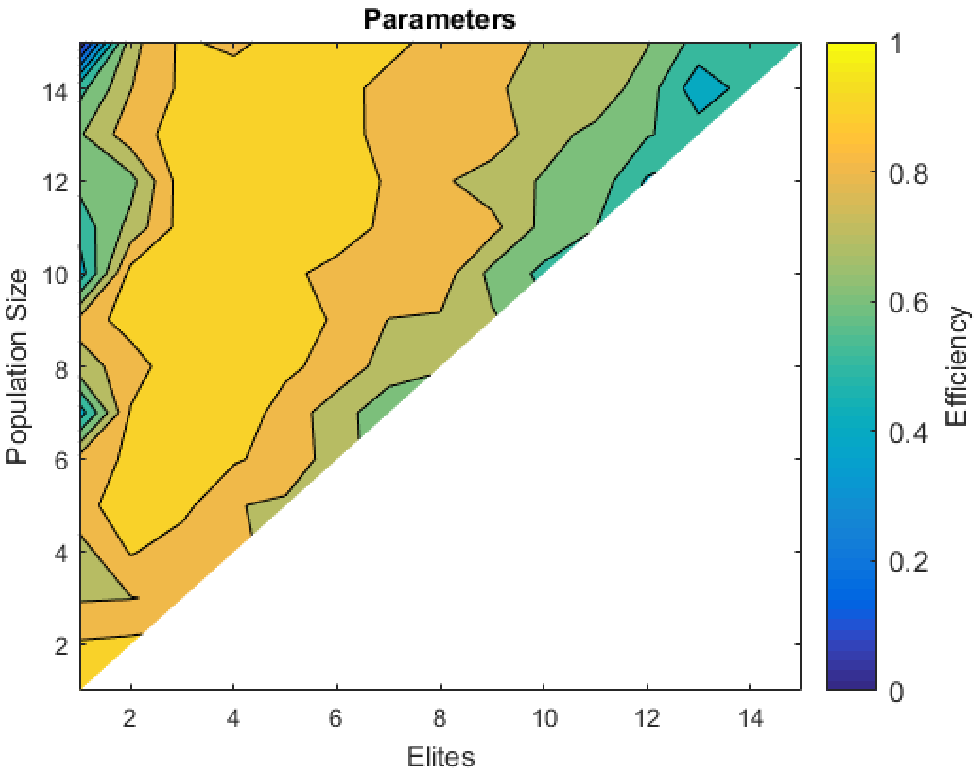
Parameters





Experiments and Results

Parameters



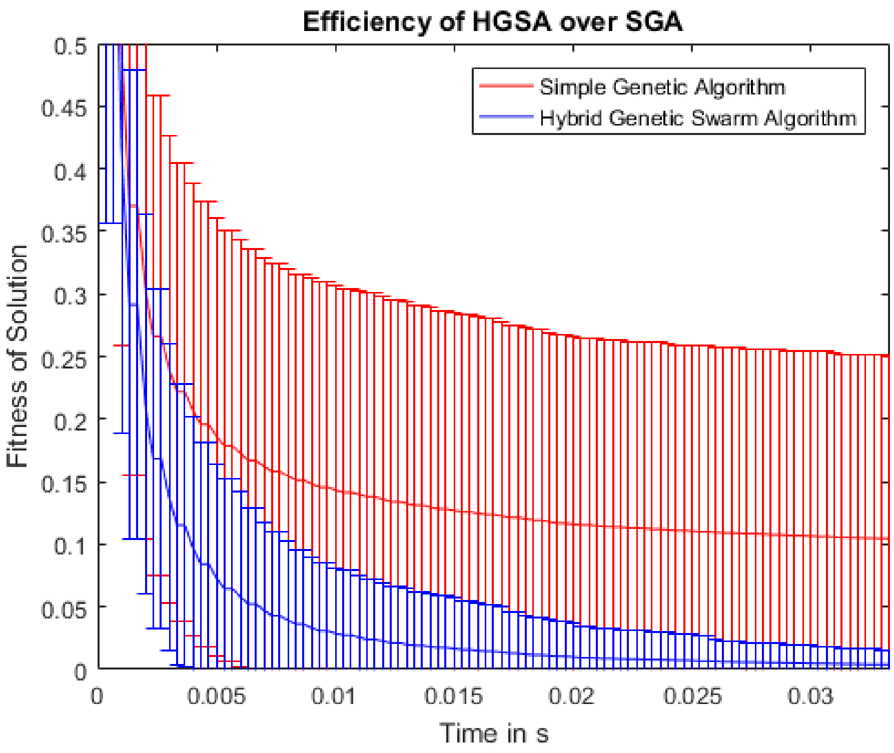
Reasonable parameter choice

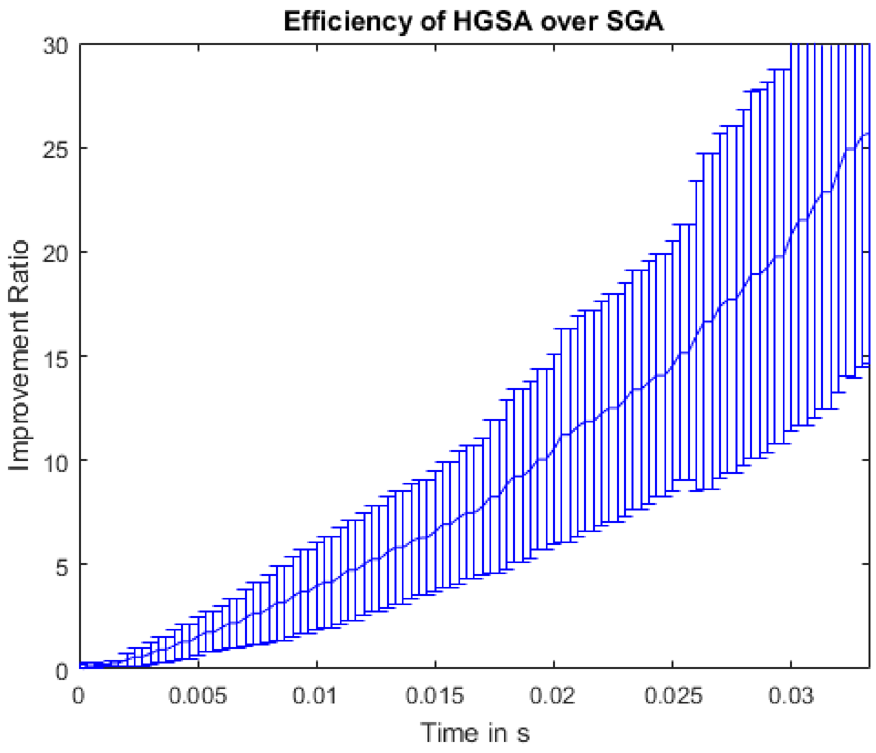
Population Size → 12

Elites → 4

Experiments and Results

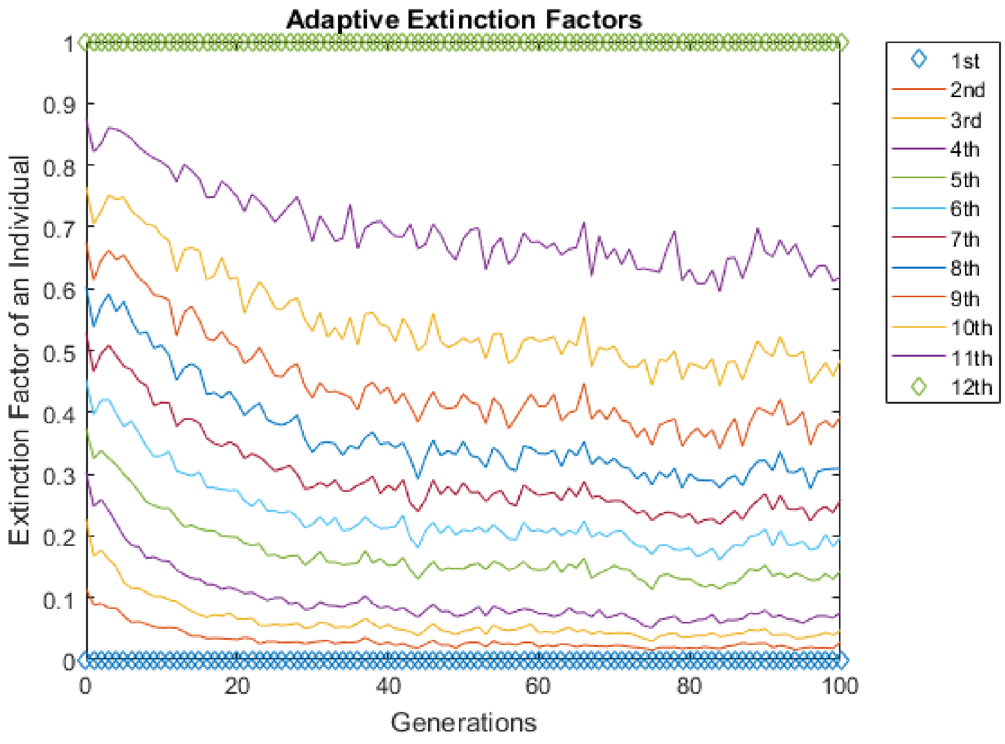
Selective Study – All versus Nothing



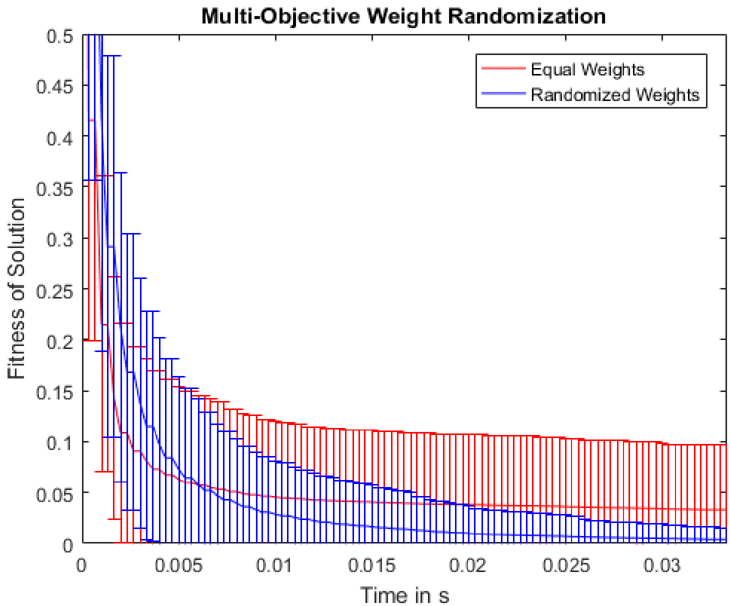


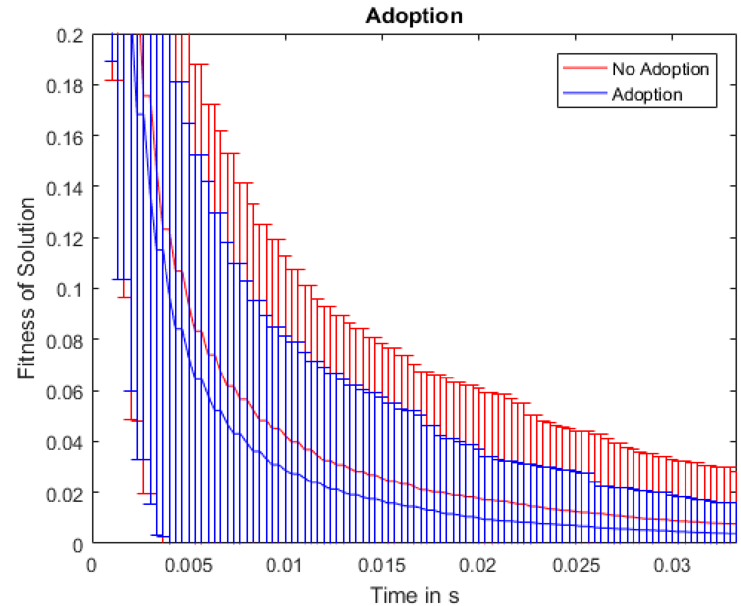
Experiments and Results

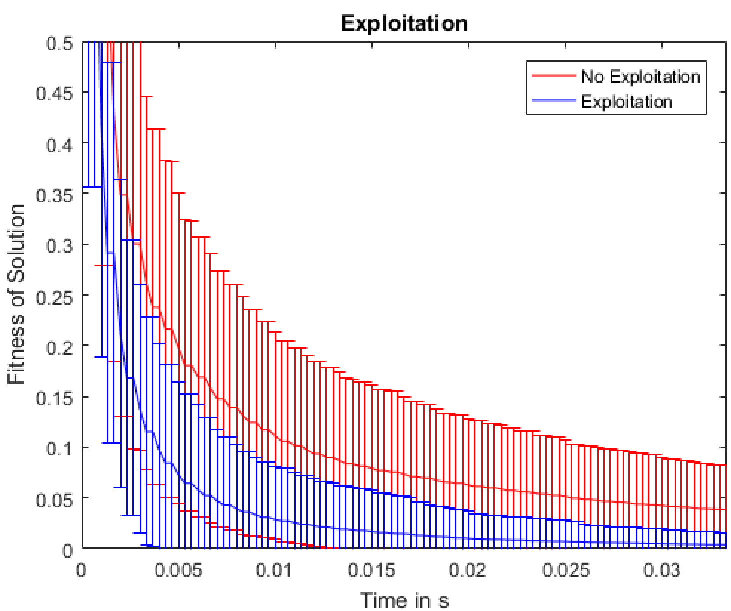
Selective Study – Extinction Factors

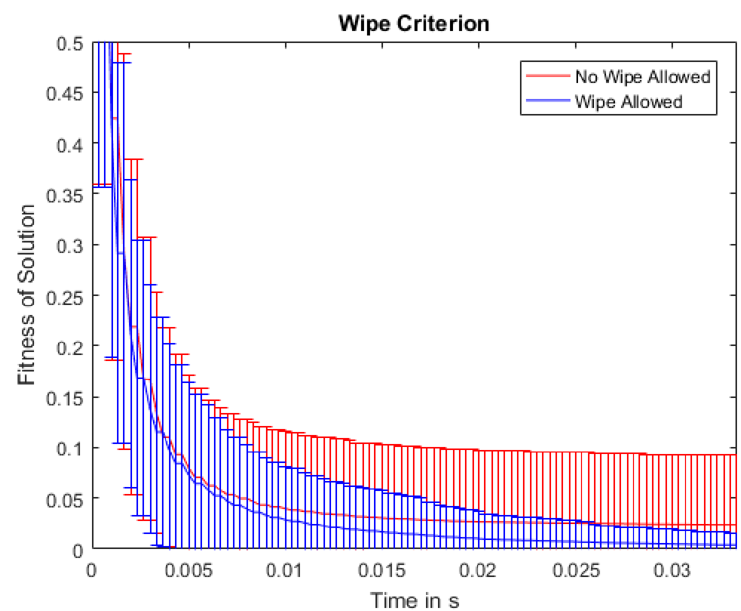


- Extinction factors **adapt** to the current evolutionary progress
- Maintains **explorative diversity**
- Ensures **local extrema sensitivity**


Multi-Objective Weight Randomization
Equal Weights
Randomized Weights
Fitness of Solution
Time in s

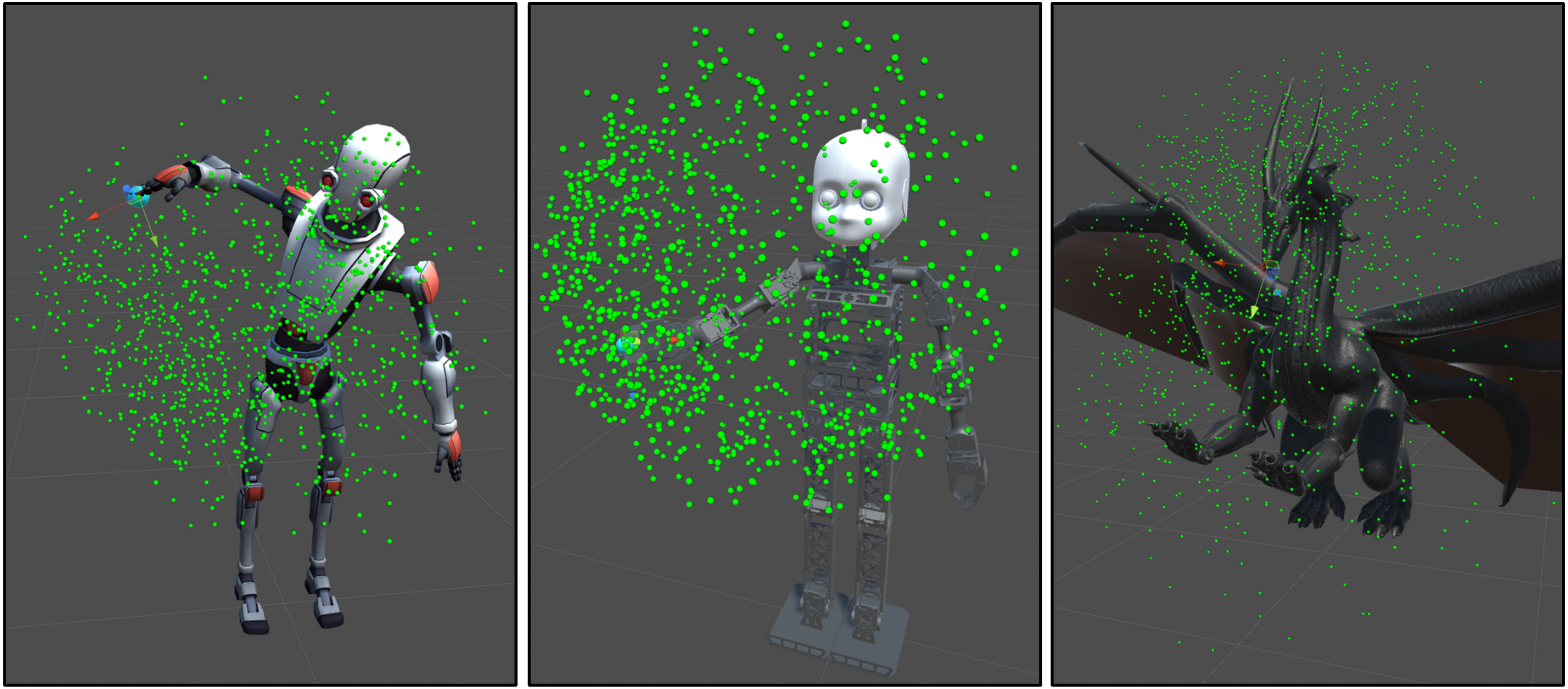

Adoption
No Adoption
Adoption
Fitness of Solution
Time in s


Exploitation
No Exploitation
Exploitation
Fitness of Solution
Time in s


Wipe Criterion
No Wipe Allowed
Wipe Allowed
Fitness of Solution
Time in s

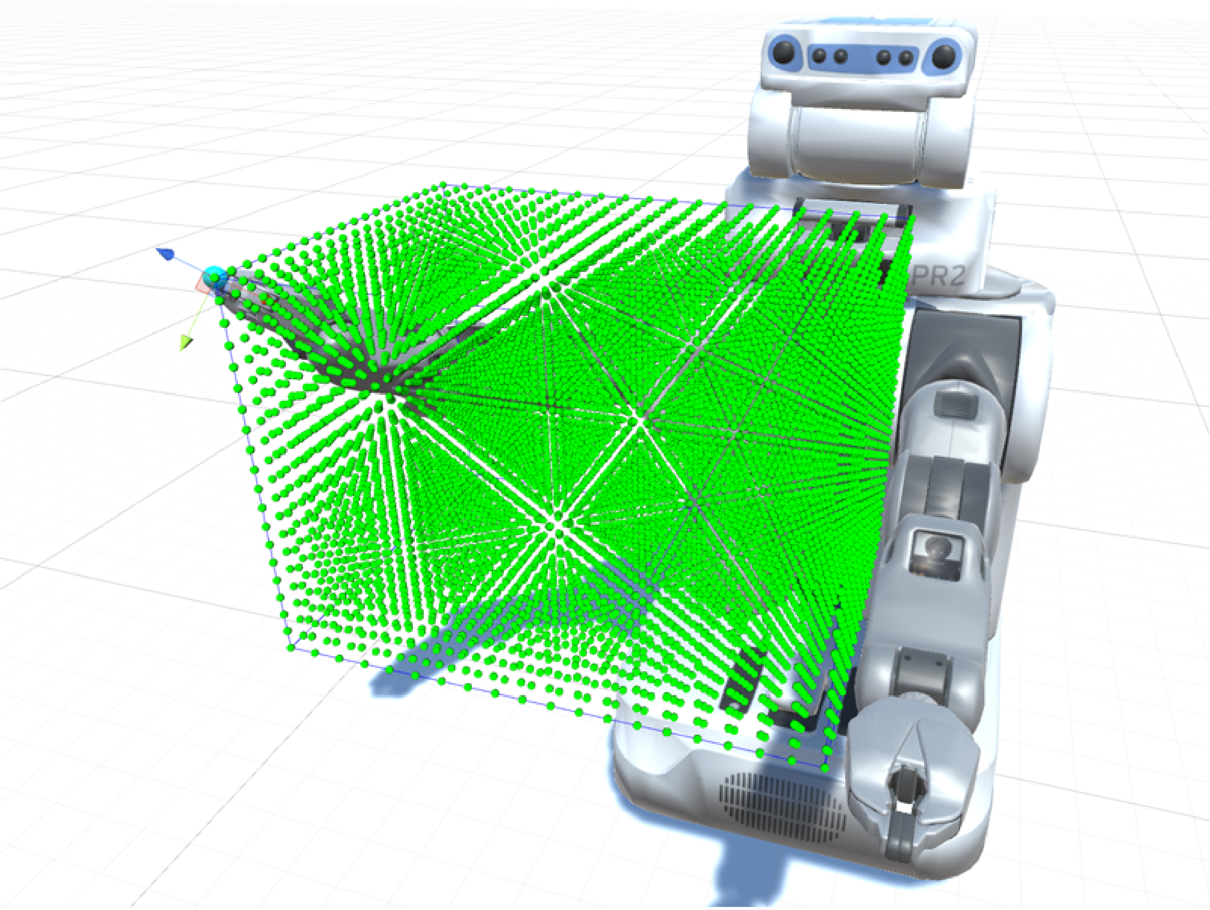
Experiments and Results

Performance Study – Success *(Pose Objective)*



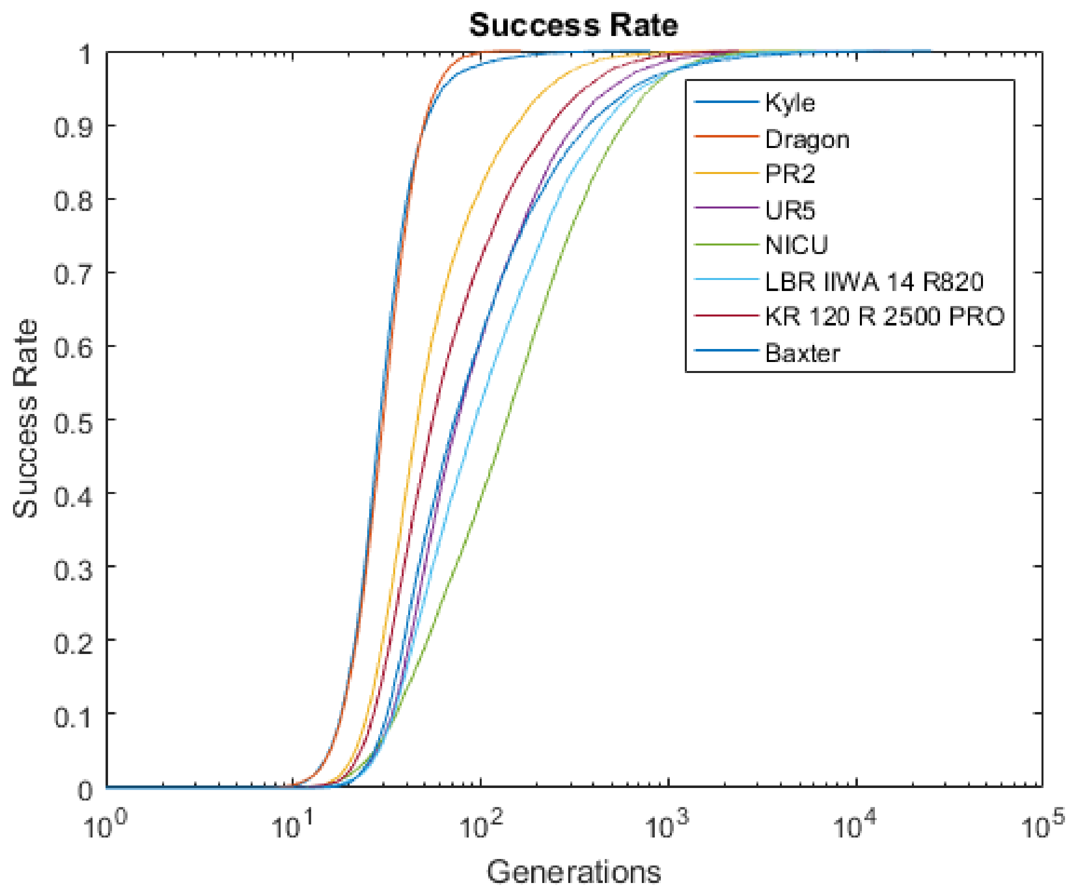
Experiments and Results

Performance Study – Success *(Position Objective)*



Experiments and Results

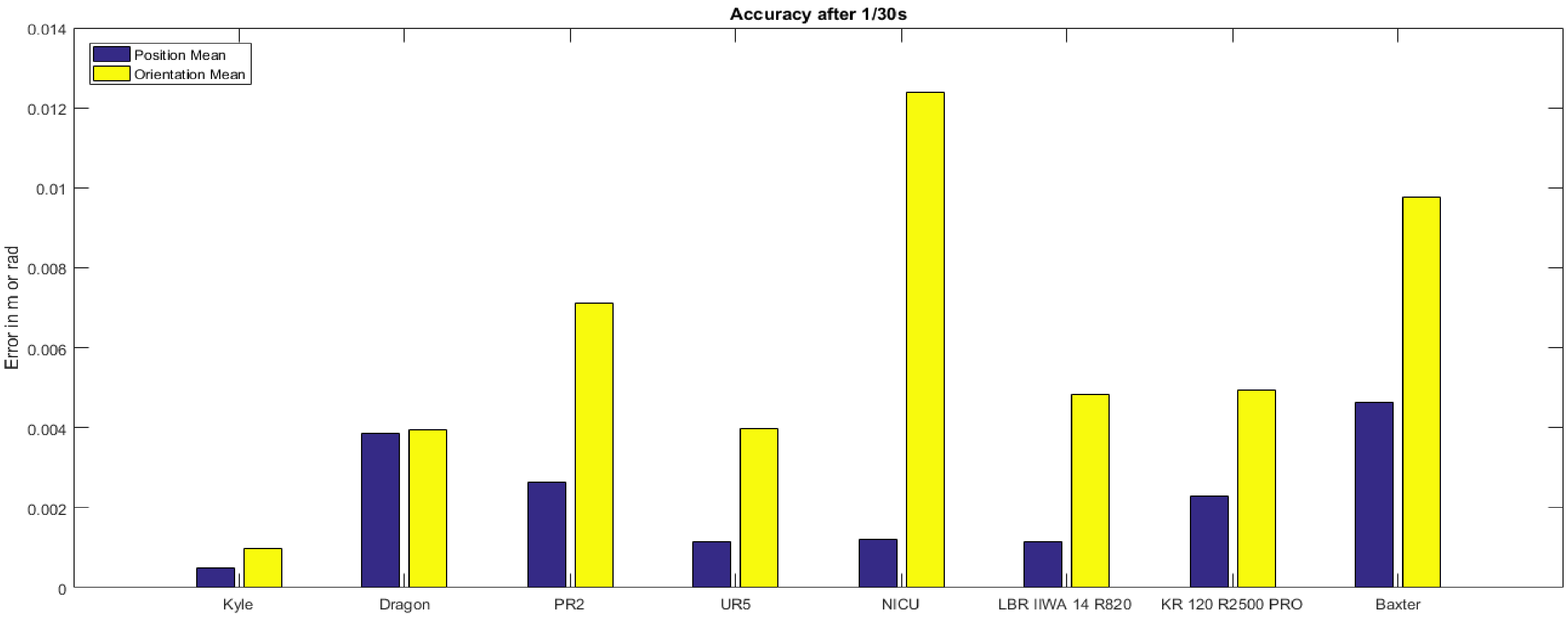
Performance Study – Success



All 10.000 random poses for 8 different models were found.

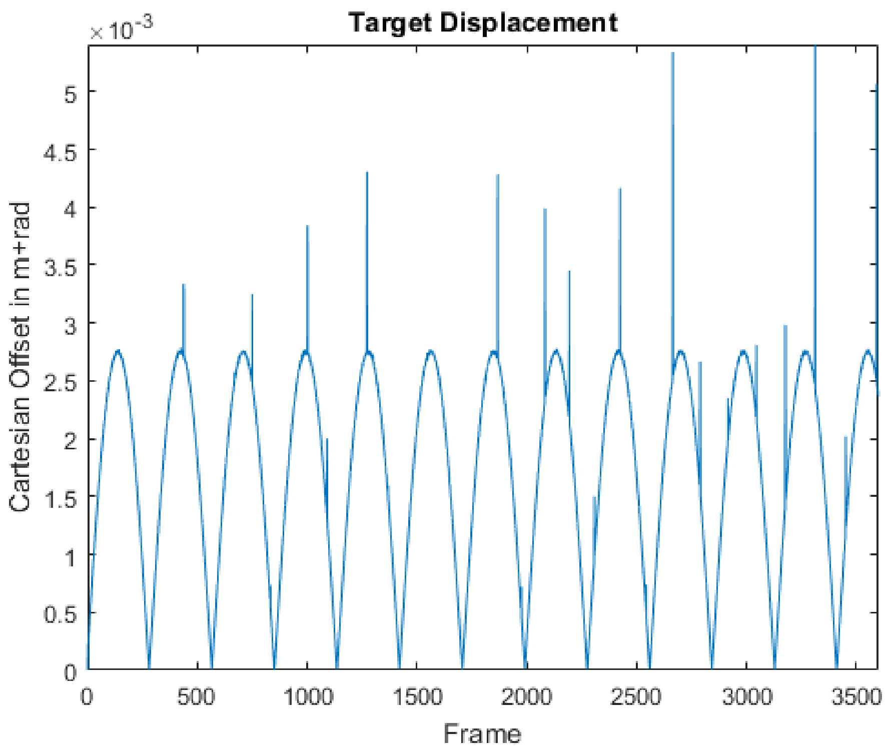
Experiments and Results

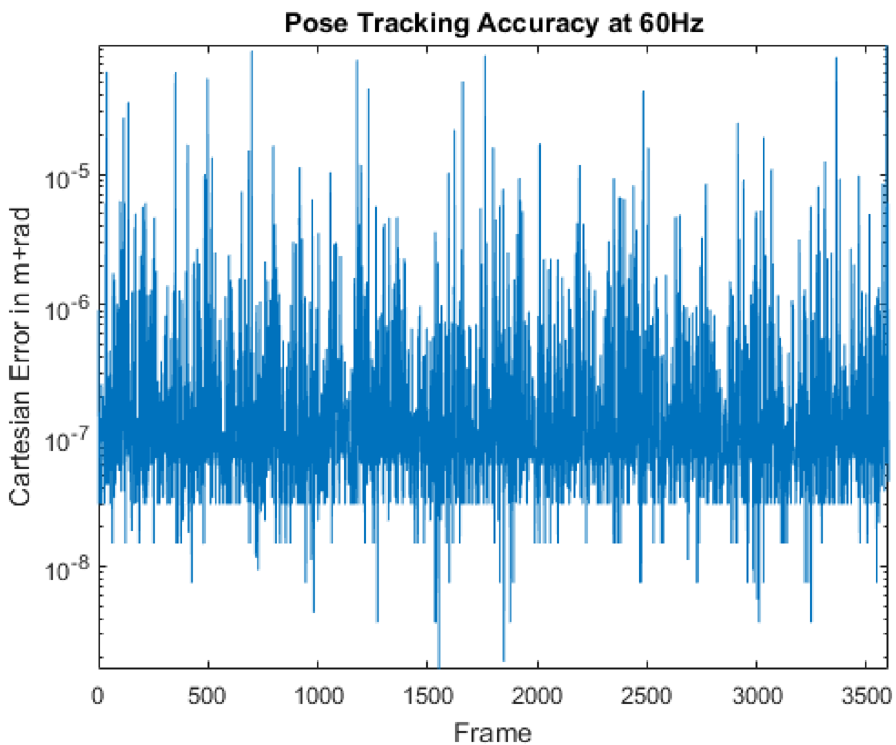
Performance Study – Accuracy



Experiments and Results

Performance Study – Accuracy

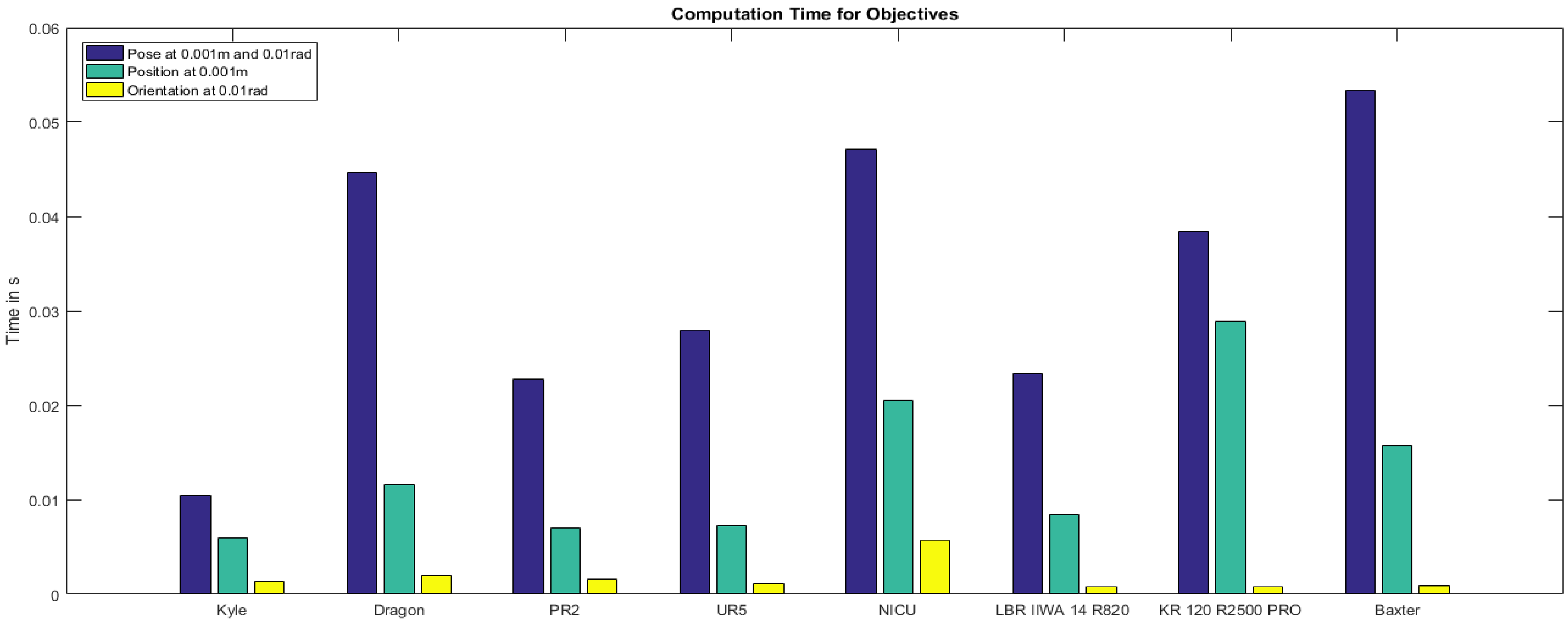




→ **Pose tracking with 10^(-6) cartesian error** *(sum of position and orientation errors)*

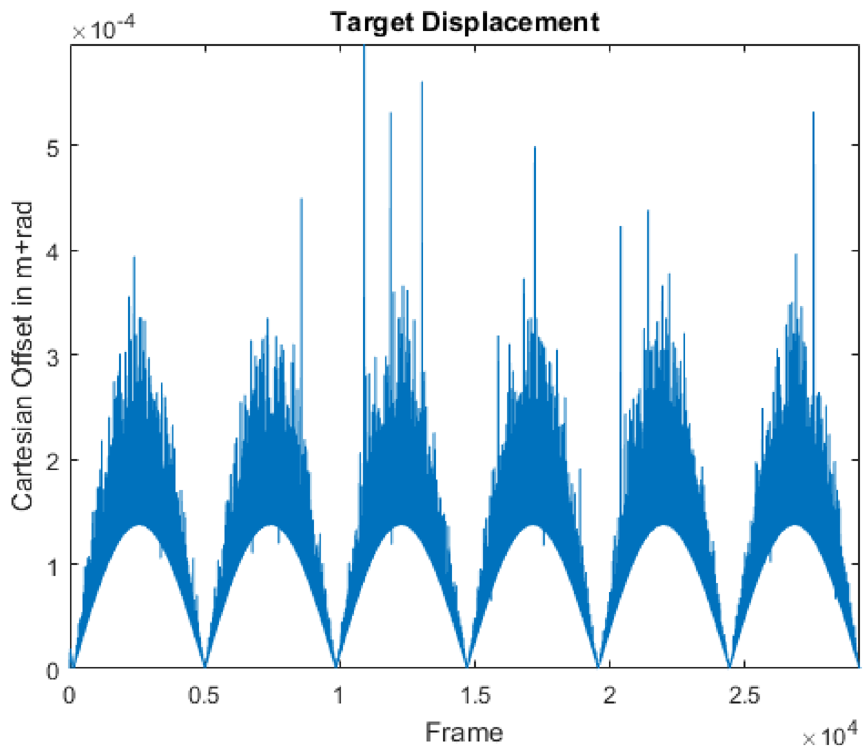
Experiments and Results

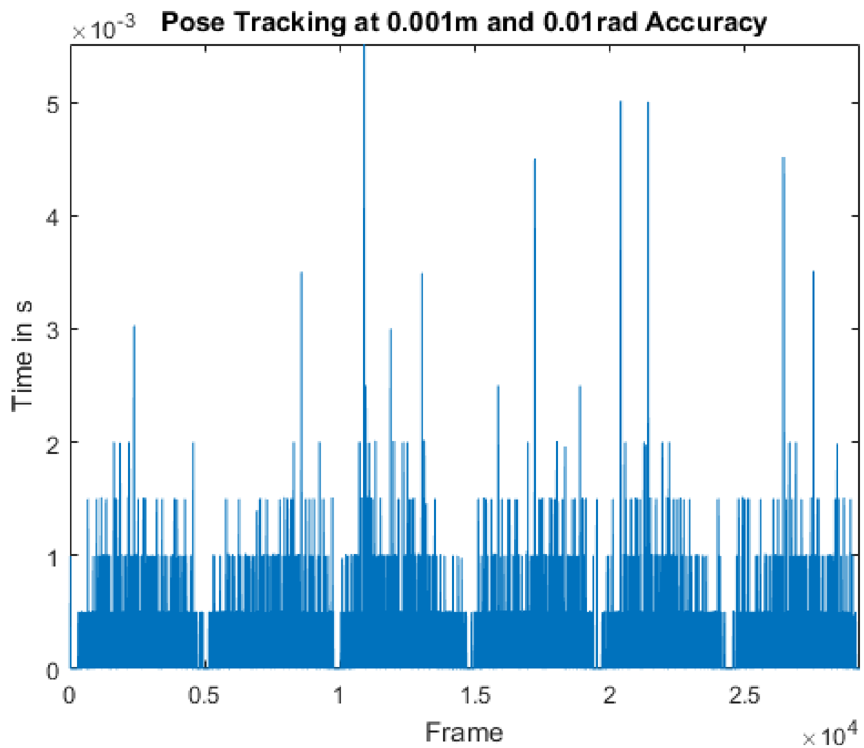
Performance Study – Time



Experiments and Results

Performance Study – Time

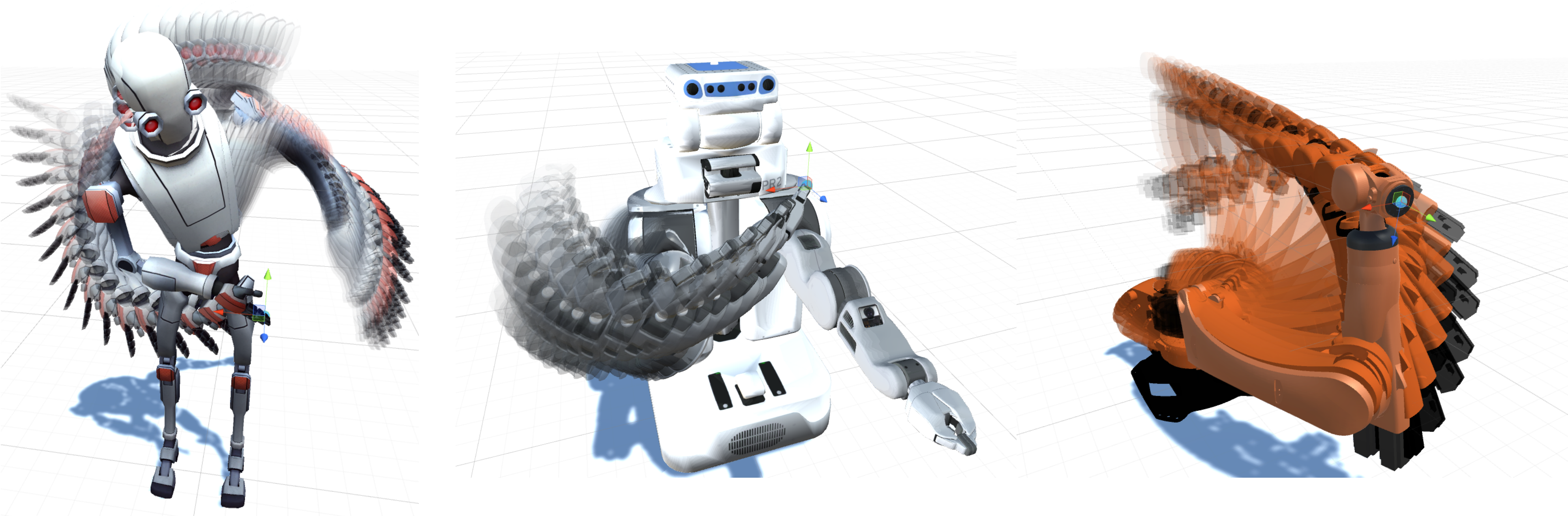




→ Accurate pose tracking at 1000-2000 Hz

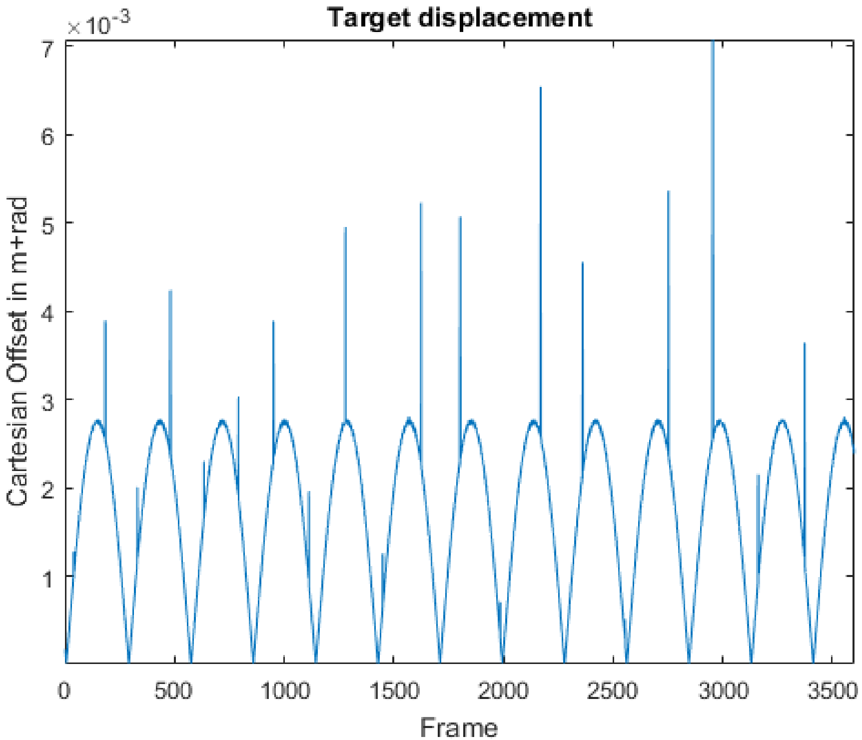
Experiments and Results

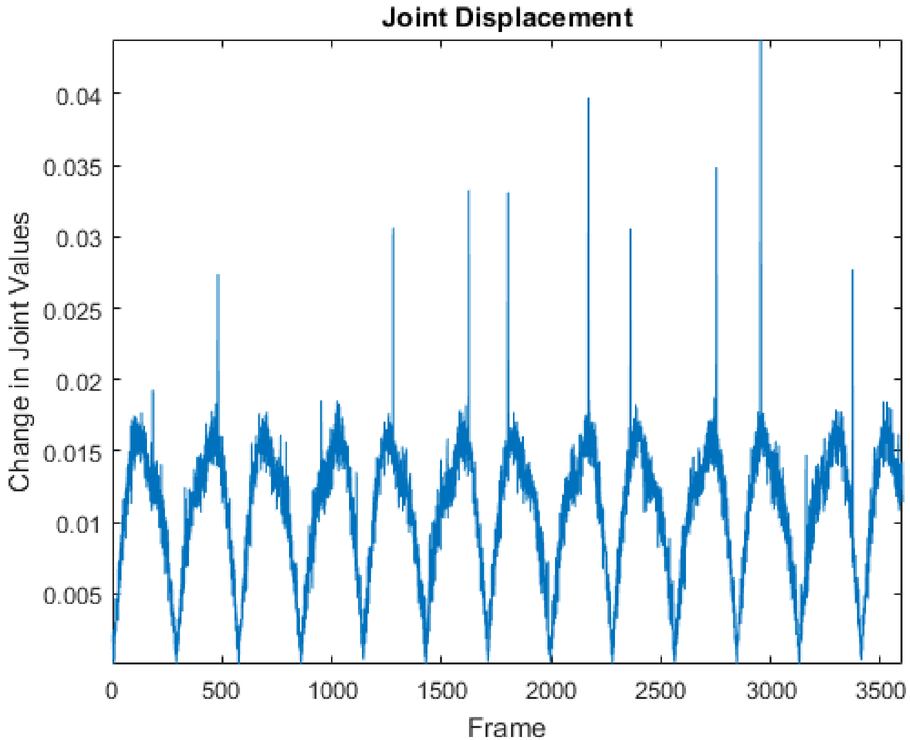
Performance Study – Displacement



Experiments and Results

Performance Study – Displacement

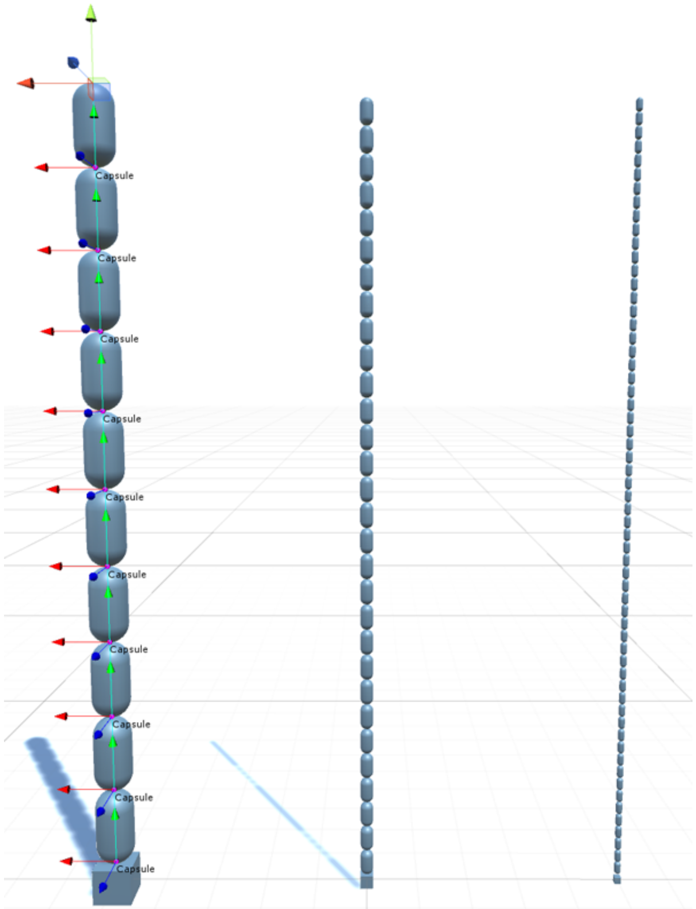




→ Responsive shape-resembling joint value change

Experiments and Results

Performance Study – Flexibility

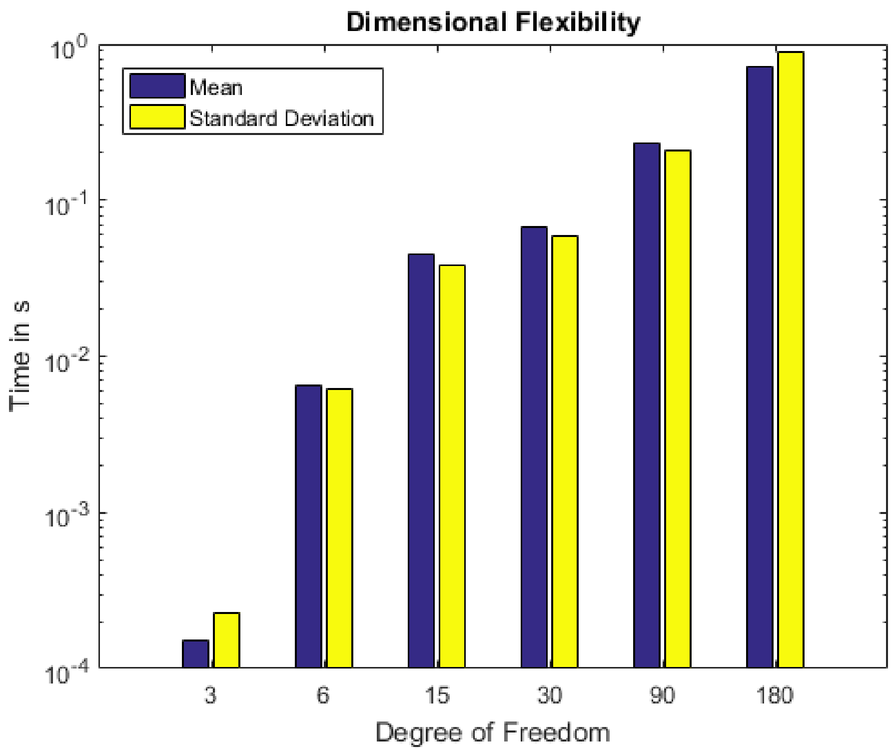


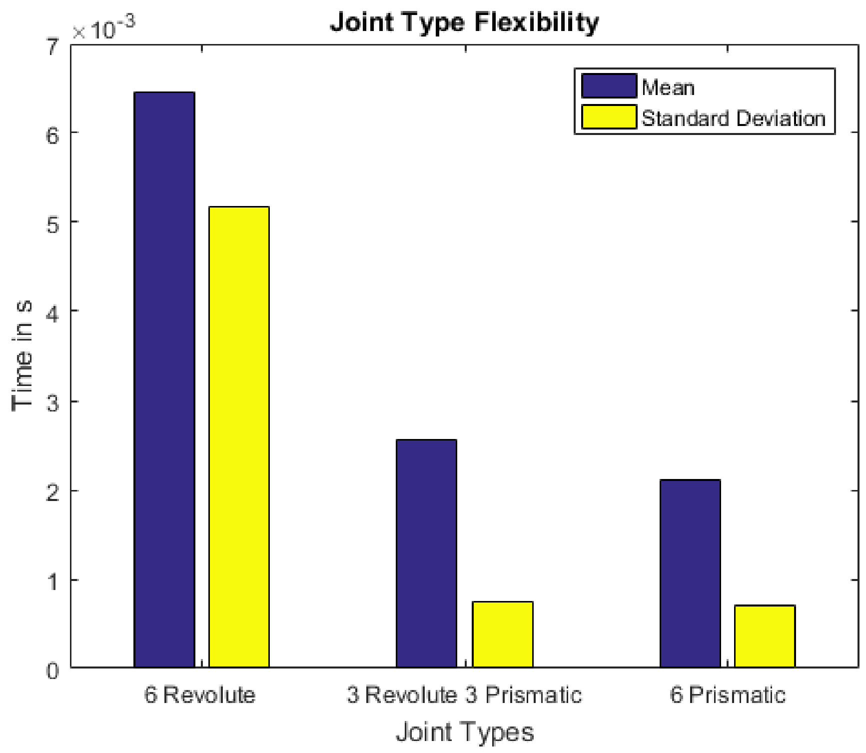
Spherical Joints

left – 30 DoF
middle – 90 DoF
right – 180 DoF

Experiments and Results

Performance Study – Flexibility





Experiments and Results

Data Comparison
Reported efficiency in literature on various robot models

	Jacobian	CCD	FABRIK	GA	PSO	NN	HGSA
Accuracy *(m | rad)*	0.00001	0.00001	0.0001	0.001	0.001	0.01	0.001
Time *(ms)*	<1 - 10	1 - 100	10-50	50 - 500	30 - 600	-	10 - 60
Robustness	Medium	Medium	Low	High	Medium	Low	High
Scalability	– –	–	+	+	+ +	– –	+ +

Experiments and Results

Data Comparison
Orocos' KDL vs TRAC-IK vs HGSA

	Orocos' KDL *(no joint limits)*		TRAC-IK *(Beeson & Ames, 2015)*		HGSA	
	Success	**Time**	**Success**	**Time**	**Success**	**Time**
PR2	83.14%	1.37ms	99.84%	0.59ms	100%	22.75ms
LBR IIWA	37.71%	3.37ms	99.63%	0.56ms	100%	23.39ms
UR5	35.88%	3.30ms	99.55%	0.42ms	100%	27.88ms
Baxter	61.07%	2.21ms	99.17%	0.60ms	100%	53.33ms

Scalability?

Joint displacement due to random restarts?

Experiments and Results

Data Comparison
PASO vs HGSA

	PASO *(Collins & Shen, 2016)*	HGSA
	Time	**Time**
30 DoF	1.57s	0.066s
90 DoF	7.46s	0.233s
180 DoF	37.03s	0.717s

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Conclusion

General

- *Universal IK solver for kinematic chains*
- *Arbitrary joint types, link geometry and degree of freedom*
- *Algorithm based on biologically-inspired evolutionary and collective concepts*

Algorithmic Improvements

Extinction Factors	Swarm Adoption	Heuristic Exploitation
Multi-Objective Weight Randomization	Wipe Criterion	

Results

- *100% success rate at high accuracy and real-time capability*
- *Minimal joint displacement and high scalability*
- *Maintains performance under various kinematic models*
- *Can compete with the State-of-the-Art*

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Future Work

Extinction Factor Study
→ Analyse loss by adaptive mutation control in contrast to model-specific optimized parameters

Parallel GPU / Multi-Core Implementation
→ >95% of time is required by fitness calculation *(FK equations)*
→ Reimplement the algorithm in C++/Python
→ Efficient parallel instead of sequential single-core fitness calculation

Multiple End Effectors
→ Currently, only serial kinematic chains are supported
→ Extend algorithm to solve for multiple end effectors simultaneously

Path Planning
→ Extend algorithm for path-planning tasks

Collision Avoidance
→ Incorporate link geometry to filter solutions that would result in collisions

Neural Learning
→ Learn mappings from previously evolved joint configurations and trajectories

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