

Machine Learning, Safety, and Industrial Robots

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What is Artificial Intelligence?

Breakthroughs in

- visual perception,
- speech recognition, and
- semantic reasoning.

Challenges in

- safe actuation
- physical manipulation, and
- physical human interaction.



Gary Kasparov vs. IBM Deep Blue, 1997.



















Challenges in

- safe actuation,
- physical manipulation, and
- physical human interaction.

Data-driven Robotics



Machine learning for perception

Machine learning for actuation

Goal: No more programming required for industrial robots

Outline



Robot Learning

Deep reinforcement learning

Transfer learning with and without physics

Safe Human-Robot Interaction

Real-time motion planning

Real-time Robot Motion Planning and Control

Hybrid control

Generic Technology Readiness Levels



Level	Technology Readiness Level	Method Readiness Level (inspired by *M.F. Peeters, M. Robicha Certification for Gas Turbine Design, ISABE-2005-1203) Method capability	ud, G. Guevremont, Analytical Process Applicability for design		
TRL 9	Actual system "flight proven" through successful mission operations	Analysis method used for a long period of time and the method is validated by <u>numerous</u> measurements and tests of relevant components in engine environment and full requirement envelop. All input data are of highest quality. Fully coherent to other company specifications.	Used for design requirement verification without further testing or verification.		
TRL 8	Actual system completed and "flight qualified" through test and demonstration (ground or space)	Analysis method used for a long period of time and the method is measurements validated by and tests in relevant components in engine environment and full requirement envelop. Input data are of good quality. Coherent to other company specifications.	Suitable for component sizing in product development but requires system verification testing.		
TRL 7	System prototype demonstration in a space environment	Analysis method used for a long period of time and the method is validated by measurements and tests in relevant components in engine environment. Input data are of good quality. Coherent to other company specifications.	Suitable for component sizing in product development but requires system verification testing. Service development programs necessary.		
TRL 6	System/subsystem model or prototype demonstration in a relevant environment (ground or space)	Analysis method used for a period of time and the method is validated by measurements and tests of relevant components in subsystem environment. Input data are of good quality.	Suitable for component sizing in product development but requires component verification testing		
TRL 5	Component and/or breadboard validation in relevant environment	Analysis method used for a period of time and the method is validated with a few measurements and tests of components. Input data are of reasonable quality.	Suitable for component sizing in product development but requires component verification testing		
TRL 4	Component and/or breadboard validation in laboratory environment	Analysis method used for a period of time and the method is validated with a few measurements and tests. Input data are of reasonable quality.	Suitable for component sizing in technology development programs		
TRL 3	Analytical and experimental critical function and/or characteristic proof-of- concept	Some experience of the analysis method within the company but verification data and design criteria are limited. Input data are estimates and of poor quality	Suitable for component sizing in technology development programs		
TRL 2	Technology concept and/or application formulated	Limited experience of the analysis method within the company and verification data and design criteria are very limited. Input data are estimates and of poor quality.	Suitable for technology component testing		
TRL 1	Basic principles observed and reported	No experience of the analysis method within the company and no validation data are available.	Not used in product development		

Learning Hand-Eye Coordination (TRL 2)

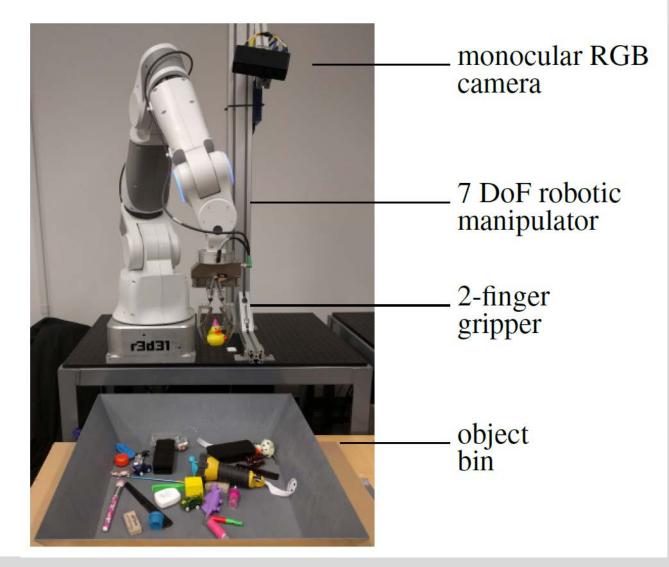


Input

512x512 pixels Finger position

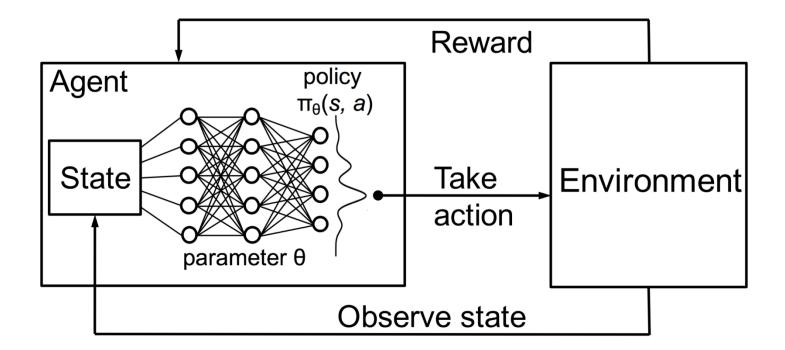
Output

Task space gripper motion



Recap: Reinforcement Learning





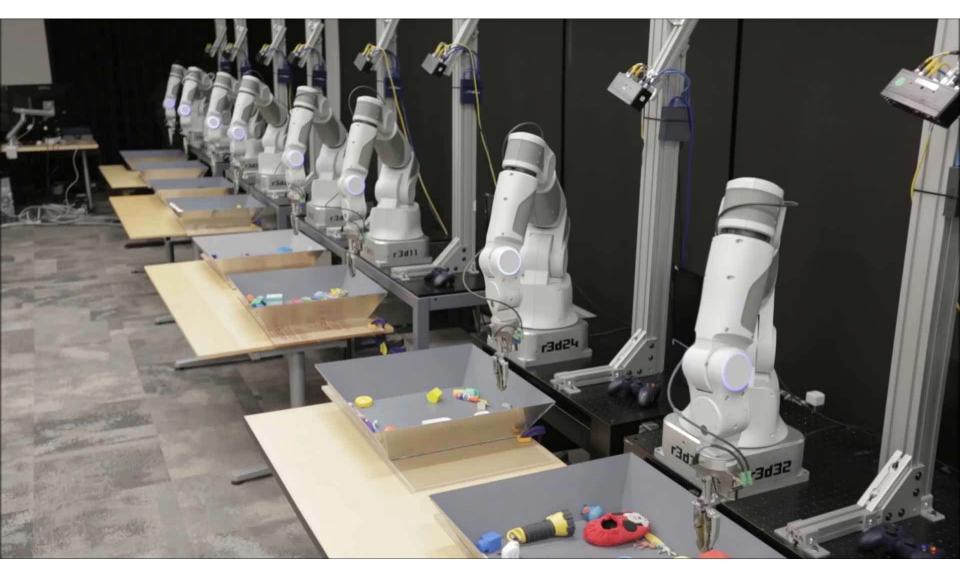
Learning Hand-Eye Coordination (TRL 2)

800,000 attempts

- 14 robot arms
- Two months
- CNNs for deep reinforcement learning
- Shared models



Data Driven Robotics (TRL 2)



Video courtesy of Google, 2016.

Different Objects, Different Grasping Strategies (TRL 2)

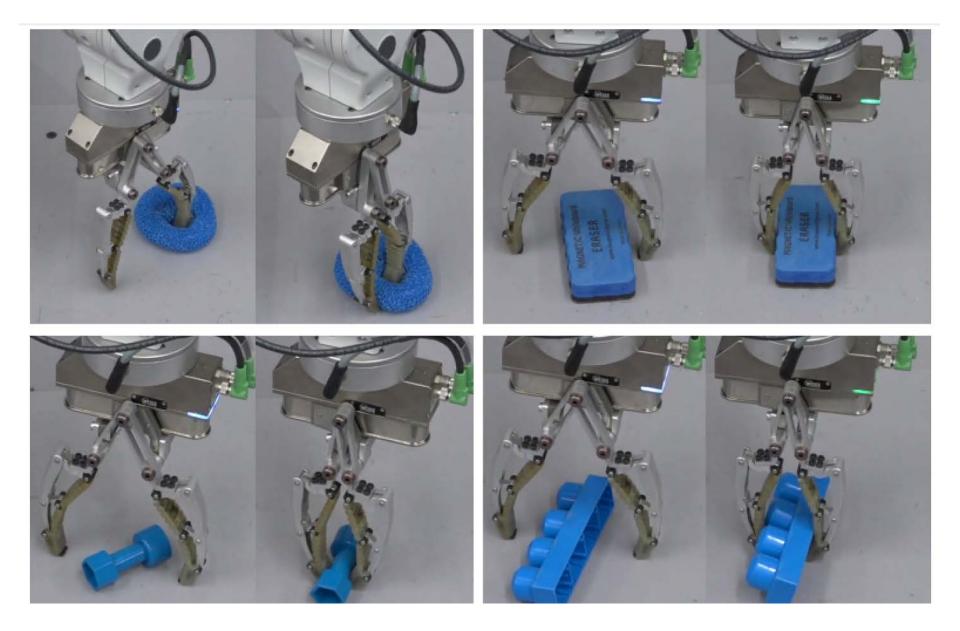


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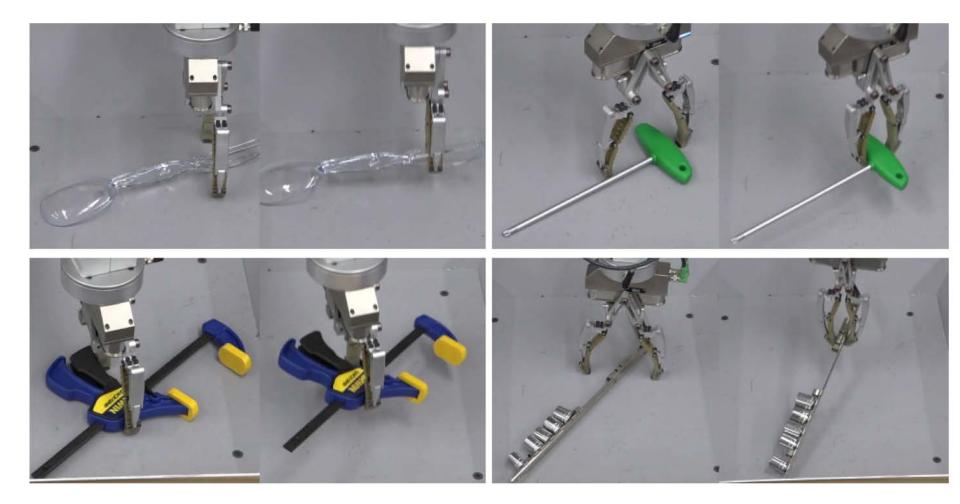
Next Generation Arm Farm



Different Objects, Different Grasping Strategies



Different Objects, Different Grasping Strategies



New (Unknown) Objects







- Machine learning means learning from data;
 Al is a buzzword
- 2. Machine learning is about data and algorithms, but mostly data
- 3. Unless you have a lot of data, you should stick to **simple models**



- 4. Machine learning can only be as good as the data you use to train it
- 5. Machine learning only works if your **training** data is representative
- 6. Most of the **hard work** for machine learning is data transformation



7. Machine learning is a revolutionary advance, but it isn't a magic bullet – it is a tool.

Nevertheless: There is a <u>huge potential</u> that will be unleashed within the next decade.

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Step 1: Learning free space motions (no contact, no physics)

Step 2: Learning manipulation (contact, physics)

Goal: No more programming required for industrial robots

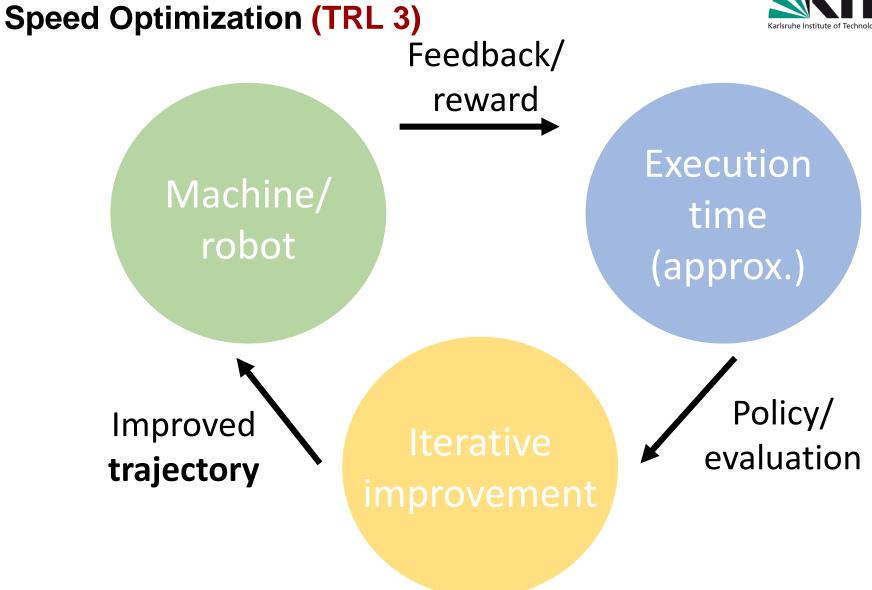
Common Topics



• Transfer learning

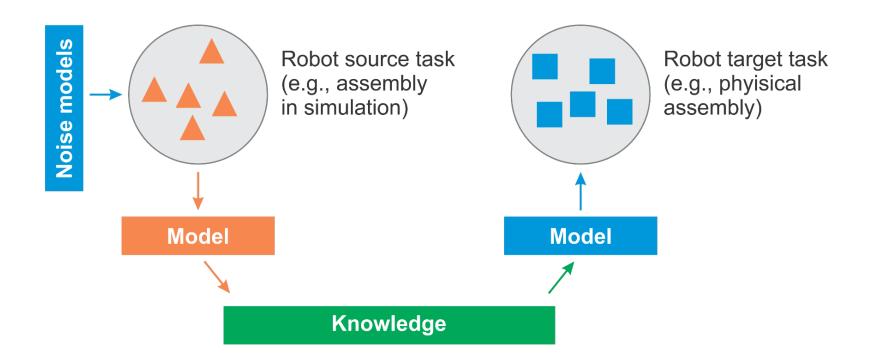
- Training in simulation
- Noise models for dynamic model parameters
- Progressive NNs to close the remaining gap
- Execution on physical systems
- Combination with traditional models (engineering)
- Safety and machine learning
- Compliance with the law





Data Generation for Reinforcement Learning





Learning in Task Space



Non-real-time framework Cloud	Applications Behaviors		Spee Perce	"pick(); move(); place(); see()" Speech Perception (Physical) object-based API			Deep learning Deep learning	
Cloud	Primitives		Conta	Contact control Task manager		learning		
Real-time framework	Task space control			Kinematics Reflexxes		controller ance control	Hybrid control	
Inamework	Joint control			Digital/analog I/O Safety		e dynamics Collision avoida	Reflexxes nce	
	Unified Motor control API					Fast Robot Interface	TCP/UDP	RS485 interface
	EtherCAT Master							
HW	Industrial robot arms (KUKA, Yaskawa)	Collaborative robot arms (KBee, UR, KUKA, YuMi)	Mobile robots (Omron, Festo)	robots (motor a Omron, contro		KUKA LBR iiwa	Proprietary robot arms and mobile bases	Kinova

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Deterministic Collision Avoidance (TRL 5)



Collision avoidance algorithm, which

- is directly used in depth space
- deploys (safe) 3D sensors
- considers
 - multiple obstacles
 - whole robot body
- uses obstacle motions for prediction (fast)
- Reflexxes framework (smooth motions, instantaneous reactions, utilize the max. kinematic and dynamic robot capabilities)
- runs deterministically in real-time





Interfaces and Software APIs

Robot arm with real-time joint control **API** (read/write)

- Joint positions (e.g., FRI/RSI)
- Joint velocities (optional)
- Joint torques (optional)

Safe **3D Camera** with point cloud **API** (read)

- Point cloud
- 3D shape

Deterministic motion planning and collision avoidance algorithm

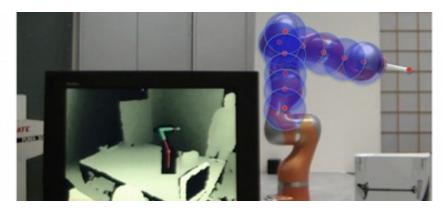
Motion Planning and Control (TRL 5)



• End effector

repulsive vector \implies repulsive velocity

Collision avoidance for the robot body



Repulsive vector

Cartesian constraints

Joint velocity limit

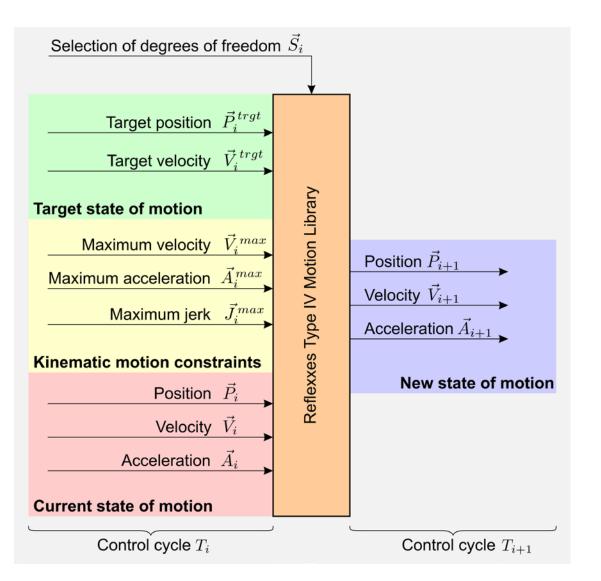
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Smooth, jerk limited motions

Deterministic real-time motion planning Utilizing the maximum kinematic and dynamic capabilities (max. joint torques and speeds)

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Reflexxes Motion Libraries



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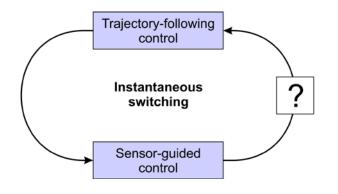
Real-time Robot Motion Planning and Control

Hybrid control

Robots, Sensors, and Programming



- Programming robot in "free space" is expensive.
- Sensor integration on different motion control levels belongs to one of the keys for future advancements of robot systems.
- In general, we distinguish between:
 - 1. Trajectory-following motions
 - 2. Sensor-guided motions
 - Force/torque control
 - Visual servo control
 - ...

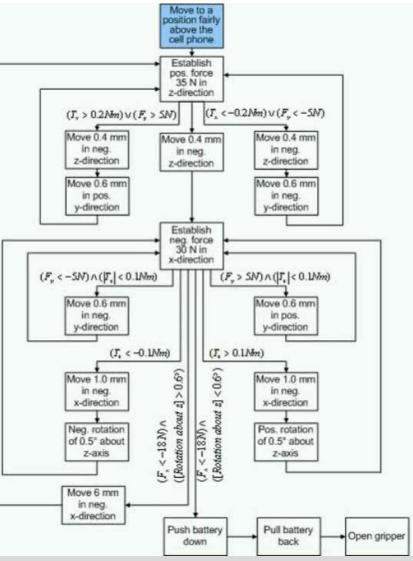


• This makes programming even more expensive.

Manipulation Primitives







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Robot Programing with Primitives

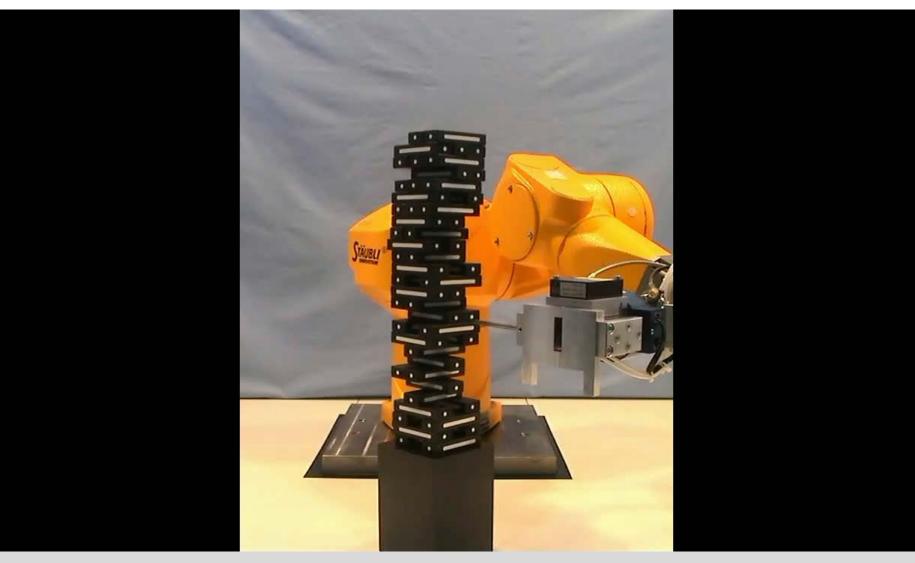


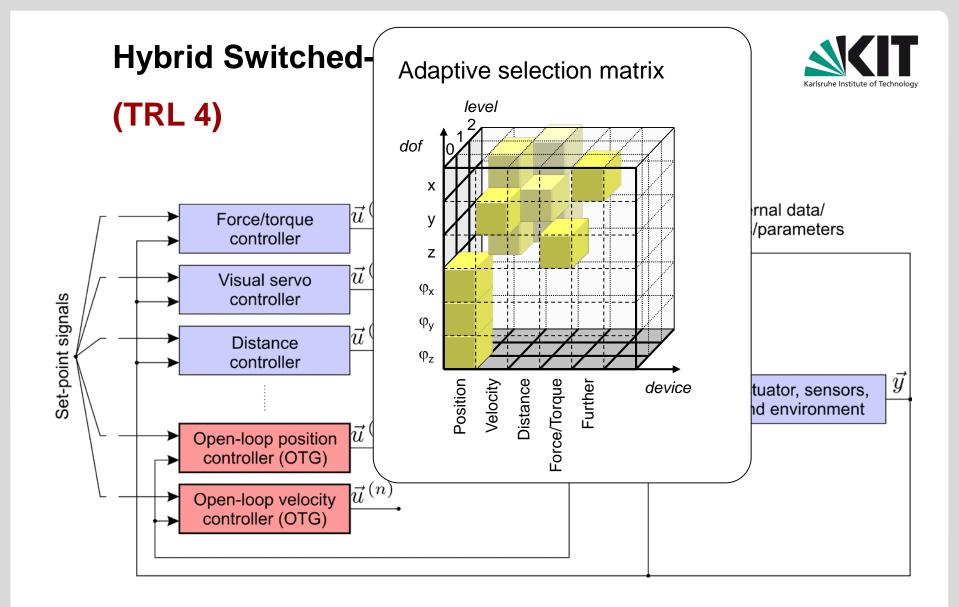
Sensor-based motions

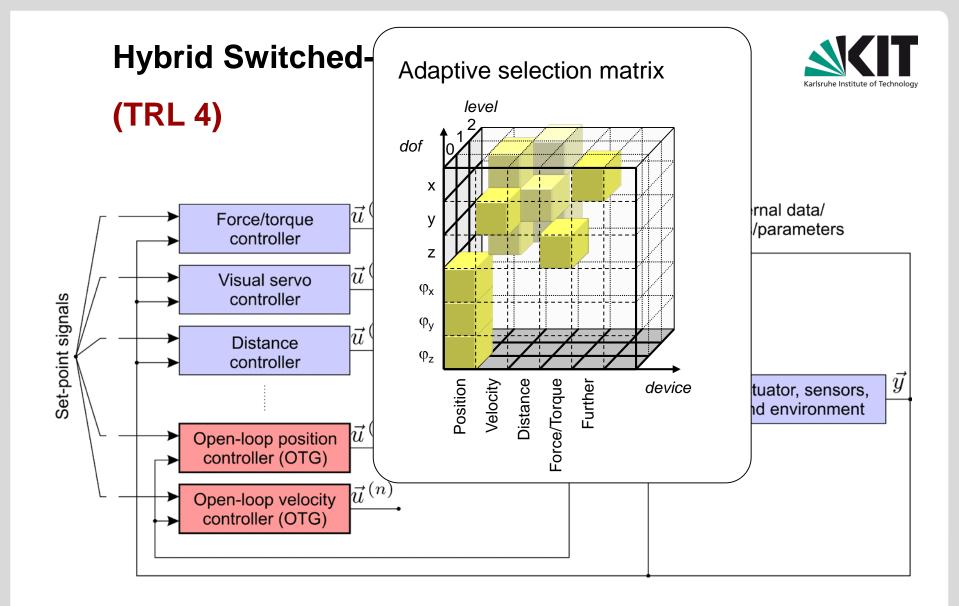
- Low-level programming APIs
 - Complex
 - Expert knowledge required
- Graphical programming interfaces
 - Simple
 - Little to no expertise required
 - Limitation of applications
- Automated based on CAD data and task descriptions
 - Not yet generic
 - Not yet robust
 - Little to no sensor integration (e.g., force/torque, distance, vision)

A Robot Playing Jenga (2005)

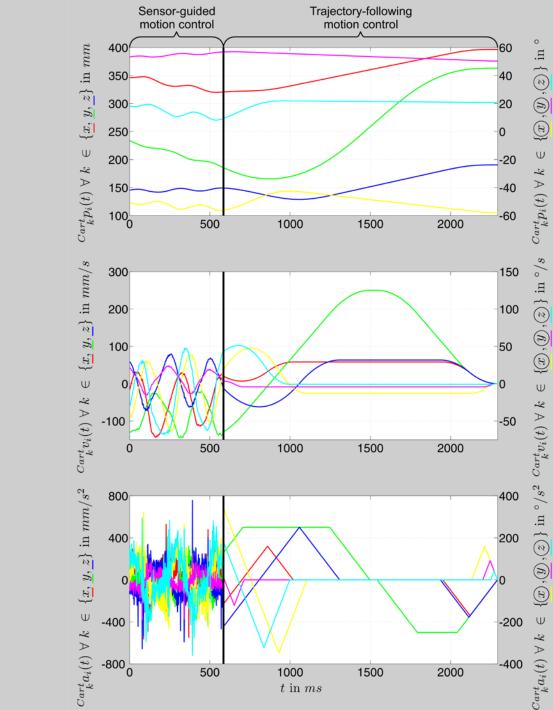


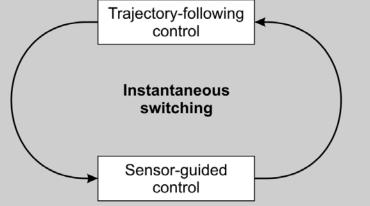






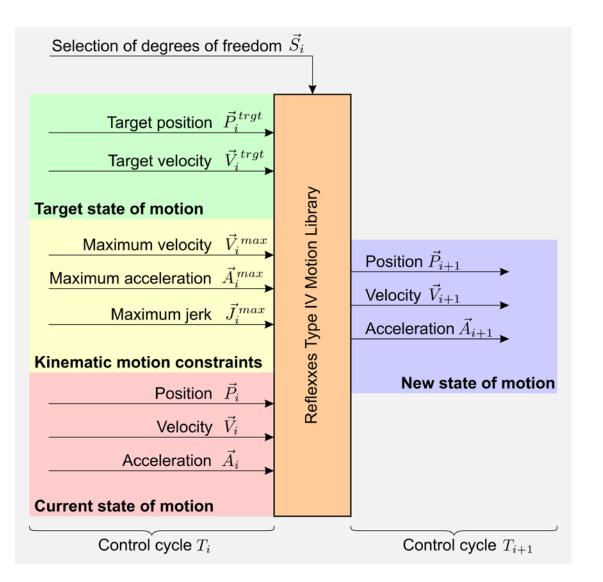
Switching from sensorguided to trajectoryfollowing robot motion control





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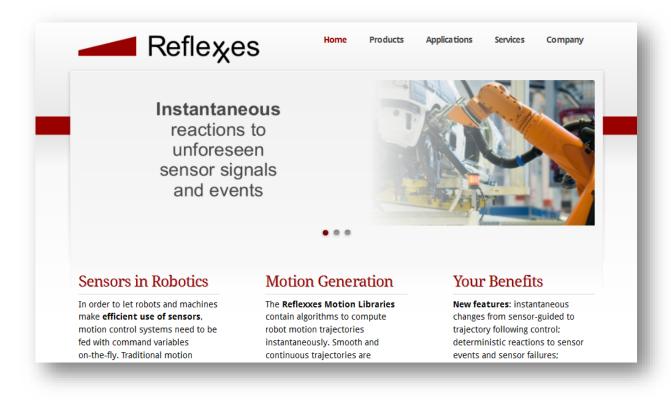
Reflexxes Motion Libraries (TRL 8)



Reflexxes Motion Libraries (TRL 8)



Open source software, tutorials, examples...



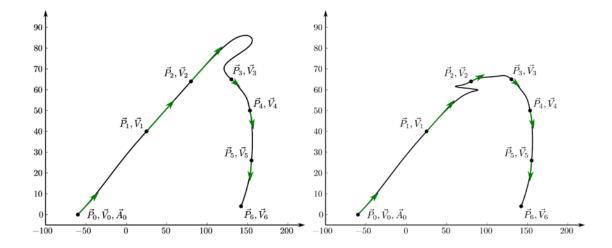
www.reflexxes.com

Outlook



Asymmetric kinematic constraints (TRL 5)

- Dynamic constraints
- Connection to (real-time) path planning (TRL 2)



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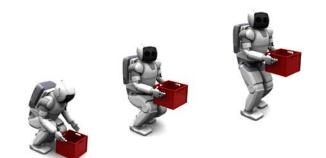
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Thank you!

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