Planning Human-like Movements for Dual-arm Robots

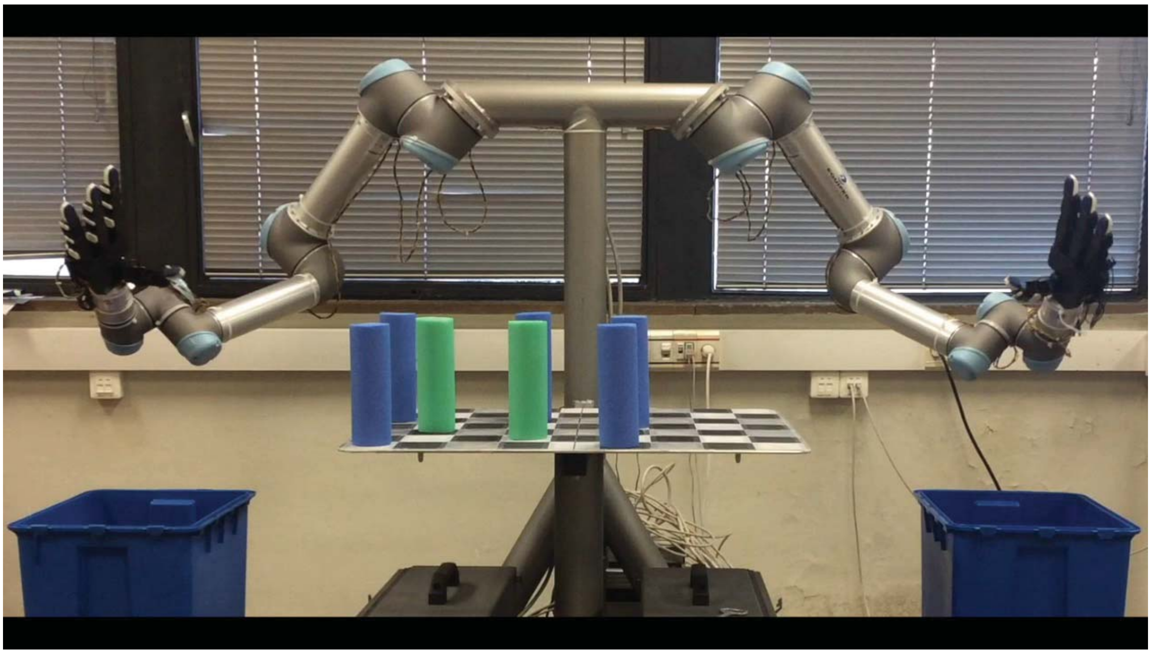
Raúl Suárez

In collaboration with Néstor García and Jan Rosell

UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Institut d'Organització i Control de Sistemes Industrials

Example

Accessing and grasping two target objects (priority left)



Using synergies for dual-arm motion planning

What do we understand by “synergies”?

In simple words:

A synergy is a correlation among the joint positions/movements when they collaborate to do something.

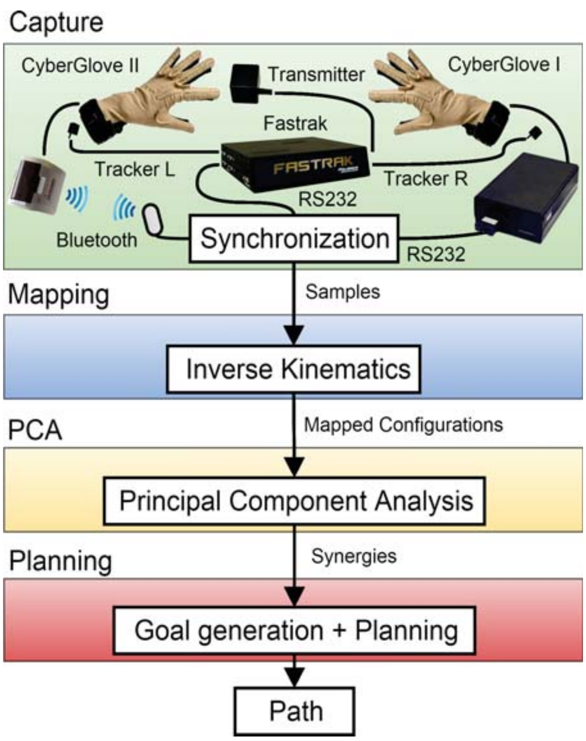
Related names:

Postural synergies (from analysis of human grasp)
Eigen-grasps (specifically for grasp planning)
Principal motion directions (oriented to motion planning)

Search of human-like movements with reduced complexity

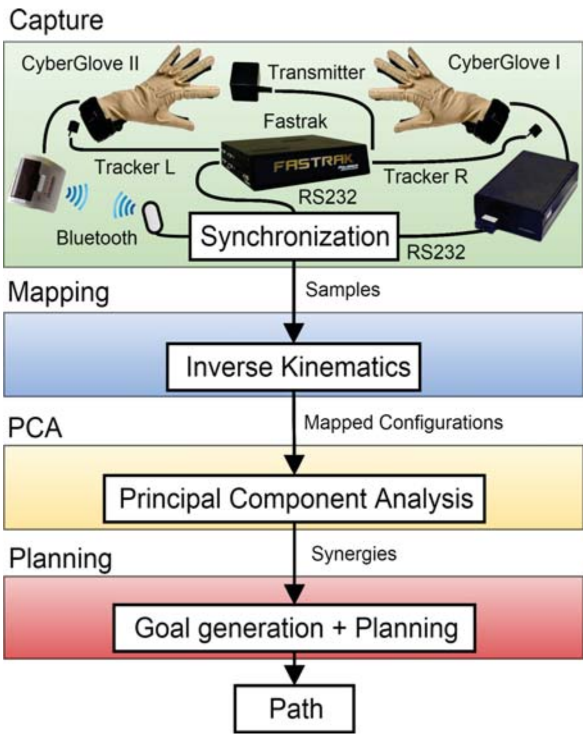
- Search for synergies of a dual-arm anthropomorphic system.
- Motion planning in a search space of lower dimension.
- Preserve human-like appearance.

Basic Approach



1. Motion capture
2. Projection of captured poses to the robotic system
3. Principal Component Analysis
4. Reduction of the configuration space dimension
5. Motion planning

Basic Proposed Approach



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Hardware & Software

UR5 & Allegro Hand

Cyberglove

Fastrak

C++ ROS

The Kautham Project

Motion capture

- Sensors synchronized at 50 Hz.
- Each sample contains:
  - Transformation matrix from transmitter to tracker.
  - 22 measurements describing hand pose and orientation.

Experiments

Pouring

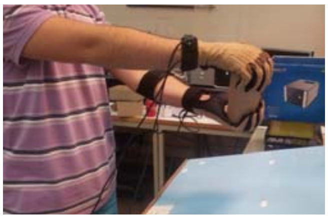
Asembly 1

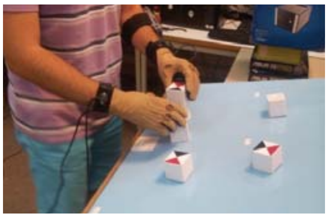
Asembly 2

Shelf

Free movements (open chain)

Free movements (close chain)





Cubes

Handkerchief

Flag

Transfer

Demonstration tasks

Assembly task

Pouring task

Box task

Free-movement task

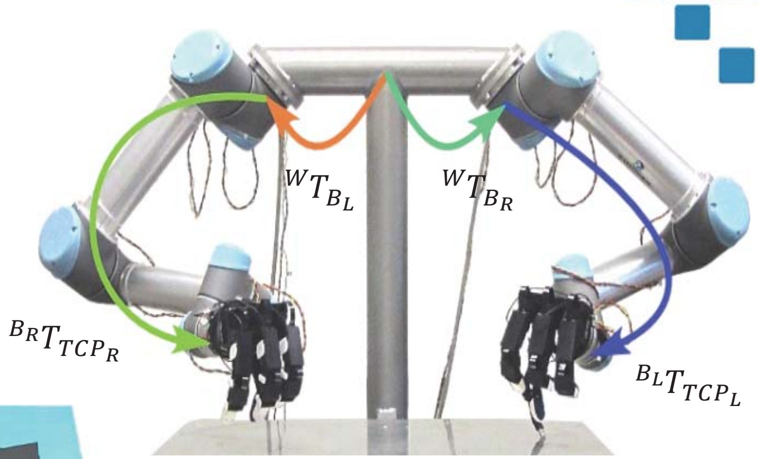
Mapping Hand Poses

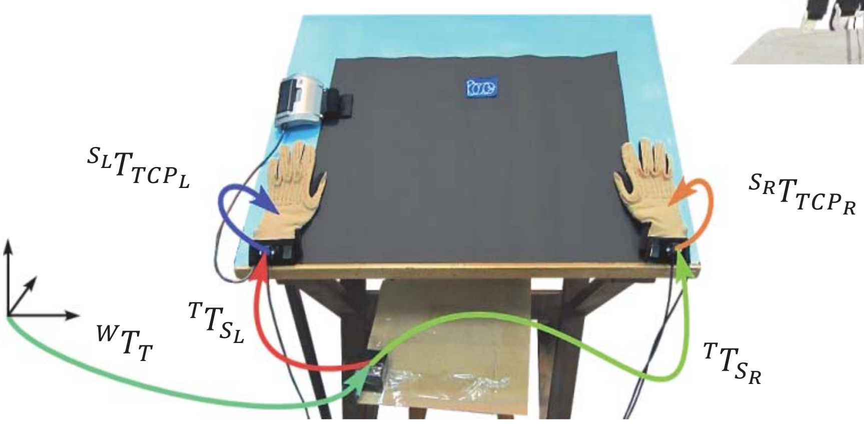
- Some sensor measurements are non-linear respect the measure angle.
- There are coupled measurements.
- A specific model is selected and adjusted for each sensor.

- Different from human hand:
  - Rigid palm.
  - Different thumb and abduction movements.
  - Different ranges of movement.
- Cannot be fully mapped joint-to-joint!

Graphical Verification

Mapping





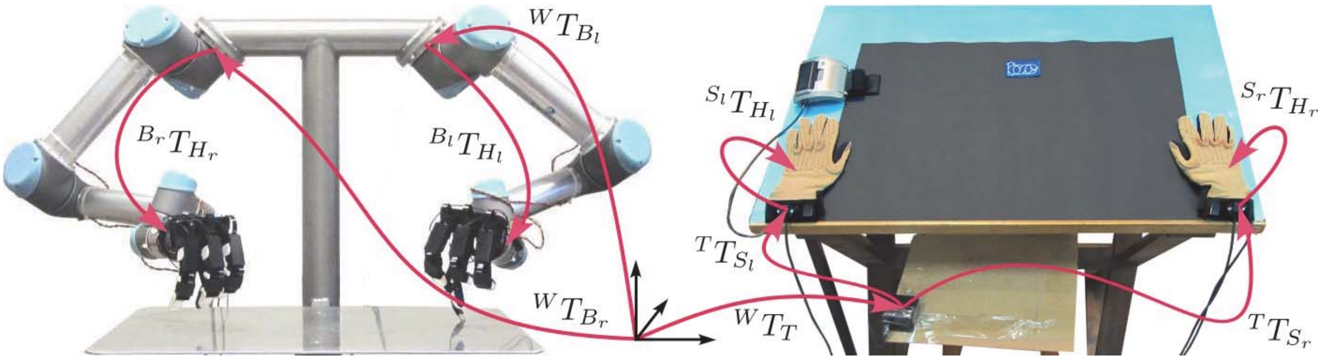
Mapping

Projection of the hand pose and then solve the inverse kinematics

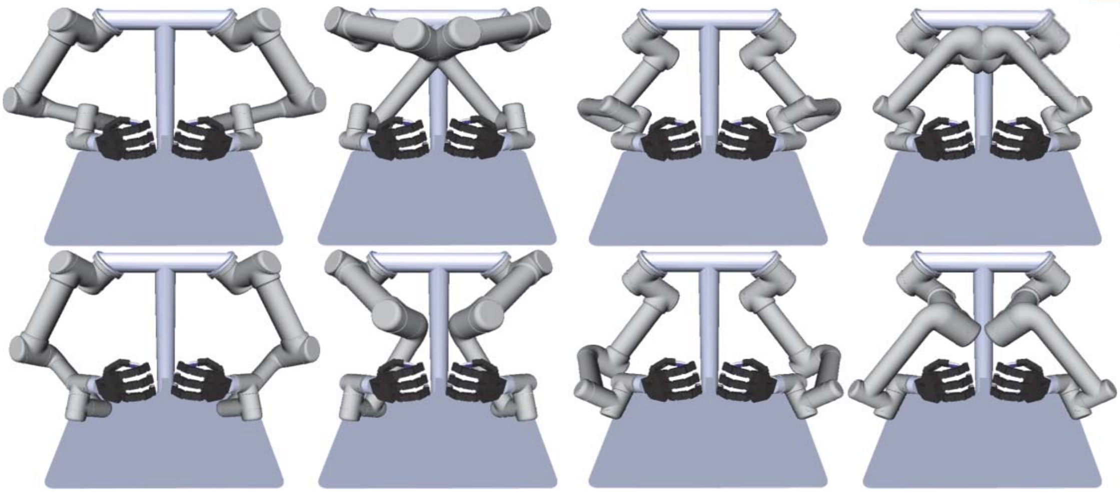
$$ {}^{W}T_{B_i}\,{}^{B_i}T_{H_i} = {}^{W}T_{T}\,{}^{T}T_{S_i}\,{}^{S_i}T_{H_i} $$

8 solutions

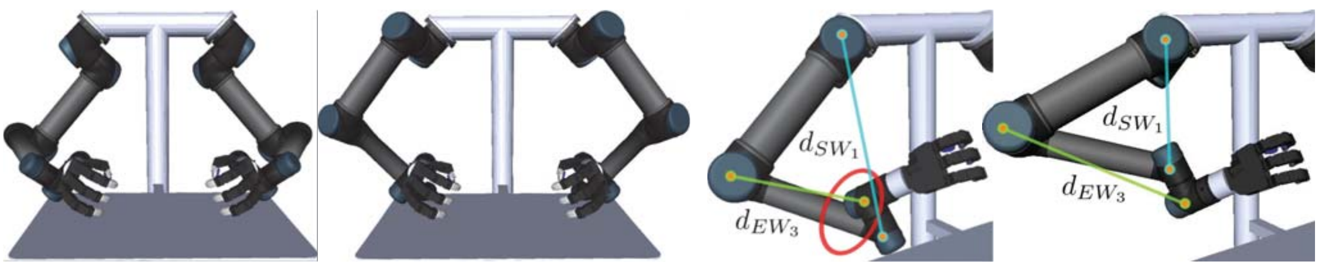
Which one to choose?



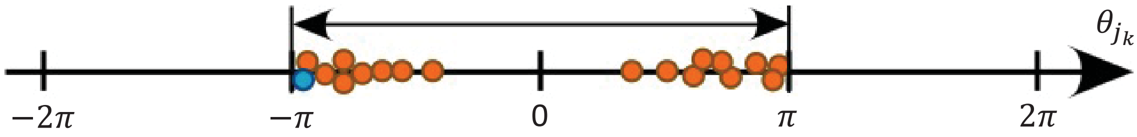
- Possible solutions:

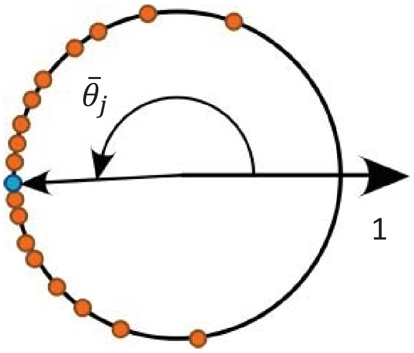


- Solution selection:



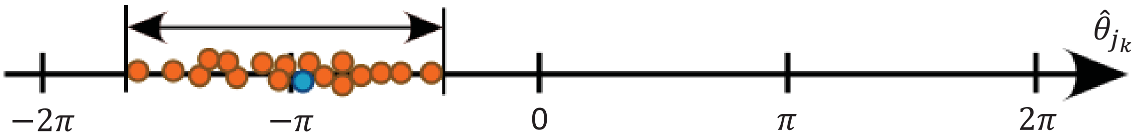
Joint angle adjustement





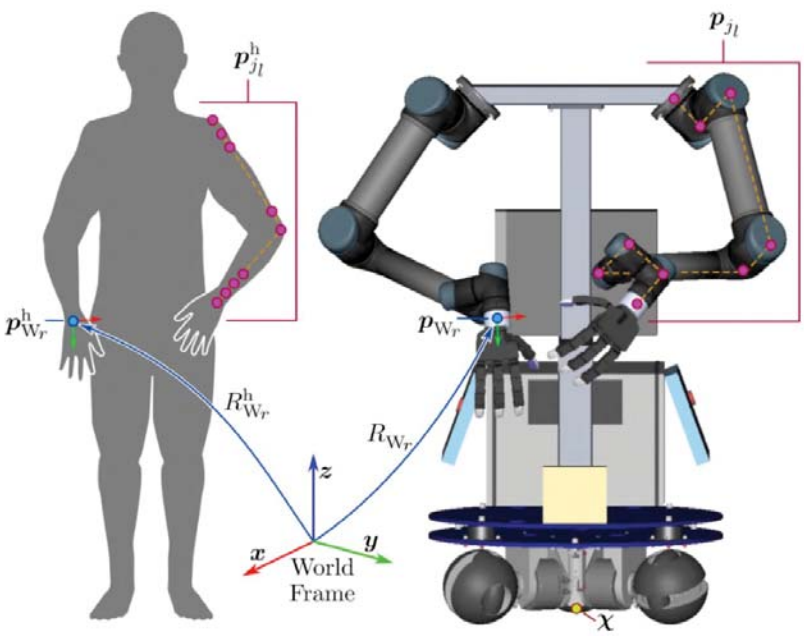
$$\bar{\theta}_j = \operatorname{atan2}\left(\frac{1}{n}\sum_{k=1}^{n}\sin(\theta_{j_k}), \frac{1}{n}\sum_{k=1}^{n}\cos(\theta_{j_k})\right)$$

$$\hat{\theta}_{j_k} = \begin{cases} \theta_{j_k} & \text{si } |\theta_{j_k} - \bar{\theta}_j| \leq \pi \\ \theta_{j_k} - \operatorname{sign}(\theta_{j_k})2\pi & \text{si } |\theta_{j_k} - \bar{\theta}_j| > \pi \end{cases}$$

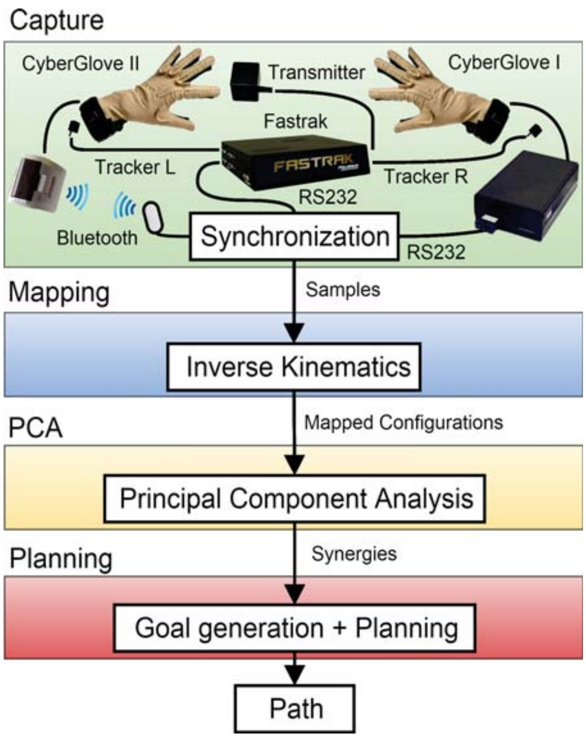


Mapping

Relation with the mobile manipulator



Basic Proposed Approach



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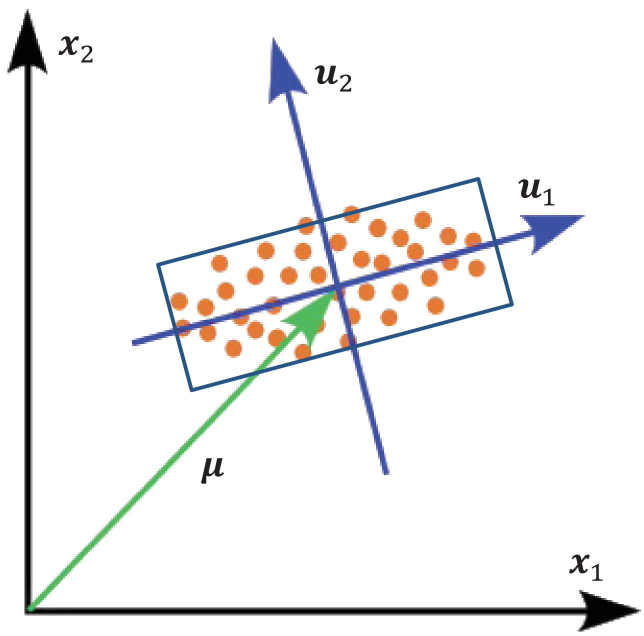
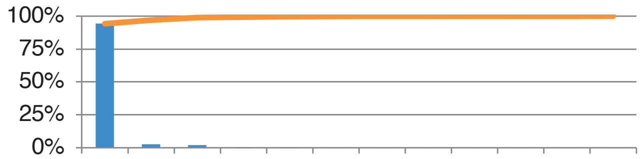
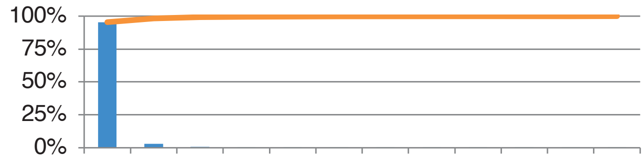
Principal Component Analysis (PCA)



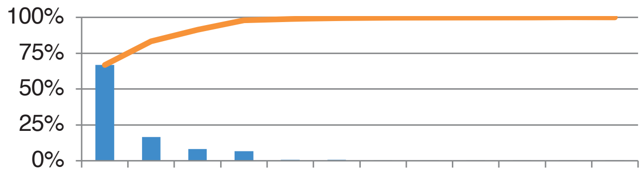
- A PCA is run over the mapped configurations.
- The directions with larger dispersion are the Principal Motion Directions (PMD).



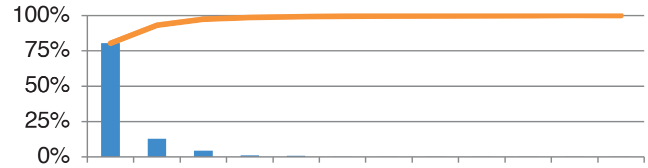
1) *Pouring*



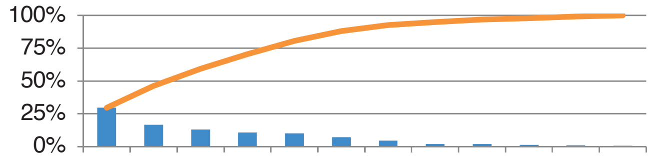
2) *Assembly 1*



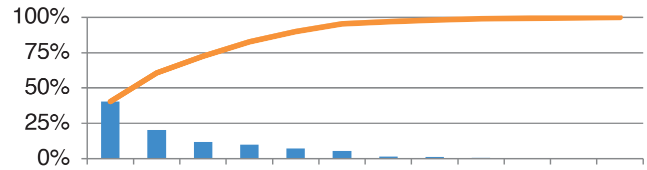
3) *Assembly 2*



4) *Shelf*

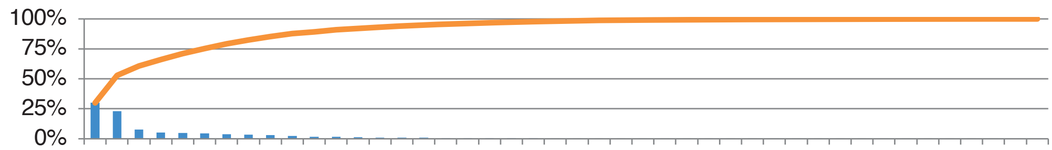


5) *Free movements (open chain)*

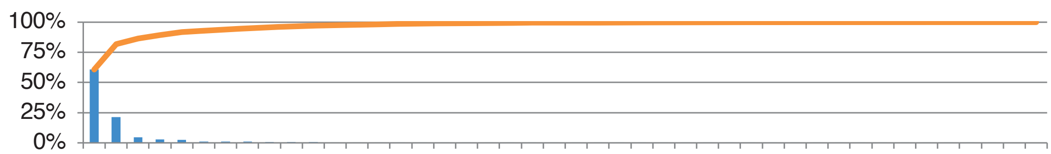


6) *Free movements (close chain)*

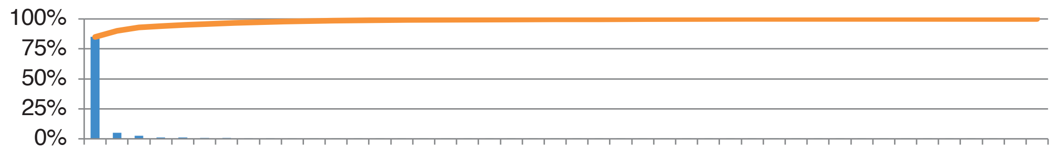
All 44 dof: 16x2 from the gloves and 6x2 from the arms



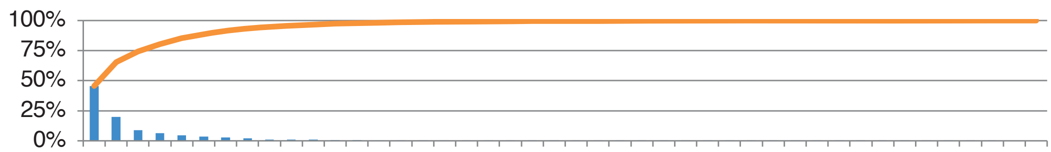
7) *Cubes*



8) *Handkerchief*

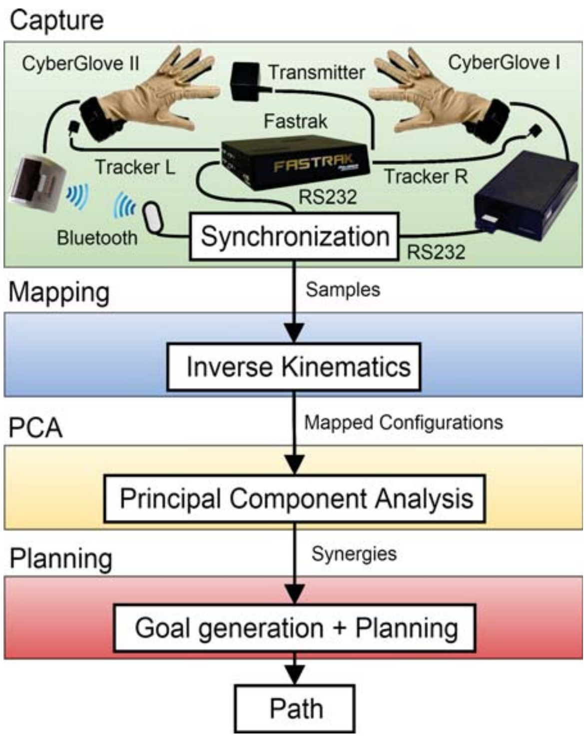


9) *Flag*



10) *Transfer*

Basic Proposed Approach



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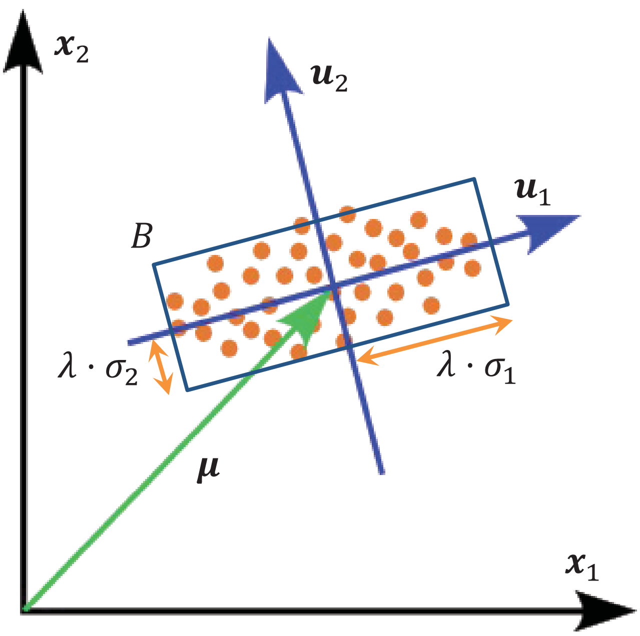
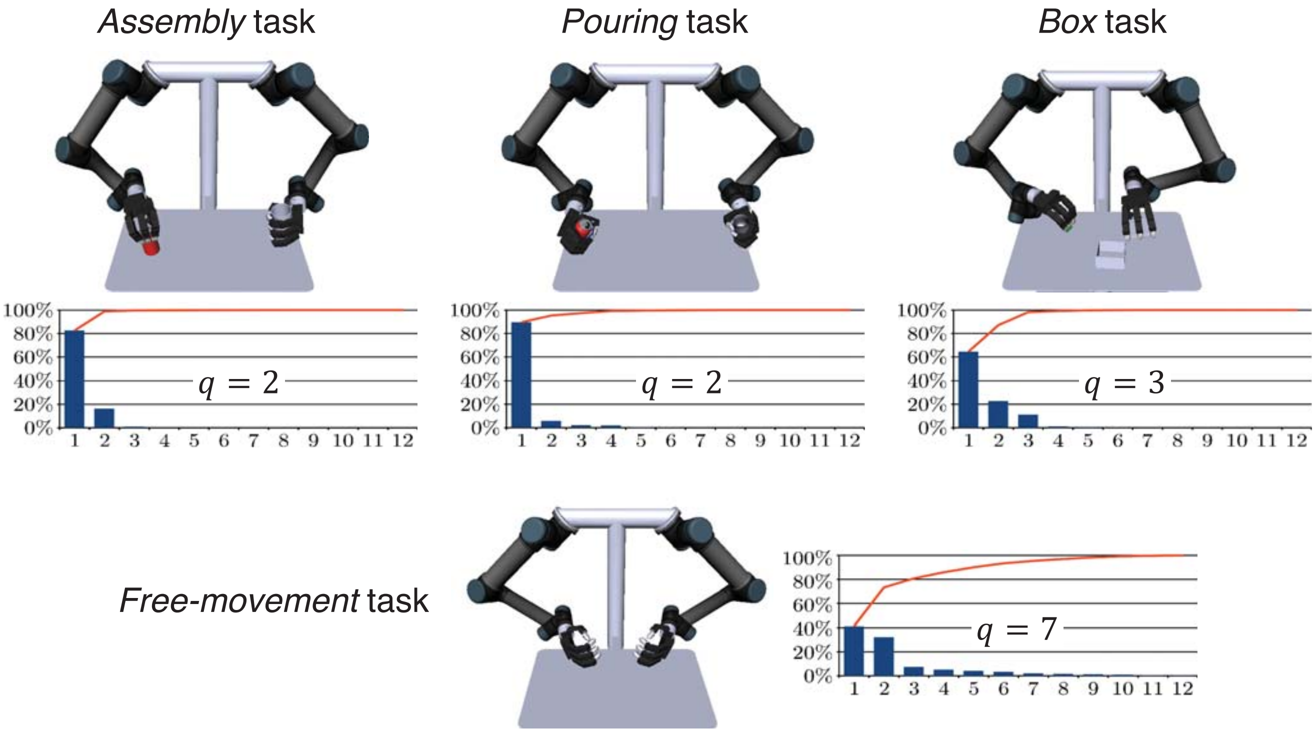
Planning subspace

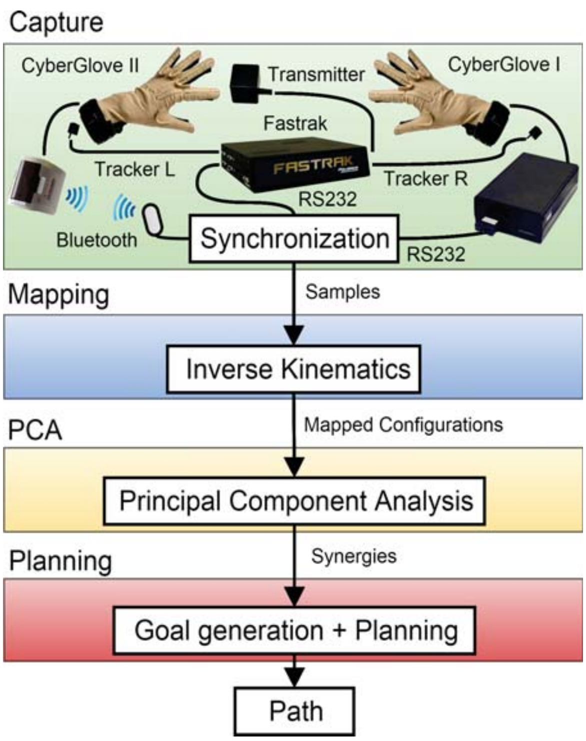


- The box B contains the 95% of the sample distribution.
- The first q PMDs accumulate the 95% of the variance.
- B_q is the box spanned by the q first PMDs and interior to B.

Selection of main PMDs



Basic Proposed Approach



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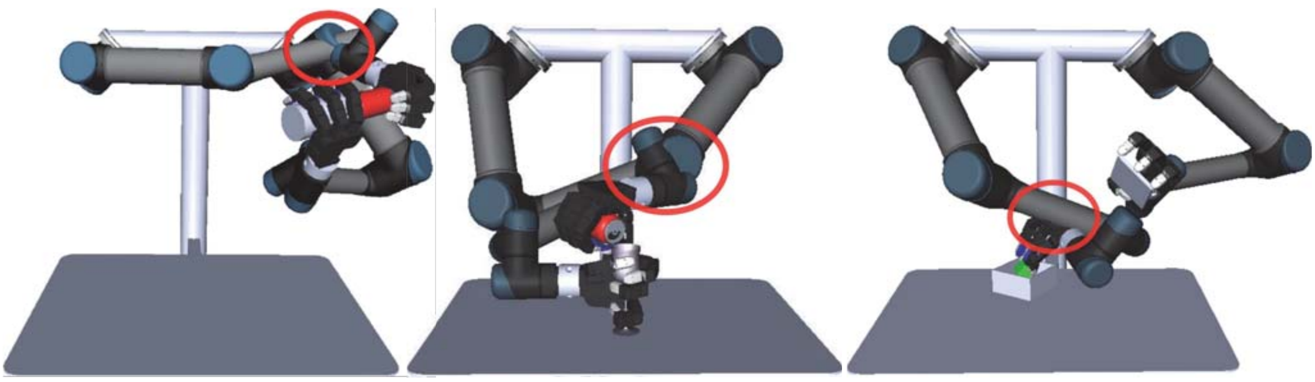
Goal sampling

- Generation of N_c feasible goal configurations

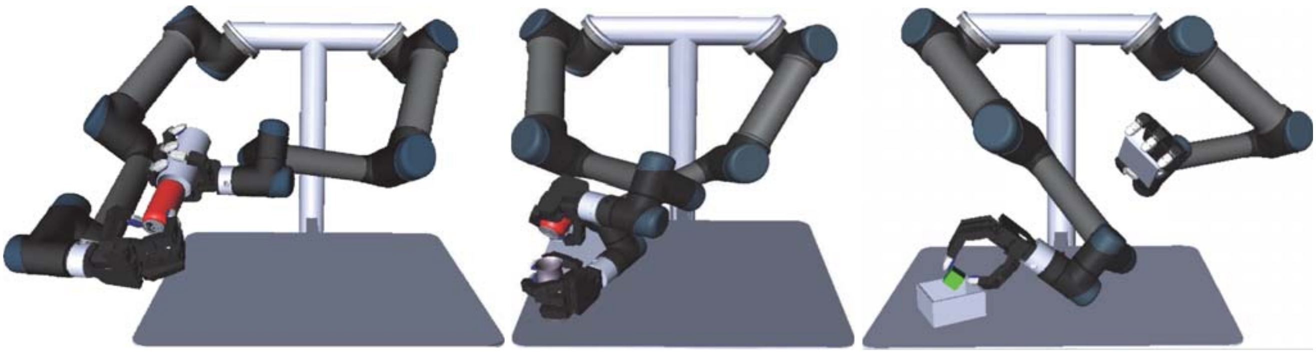
Goal sampling

- Configurations must be collision-free!



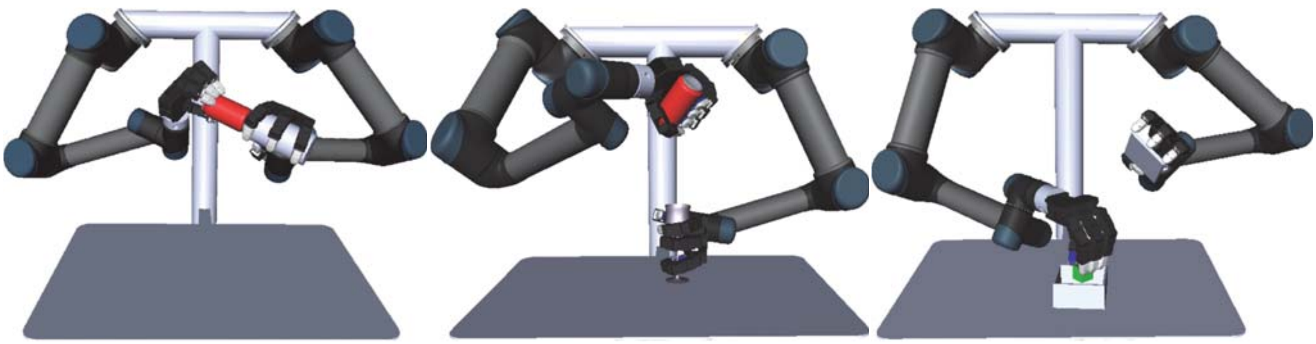
Goal sampling

- Configurations must be near to the search subspace B_q.

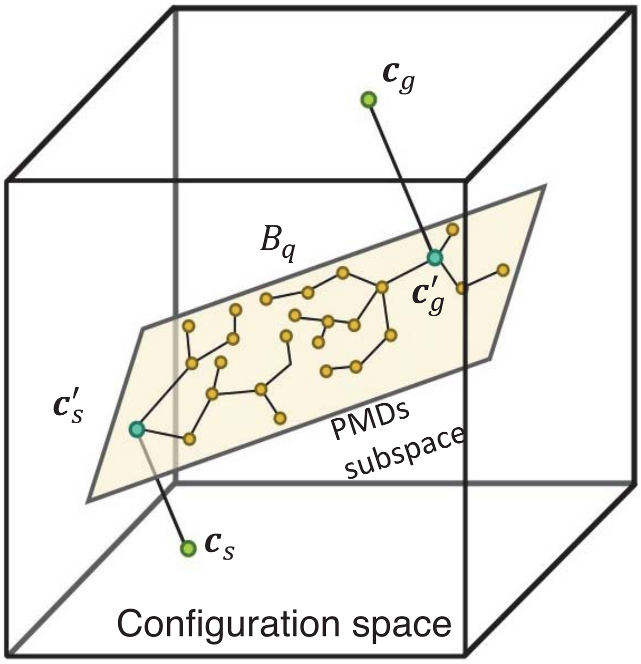


Goal sampling

- The projected configurations into B_q and the projection path must be collision-free.



Planning procedure



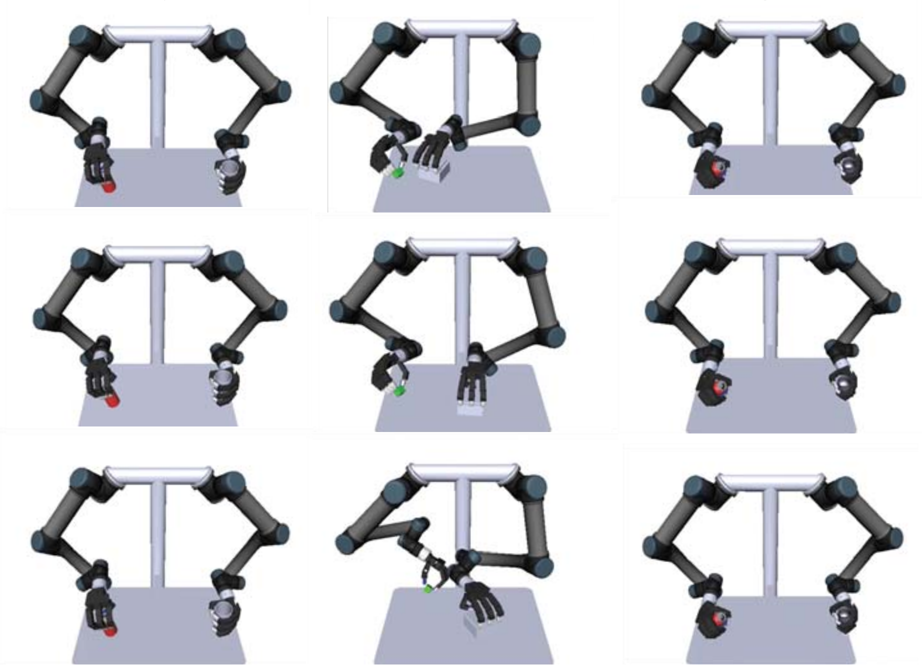
- n_c of the N_c sampled goals closest to B_q are selected.
- One RRT-Connect per goal.
- All instances in parallel.
- Once a solution is found, the planning is stopped.

Experimental results

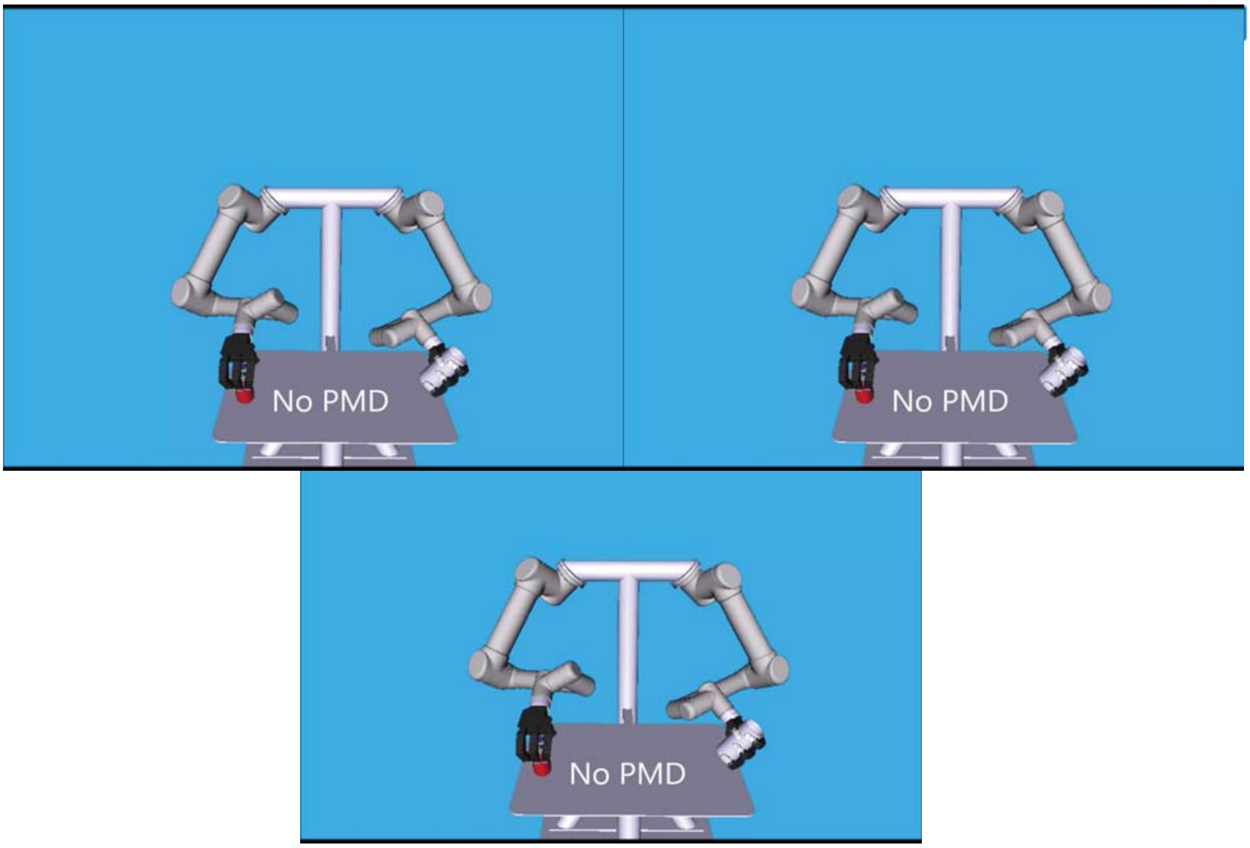
Case	Without PMDs	Task specific PMDs	Other PMDs
Used PMDs	0	4	8
Space dimension	12	4	8
Success rate	100 %	100 %	100 %
Used memory	63.36 Mb	28.64 Mb	48.56 Mb
Used time	2.66 s	0.35 s	1.35 s
Solution length	21.40 rad	4.99 rad	13.49 rad
Valid segments	20 %	69 %	42 %

100-executions average results limited to 100 s, run in a 2.13-GHz Intel Core 2, 4-GB RAM PC.

Motion planning



Experimental results



Motion planning

- The use of synergies (or PMDs):
    - Reduces the planning time.
    - Results in more human-like motions.
    - Reduces the tree size and the probability of collisions.
- Best results with the task specific synergies.
- Free-movement synergies useful for general application.

Task-dependent synergies for dual-arm motion planning

Exploiting Task Similarities

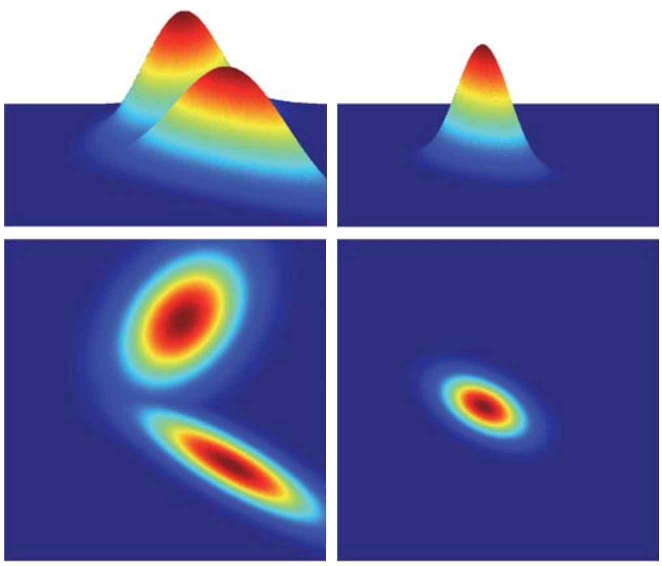
- Search task similarities based on the corresponding synergies of a dual-arm anthropomorphic system.
- Improve the motion planning using such similarities.
- Preserve/Improve human-like appearance.

Task likeness

- Likeness index of two tasks using the synergy information:

$$\mathcal{L}(S_A, S_B) = \frac{\Phi_{AB}}{\Phi_{AB_{\max}}} \in [0,1]$$

$$\Phi_{AB_{\max}} \geq \Phi_{AB} = \int_{-\infty}^{\infty} \mathcal{N}_A \mathcal{N}_B \, d\boldsymbol{x}$$



$\mathcal{N}_A$ and $\mathcal{N}_B$ $\quad$ $\mathcal{N}_A \mathcal{N}_B$

Task likeness

In practice, task likeness can be computed as:

$$\Phi_{AB} = \int_{-\infty}^{\infty} \mathcal{N}_A \mathcal{N}_B \, d\boldsymbol{x} = \frac{e^{-\frac{1}{2}(\mu_A-\mu_B)^{\intercal}(\Sigma_A+\Sigma_B)^{-1}(\mu_A-\mu_B)}}{\sqrt{(2\pi)^m |\Sigma_A + \Sigma_B|}}$$

$$\Phi_{AB_{\max}} = \frac{1}{\sqrt{\pi^m} \prod_{j=1}^{m} \sigma_{A_j} + \sigma_{B_j}}$$

Task likeness

LIKENESS $\mathcal{L}(S_A, S_B)$

Tasks	Assembly	Pouring	Box	Free-mov.
Assembly	1	0.1081	0.0114	0.6104
Pouring	0.1081	1	0.0035	0.5699
Box	0.0114	0.0035	1	0.6829
Free-mov.	0.6104	0.5699	0.6829	1

Optimizing the motion planning

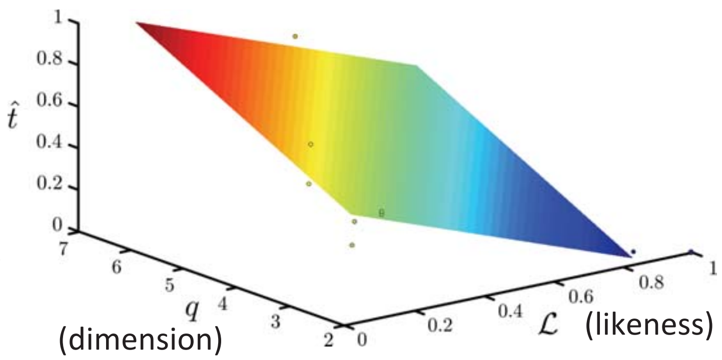
Time normalized to

$\hat{t} \in [0,\ 1]$

- First-order approximation:

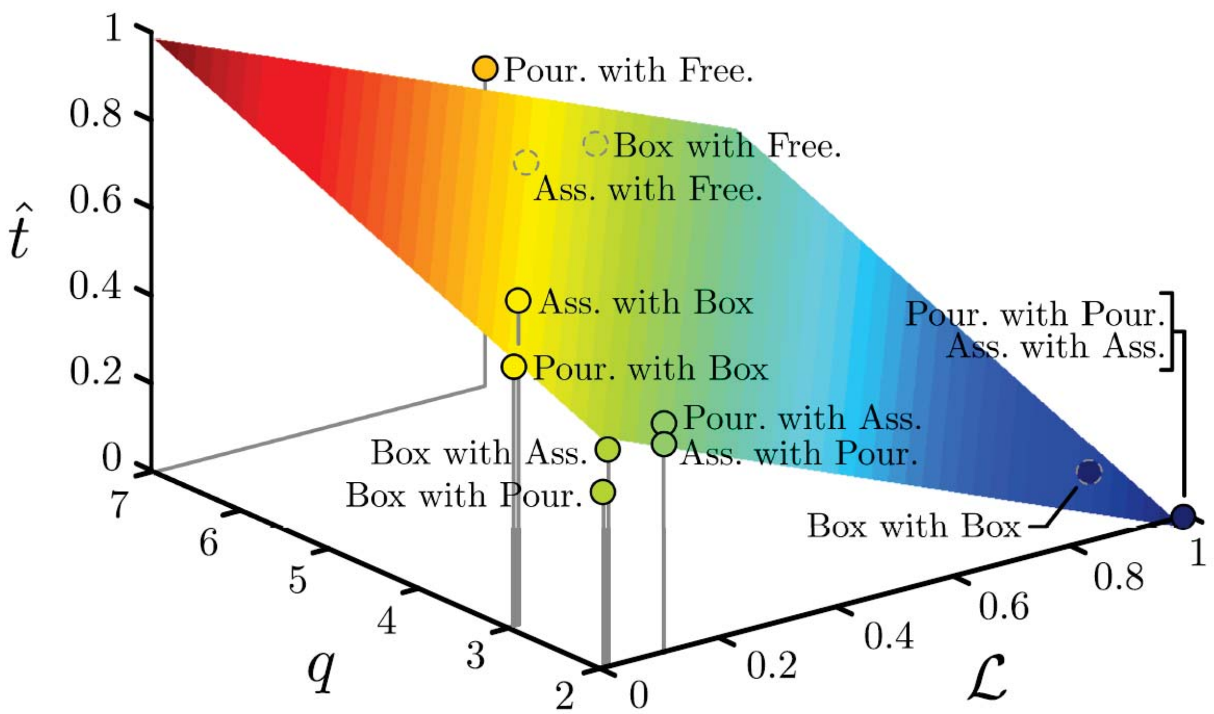
$$\hat{t} = \kappa_0 + \kappa_{\mathcal{L}}\mathcal{L} + \kappa_q q$$

- $\kappa_{\mathcal{L}} < 0 \Longrightarrow \hat{t}$ decreases with $\mathcal{L}$



- The PMDs of a task with a high $\mathcal{L}$, produces better results.

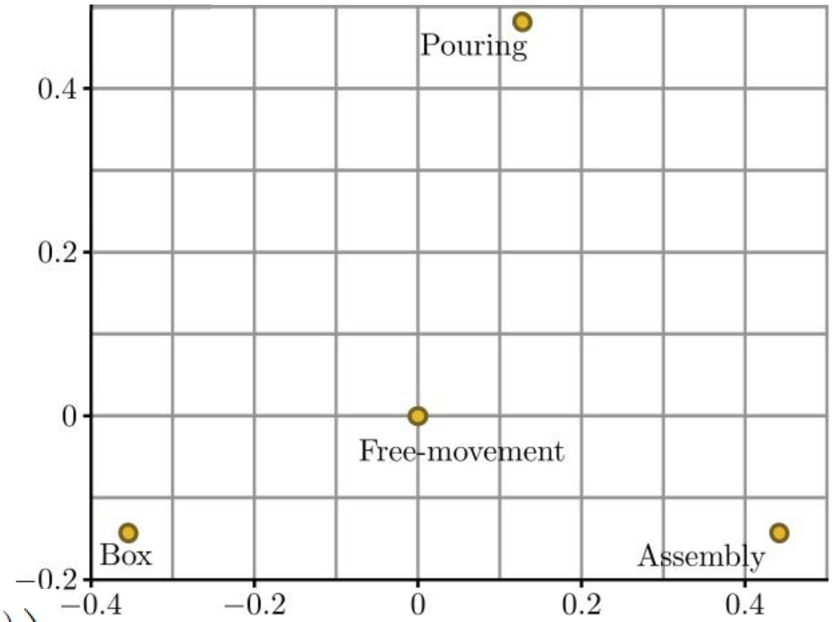
Optimizing the motion planning



Task classification

$$\mathcal{D}(S_A,\, S_B) = 1 - \mathcal{L}(S_A,\, S_B) \in [0,\, 1]$$

(Pseudo-distance, does not satisfy the triangle inequality)



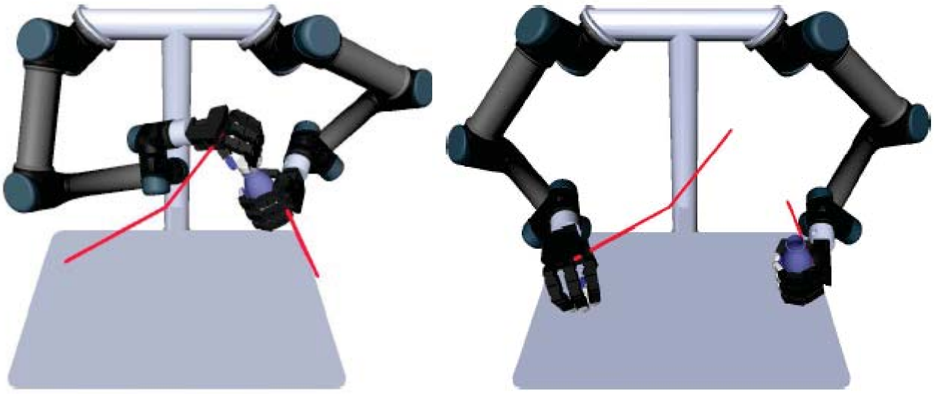
minimizing

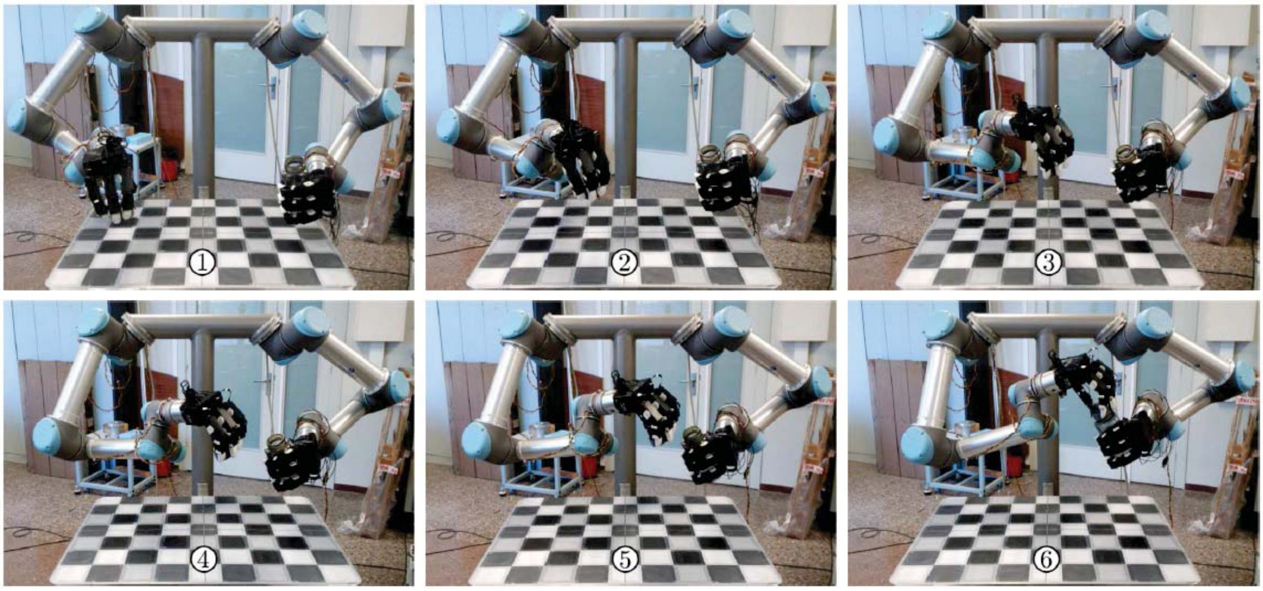
$$\max_{i \neq j} \left(\frac{d(S_i,\, S_j) - \mathcal{D}(S_i,\, S_j)}{\mathcal{D}(S_i,\, S_j)} \right)$$

Optimizing the motion planning

- If there is a "new task" and a task-specific synergy basis is not available:
  - Obtain a path with the free-movement PMDs.
  - Obtain the synergies of this path.
  - Find the more alike synergy basis S_A.
  - Use S_A to produce a better plan.

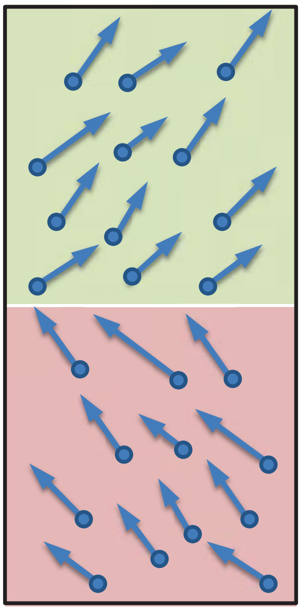
Example:
Puting a bottle top
using
Assembly PMDs





Extending synergies to the velocity space

Extending synergies to the velocity space



Directions of the position synergies ≠ Most common velocity directions

Zero-order synergy → First-order synergy

joint positions correlations — joint velocities correlations

Synergies vary along the configuration space → Partition method

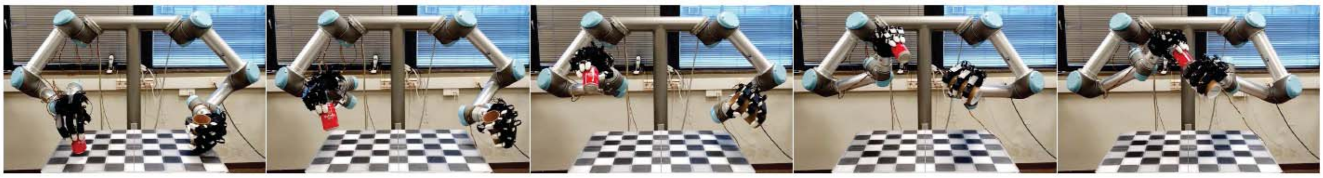
Human-like movements

Human like index

Definition of an index to determine how much human-like is a given movement

$$\mathcal{Q}_{\mathcal{P}} = 1 - \frac{1}{L}\int_{\mathcal{P}} \textsc{Misalignment}(\boldsymbol{q}, \boldsymbol{v})\ \mathrm{d}\boldsymbol{q}$$

Misalignment between the path and the first order synergies of free movements



Human like index

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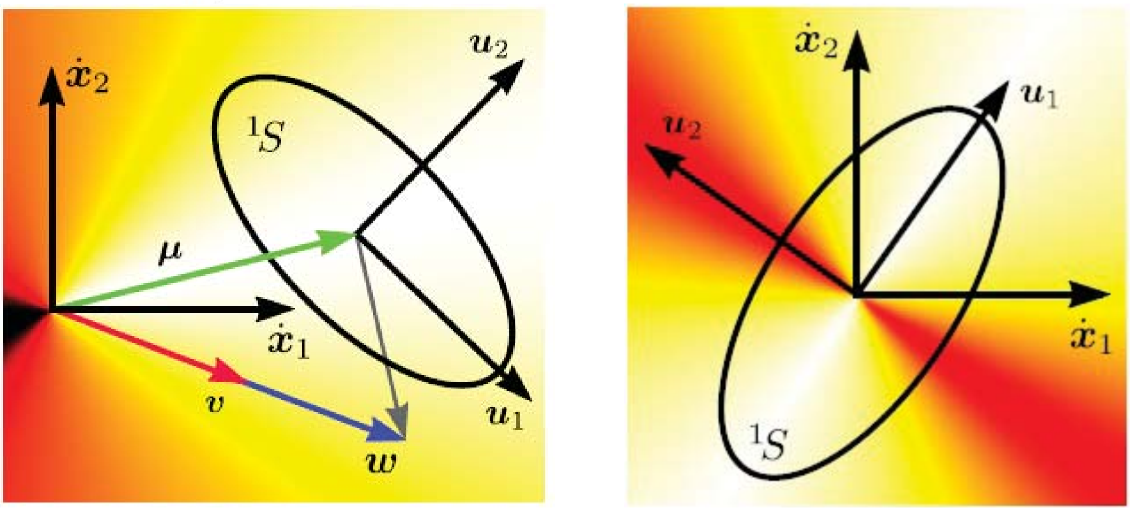

Bright yellow denotes better alignments than dark red.

Human like index

$$\mathcal{Q}_{\mathcal{P}} = 1 - \frac{1}{L}\int_{\mathcal{P}} \textsc{Misalignment}(\boldsymbol{q}, \boldsymbol{v})\, \mathrm{d}\boldsymbol{q}$$

$\textsc{Misalignment}(\boldsymbol{q}, \boldsymbol{v})$ returns the misalignment η

$$\eta = \frac{1}{\pi}\,\mathrm{acos}\left((1-\rho)\,\Phi_{\boldsymbol{\mu}} + \rho\,\Phi_{\Sigma}\right)$$

- $\rho \in [0,1]$ is a weighting variable that represents the proximity of the basis ${}^{1}S(\boldsymbol{\mu}, \Sigma)$ to the origin of the velocity space, i.e. ρ increases as the origin of ${}^{1}S$ gets closer to the origin of the velocity space.

  ρ is computed as two times the probability P that a random vector $\boldsymbol{x}$ obtained from the normal multivariate distribution $\mathcal{N}(\boldsymbol{\mu}, \Sigma)$ satisfies $\boldsymbol{\mu} \cdot \boldsymbol{x} < 0$.

Human like index

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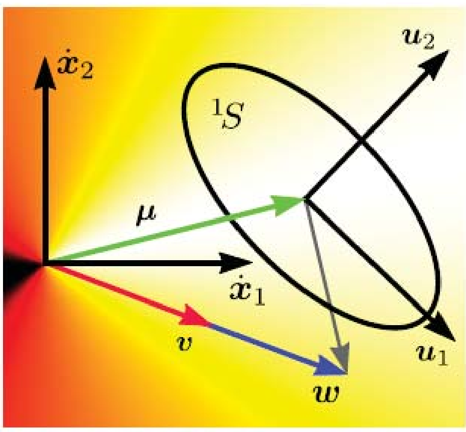

$\Phi_{\boldsymbol{\mu}} \in [-1, 1]$ is a measure that represents the alignment between $\boldsymbol{v}$ and $\boldsymbol{\mu}$

$\Phi_{\boldsymbol{\mu}}$ is computed as

$$\Phi_{\boldsymbol{\mu}} = \mathrm{sgn}(\boldsymbol{v} \cdot \boldsymbol{\mu})\, e^{-\frac{1}{2}(\boldsymbol{w}-\boldsymbol{\mu})^{\intercal}\Sigma^{-1}(\boldsymbol{w}-\boldsymbol{\mu})}$$

Human like index

$$\mathcal{Q}_{\mathcal{P}} = 1 - \frac{1}{L}\int_{\mathcal{P}} \textsc{Misalignment}(\boldsymbol{q}, \boldsymbol{v})\, \mathrm{d}\boldsymbol{q}$$

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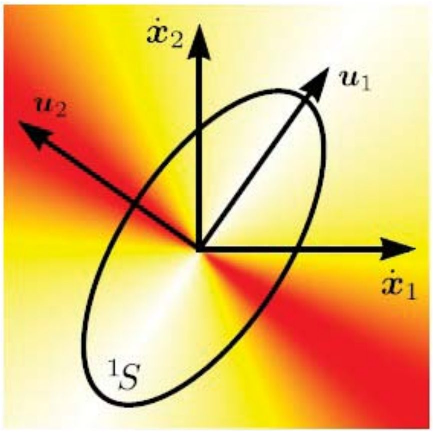


$\Phi_\Sigma \in [-1, 1]$ is a measure that represents the alignment of $\boldsymbol{v}$ and the direction $\boldsymbol{u}_1$ of largest variance of Σ

Φ_Σ is computed as

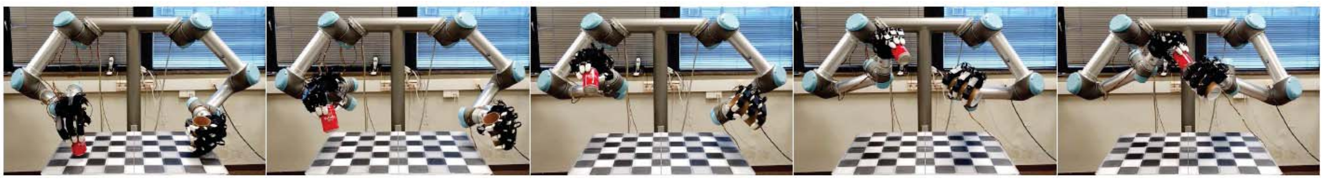
$$\Phi_\Sigma = 2\,\frac{\hat{\boldsymbol{v}}^{\intercal}\Sigma\hat{\boldsymbol{v}}}{\boldsymbol{u}_1^{\intercal}\Sigma\boldsymbol{u}_1} - 1 \quad \text{with} \quad \hat{\boldsymbol{v}} = \frac{\boldsymbol{v}}{\|\boldsymbol{v}\|}$$

Human like index

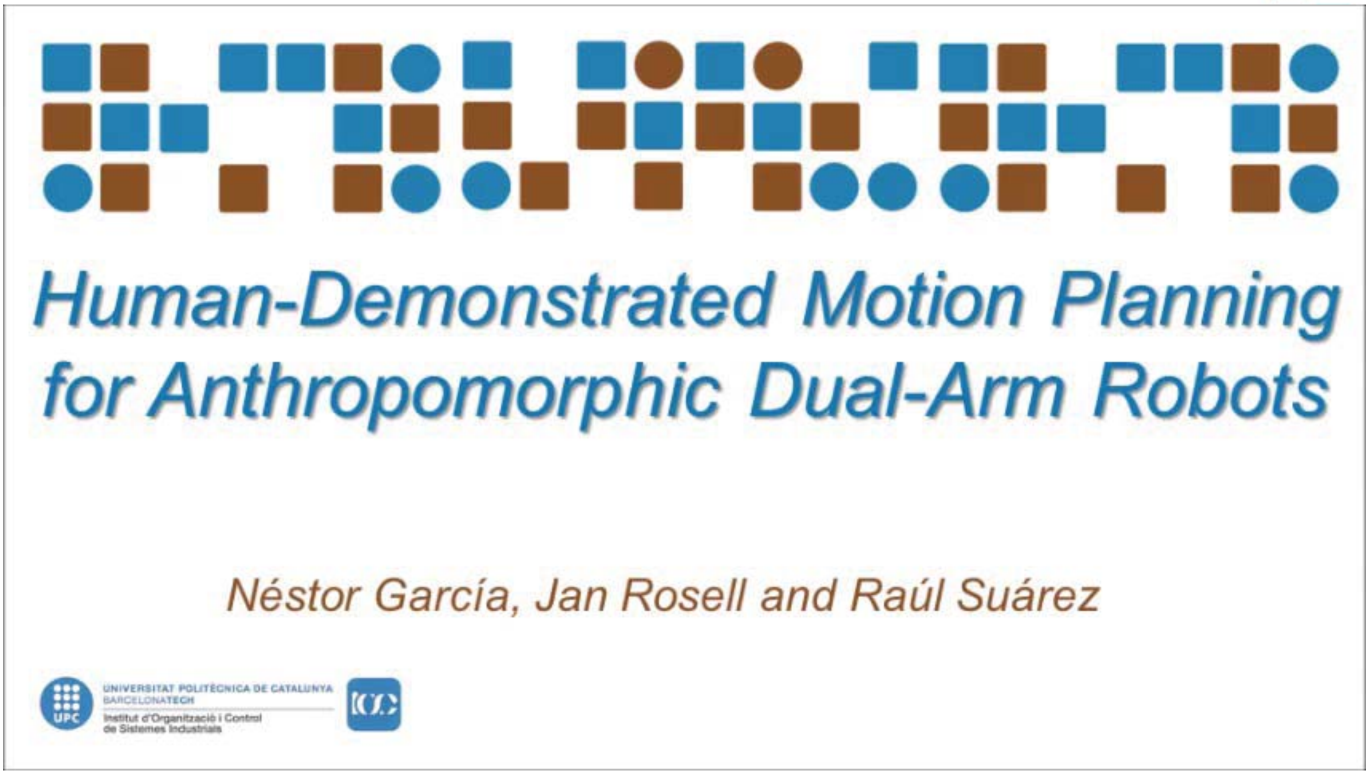
$$\mathcal{Q}_{\mathcal{P}} = 1 - \frac{1}{L}\int_{\mathcal{P}} \textsc{Misalignment}(\boldsymbol{q}, \boldsymbol{v})\, \mathrm{d}\boldsymbol{q}$$

Practical implementation for each segment of the movement path

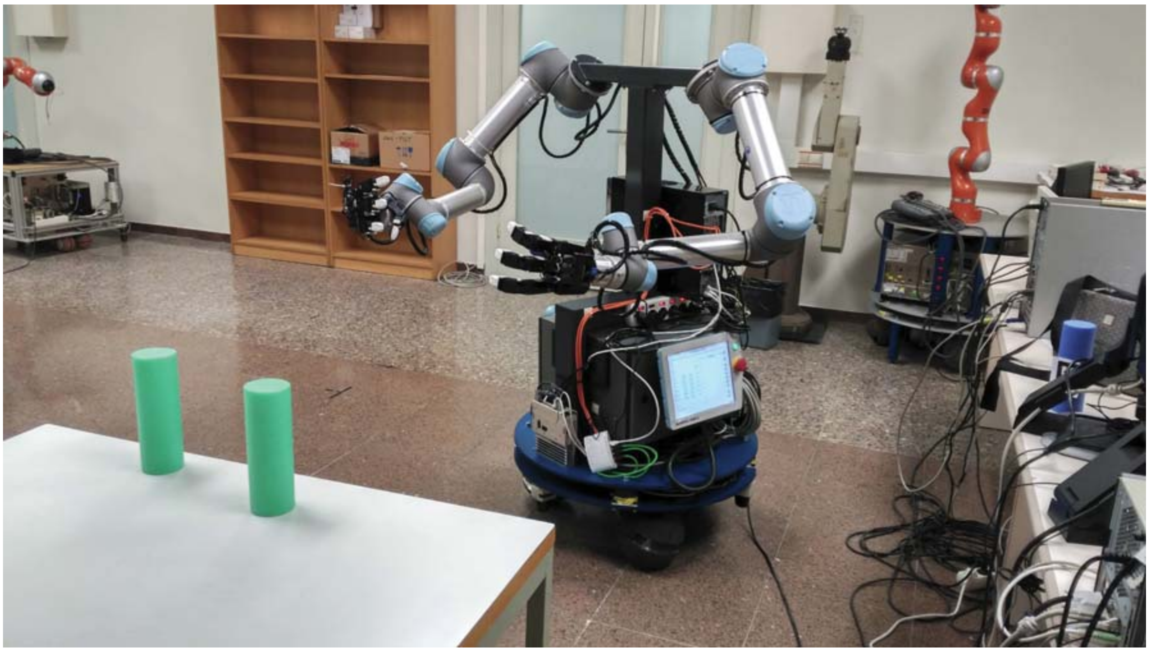
$$\mathcal{Q}_{\mathcal{P}} \approx 1 - \sum_{i=1}^{n-1} \textsc{Misalignment}(\boldsymbol{q}_i, \boldsymbol{q}_{i+1} - \boldsymbol{q}_i)\,\frac{\|\boldsymbol{q}_{i+1} - \boldsymbol{q}_i\|}{L}$$



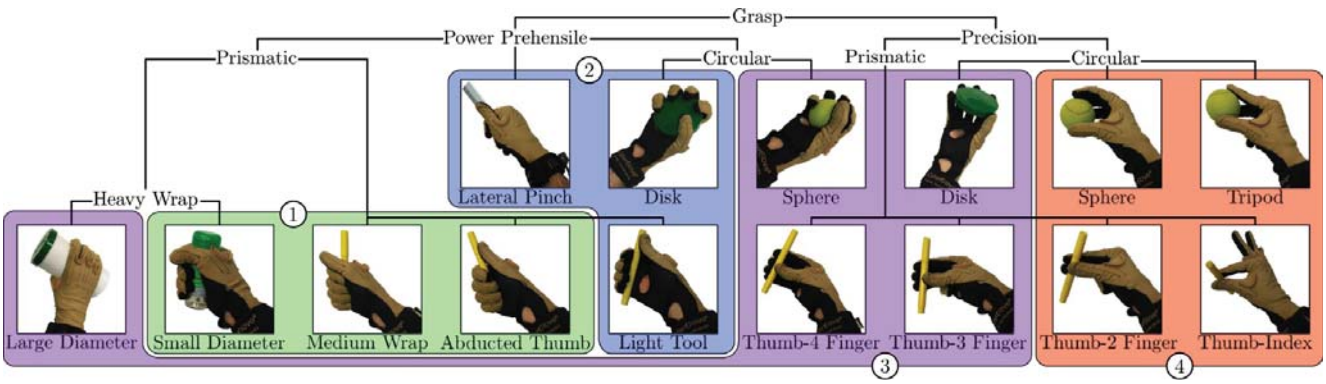
Example



Including hand movements



Grasp taxonomy



Approach

1. Capture human grasping motions
2. Map movements to the robot whose motions will be planned
3. Identify the grasping phases
4. Compute the synergies of each phase and grasp type
5. Design a bidirectional planner that
   a) Considers simultaneously different potential grasps
   b) Biases the tree growth towards the directions of synergies
   c) Reduces the dimension of the search space

Motion capture

- Human motions recorded using a Cyberglove (50 Hz sampling frequency, 22 variables per sample)
  - 12 repetitions per 15 different grasp types on 9 objects (>15000 configuration samples).
- Captured samples are mapped to the robotic system (the mapping depends on the robotic system)
  - Hand-arm system composed of two UR5 arms equipped with 4-finger Allegro hands.
- Mapping:
  - Flexion/extension joints of the fingers and the thumb are computed with a joint-to-joint mapping.
  - Remaining joints (i.e. the thumb-opposition joint and the abduction/adduction joints of the fingers and the thumb) are computed with a fingertip-position mapping.

Analysis

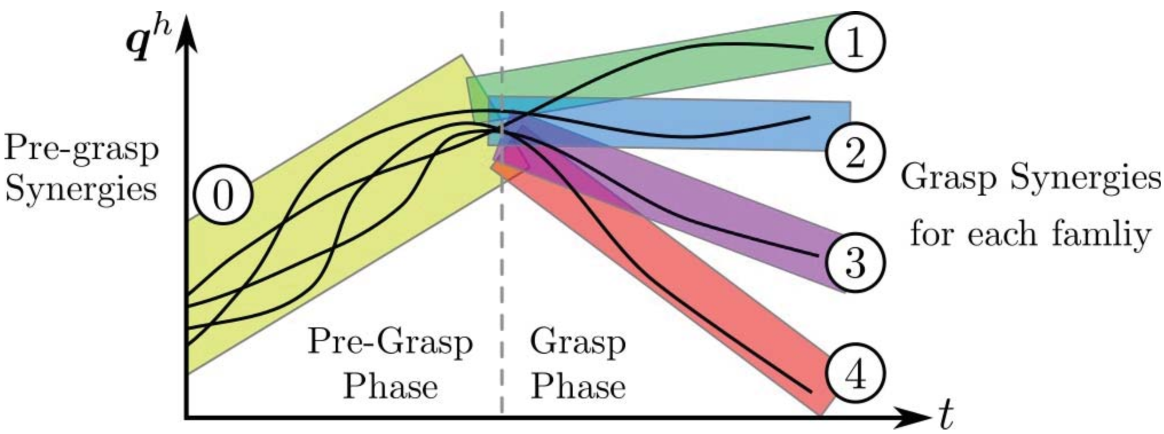
- Mapped configurations analyzed with PCA
  (each axis represents a synergy)

- Movements has two phases
  - Pre-grasp phase: trajectories of the hand joints are common regardless of the grasp type performed.
  - Grasp phase: trajectories differ and specialize for each type of grasp.

- Transition between phases is diffuse
  - Determined minimizing the likeness of the samples in each phase (overlapping of the sample distributions)

$$\mathcal{L}(Q_A, Q_B) = \frac{e^{-\frac{1}{2}(\boldsymbol{\mu}_A - \boldsymbol{\mu}_B)^{\intercal}(\Sigma_A + \Sigma_B)^{-1}(\boldsymbol{\mu}_A - \boldsymbol{\mu}_B)}}{\sqrt{(2\pi)^{1+2n}\,|\Sigma_A + \Sigma_B|}}$$

- Pre-grasp (approximation) and grasp synergies



Synergies

- All pre-grasp synergies merged to explain the motion in the pre-grasp phase for all the grasps
  - Represented by the first 6 synergies (to cover 95% of the samples)
- Grasp synergies merged per families to explain the motion in each family
  - Represented by the first 4 or 5 synergies (to cover 95% of the samples)

k	Pre-Grasp	Grasp Family			
		1	2	3	4
1	65.575 %	79.474 %	64.234 %	63.280 %	88.568 %
2	77.795 %	86.125 %	81.877 %	84.238 %	91.955 %
3	84.586 %	91.442 %	88.091 %	91.428 %	94.921 %
4	90.316 %	94.015 %	92.225 %	94.377 %	**96.606 %**
5	93.260 %	**96.229 %**	**95.108 %**	**96.394 %**	97.676 %
6	**95.996 %**	97.665 %	96.781 %	97.664 %	98.685 %
7	97.262 %	98.315 %	97.850 %	98.569 %	99.160 %
⋮	⋮	⋮	⋮	⋮	⋮
16	100 %	100 %	100 %	100 %	100 %

Planning Human-like Movements for Dual-arm Robots

Planning Approach

Proposed planner is RRT-Connect with some modifications:

- *Extend the trees following the synergies*:

The tree growing is steered towards its projection into the subspace of grasp synergies.

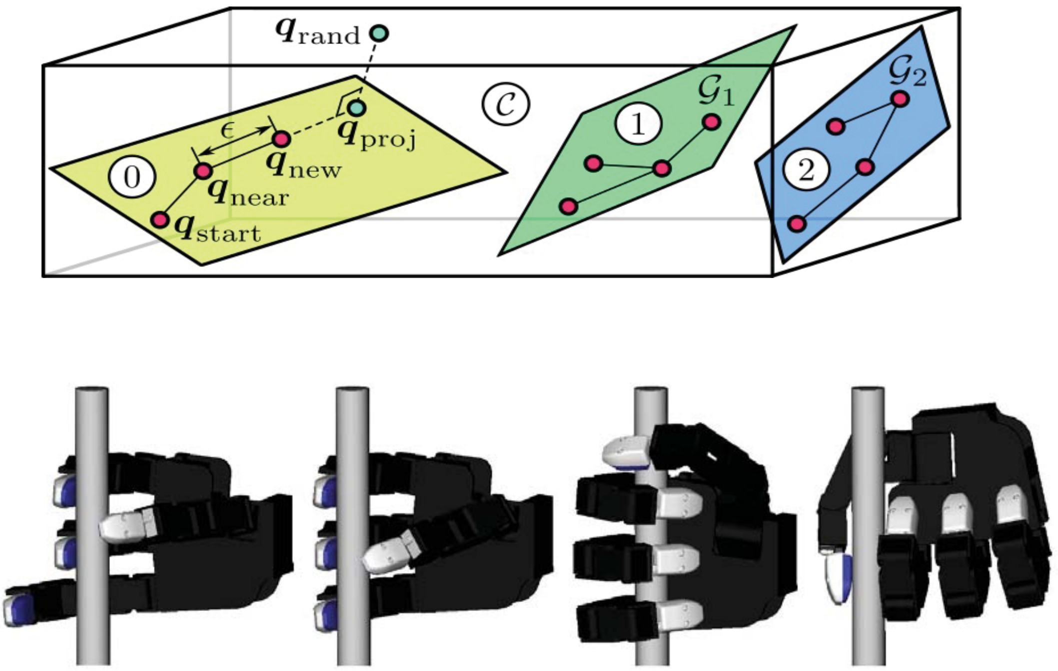
- *Deal with multi-goal queries*:

Planner maintains a tree for each goal configuration.

- *Connect the trees less greedily:*

Instead of growing one tree until the other is reached, both trees are alternatively steer to each other following the synergies.

Planning Approach



Experimental results

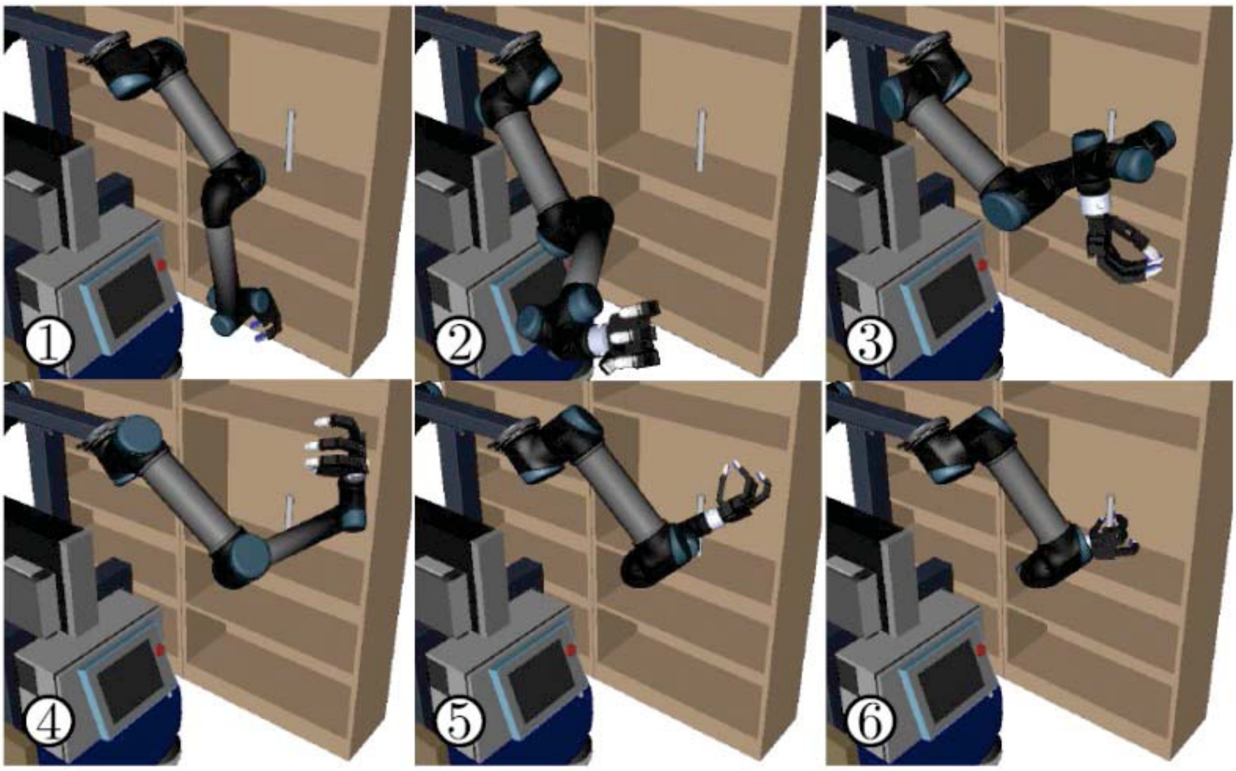
Average results of the motion planning when running:

a) the classic RRT-Connect
b) the proposed approach with the proper grasp synergies
c) the proposed approach with mismatched grasp synergies

Case	Success rate	Planning time	#Planning iterations	# Collision checks	Valid motion rate	Solution length	Human-Likeness $\mathcal{Q}_{\mathcal{P}}$
a)	97%	51.80 s	1834	32231	68.3%	14.18 rad	73.6%
b)	100%	6.21 s	274	10649	80.0%	7.79 rad	83.1%
c)	100%	11.79 s	484	13667	75.3%	8.35 rad	81.9%

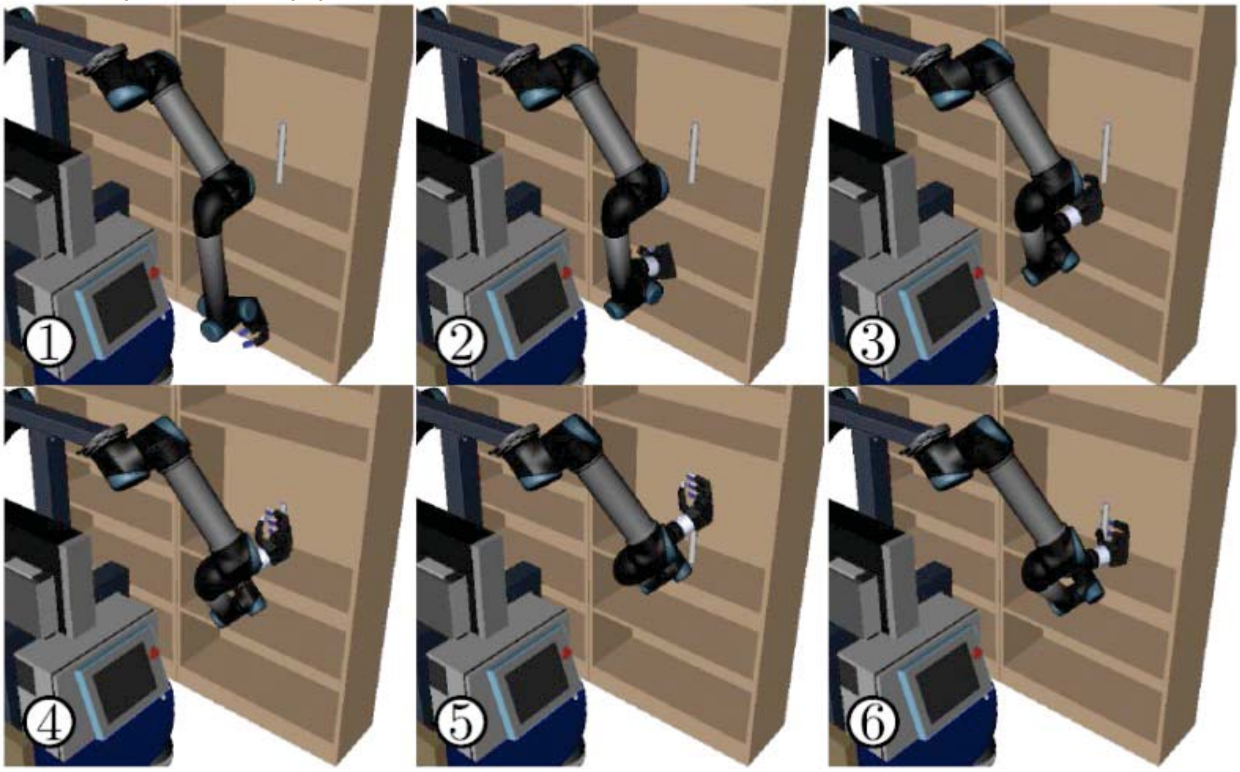
Experimental results

- RRT-Connect



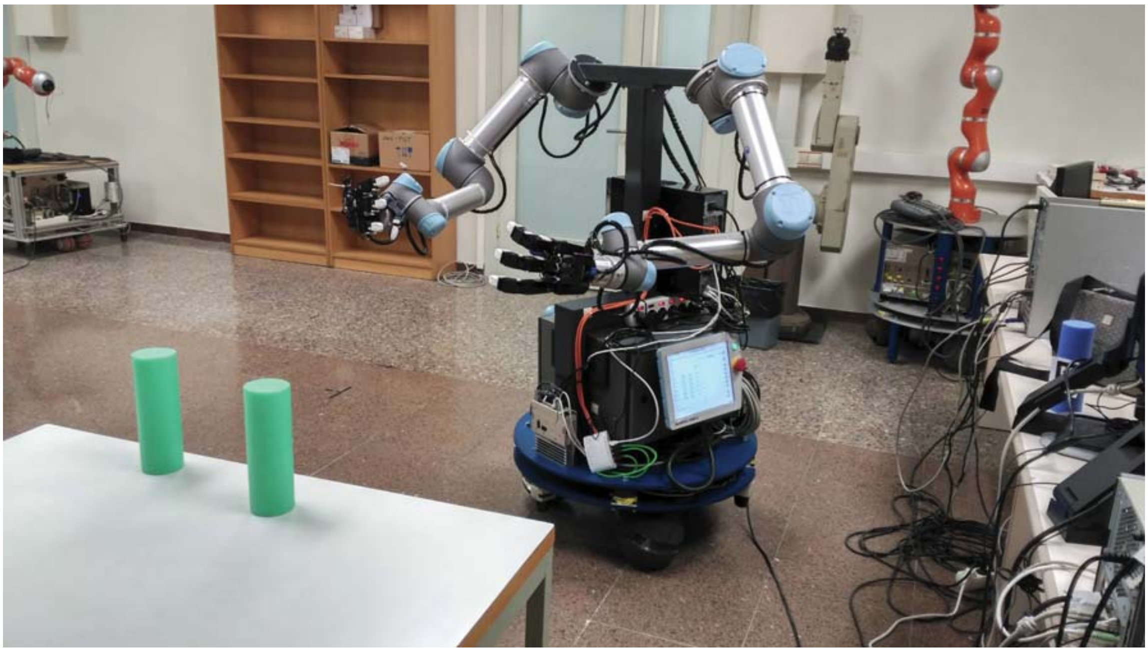
Experimental results

- Proposed approach



Including base movements

Goal: plan coordinate motions of the base and the arms of a mobile anthropomorphic dual-arm robot mimicking human movements.



Approach overview

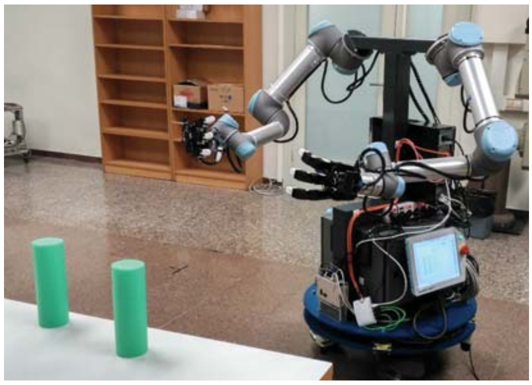
1. Capture and map human movements
2. Extract synergies (correlations) between robot position and torso configurations.
3. Cartesian-space discretization:

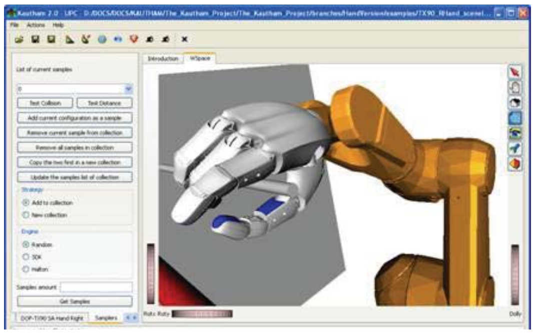
   Different base positions → Different arm synergies.

4. Use the compute synergies to define subspaces where a standard motion-planning algorithm plans the solution path.

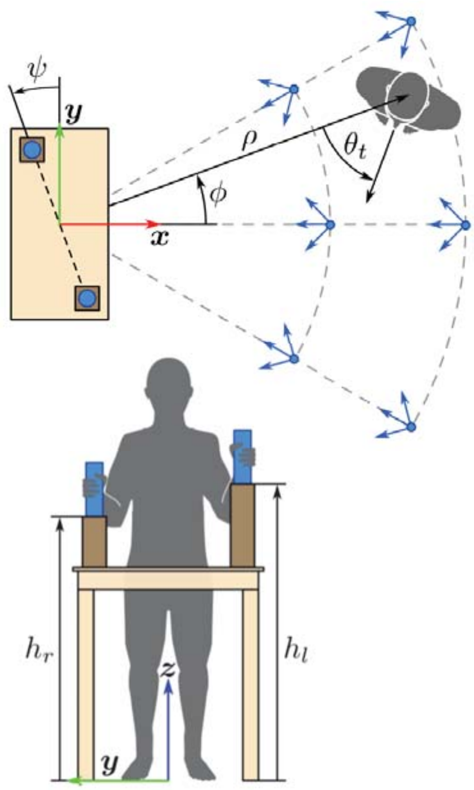
Experimental Setup

- A mobile anthropomorphic dual-arm robot.
- An optical motion-capture system formed by reflective markers and infrared cameras.
- ***The Kautham Project***, a simulation tool with capabilities for collision checking, motion planning and graphical visualization.





Motion capture



- Captured human motions walking towards a table and grasping two cylinders placed on pedestals.
- Parametrized initial and final positions.

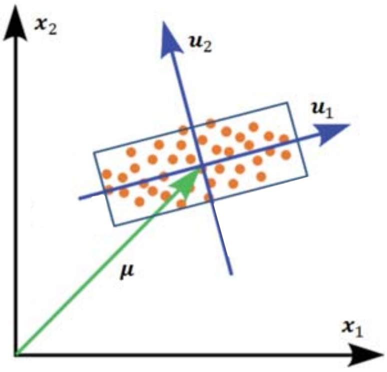
$$
\begin{aligned}
&\theta_t \in \{-\tfrac{\pi}{4}, 0, \tfrac{\pi}{4}\} \text{ rad} \\
&\rho \in \{2, 3\} \text{ m} \\
&\phi \in \{-\tfrac{\pi}{6}, 0, \tfrac{\pi}{6}\} \text{ rad} \quad \Rightarrow \quad \text{216 experiments} \\
&\psi \in \{-\tfrac{\pi}{6}, 0, \tfrac{\pi}{6}\} \text{ rad} \\
&h_l, h_r \in \{1, 1.5\} \text{ m}
\end{aligned}
$$

- 3D position of the shoulders, elbows and wrists and palm orientation captured using markers.

Synergies

- Dual-arm synergies are obtained running a PCA over the mapped torso configurations.

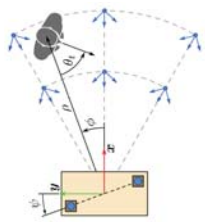
- The directions with larger dispersion are the **synergies**. (Equivalent to a single degree of freedom).



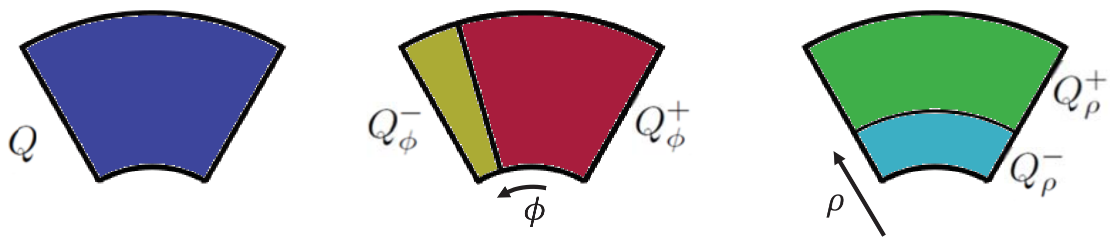
- Dual-arm synergies depend on robot position χ ⇒ Cartesian-space discretization

- Recursive partition into sectors of annuli centered on the table, such that the synergies of each annular sector are different to the ones from the neighboring sectors.

Synergies

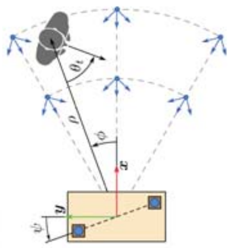


- Division of the space within a given annular sector, for a given angle ϕ and radius ρ:



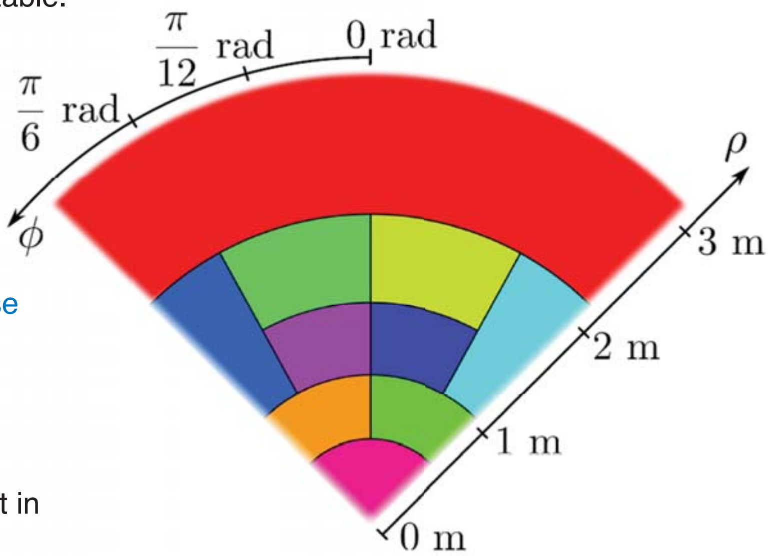
- Likeness $\mathcal{L}(Q_A, Q_B)$ between two sets Q_A and Q_B of configurations defined as the overlapping between distributions of the configurations in the sets.
- The best position to divide a sector is the one that minimizes the objective function f:
  - $f = \max(\mathcal{L}(Q, Q_\phi^-), \mathcal{L}(Q, Q_\phi^+))$, if splitting by ϕ.
  - $f = \max(\mathcal{L}(Q, Q_\rho^-), \mathcal{L}(Q, Q_\rho^+))$, if splitting by ρ.
- Partition procedure recursively self-invoked until no valid partitions are found, according to a given aspect ratio and number of samples it contains

Result



Free-walk phase

- Synergies similar if far from the table.
    - Arms mostly at resting



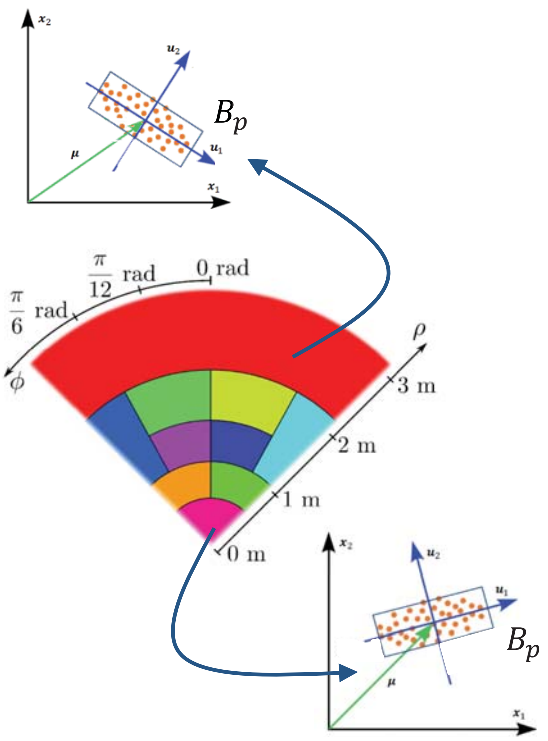
Transition

- Synergies differ and are grouped into different sectors
    - Arms prepare for the goal pose

Grasping phase

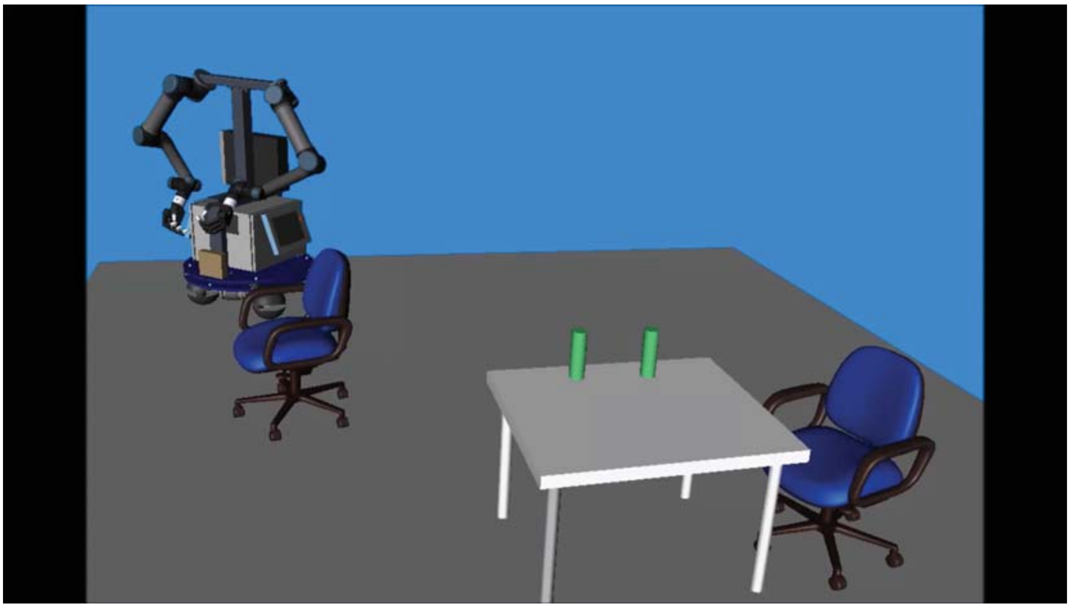
- A unique set of synergies if robot in front of the table
    - Arms reach the goal

Motion planning



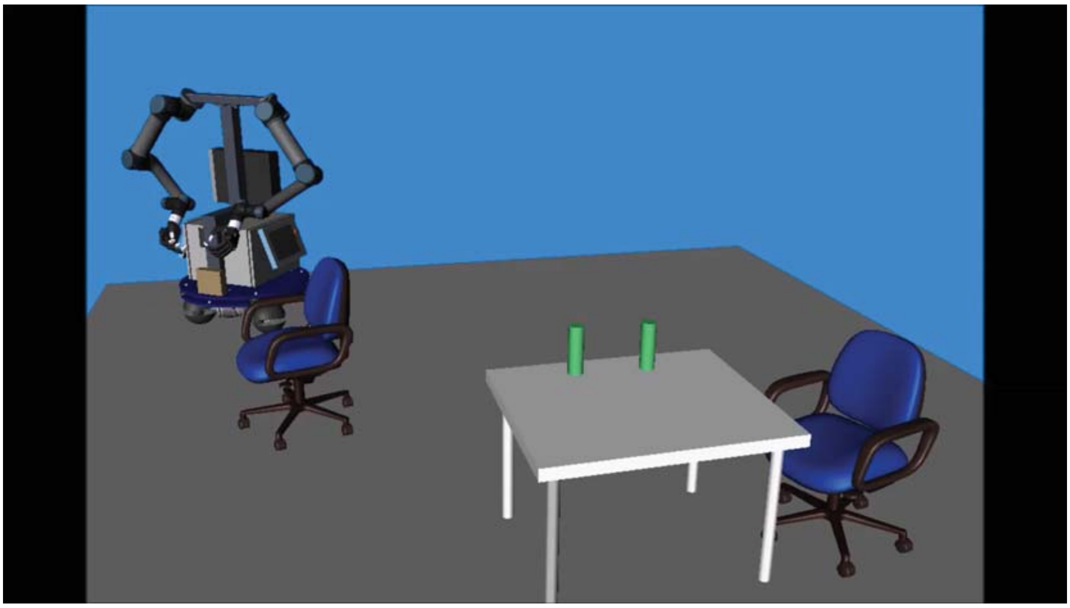
- The first p dual-arm synergies span a lower-dimensional subspace $\boldsymbol{B_p}$.
- The first p synergies accumulate more than the 95% of the total sample variance.
- B_p still represents accurately the mapped torso configurations.
- Each annular sector has a **different** B_p.
- If the motion planning performed in B_p ,
    - The planning complexity is reduced
    - Human-like motions obtained.

Experiment (Classic RRT-connect)



Planner	Success rate	Planning time	Iterations	Collision checks	Valid segments	Path length
Proposed	100%	2.923 s	290	2156	74.09%	4.378 rad
RRT-Connect	100%	11.378 s	1940	6532	63.32%	4.731 rad

Experiment (Proposed with synergies)



Planner	Success rate	Planning time	Iterations	Collision checks	Valid segments	Path length
Proposed	100%	2.923 s	290	2156	74.09%	4.378 rad
RRT-Connect	100%	11.378 s	1940	6532	63.32%	4.731 rad

Gracias por la atención!

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Raúl Suárez

In collaboration with Néstor García and Jan Rosell

UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Institut d'Organització i Control
de Sistemes Industrials