The Neuroinformatics Group

SOM-based Experience Representation for Dextrous Grasping

Jan Steffen, Robert Haschke and Helge Ritter

Neuroinformatics Group
Faculty of Technology

Bielefeld University

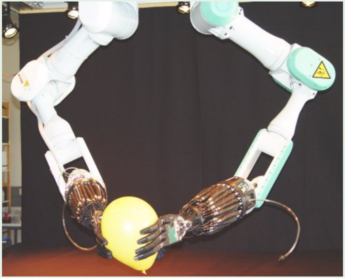
WSOM 2007, Bielefeld

Outline

Robot grasping in our group

1. Two arm setup

- 2x 7DOF PA10 arm
- 2x 24DOF Shadow Hand



Robot grasping in our group

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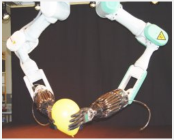

2. Vision & audio

- Stereo camera head
- gesture & object recognition
- Speech recognition/generation

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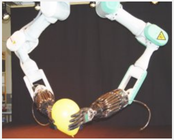
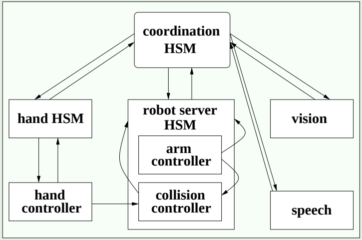


2. Vision & audio

3. Hierarchical Control

- Hierachical State Machine



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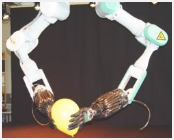
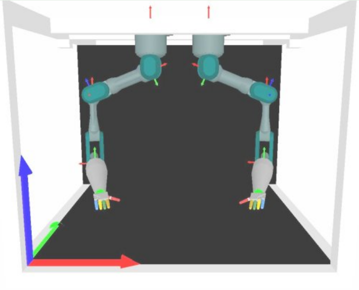


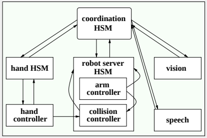
2. Vision & audio

4. Simulation

- Physics-based 3D Simulation



3. Hierarch. Ctrl



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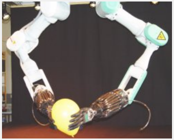
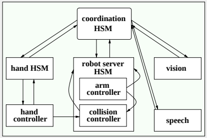


2. Vision & audio

Grasping goals

- dextrous 5-fingered grasping
- intelligent control in 24 dim.
- manipulation
- bimanual interaction

3. Hierarch. Ctrl



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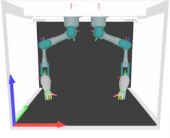


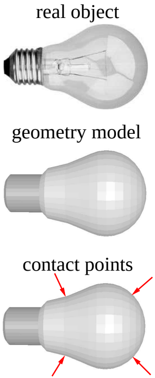
Dextrous robot grasping

1. geometry-based

- uses object geometry model
- precomputes (optimal) contact points
- precomputes corresponding grasp posture
- $\Rightarrow$ geometry-specific grasping knowledge

problems:

- not applicable to unknown geometries
- inaccurate models result in quality loss



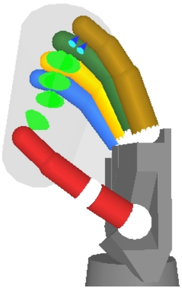
Dextrous robot grasping

2. tactile-driven

- no object/geometry knowledge
- reacts on occurring contacts
- dynamically adapts grasp
- $\Rightarrow$ gathers object knowledge (contact points)

problems:

- no object-specific grasp planning
- cannot exploit gathered object knowledge



Experience-based grasping

combine geometry-based and tactile-driven approach

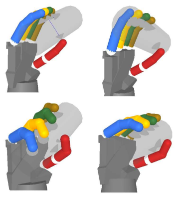
1. geometry-based

grasping knowledge

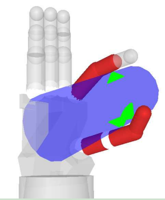
2. tactile-driven

current object knowledge

final grasp postures $\{\vec{\Theta}\}$



contact information



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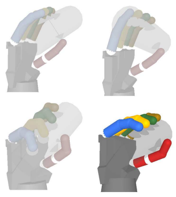
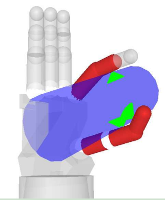


dynamic matching



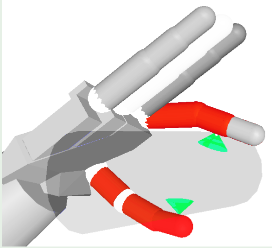
Matching object and grasping knowledge

The *Partial Contact Posture (PCP)*

$$\vec{\Theta}^{pcp} = [\Theta^{pcp}_{1,1}, .., \Theta^{pcp}_{1,N_1}, \Theta^{pcp}_{2,1}, .., \Theta^{pcp}_{I,N_I}]^t \quad \text{where:}$$

$$\Theta^{pcp}_{i,j} = \begin{cases} \Theta_{i,j} & \text{if a segment } S_{i,(k \geq j)} \text{ has contact} \\ \star & \text{otherwise.} \end{cases}$$

$\Theta_{i,j}$: joint angle of joint j in finger i



Best-match search in database grasp postures $\{\vec{\Theta}^{xp}\}$

$$\vec{\Theta}^{xp,\star}(\vec{\Theta}^{pcp}) = \arg\min_{\vec{\Theta}^{xp}} \sum_{i,j} s_{i,j} \cdot (\Theta^{xp}_{i,j} - \Theta^{pcp}_{i,j})^2 \qquad , s_{i,j} \in \{0, 1\}$$

Example of best-match search

Best-match search in database grasp postures $\{\vec{\Theta}^{xp}\}$

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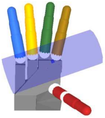
Partial Contact Posture $\vec{\Theta}^{pcp}$

best-match $\vec{\Theta}^{xp,\star}(\vec{\Theta}^{pcp})$

Overview of the algorithm

pregrasp



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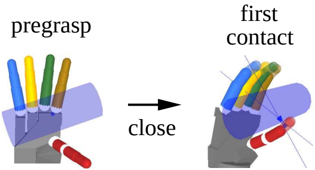

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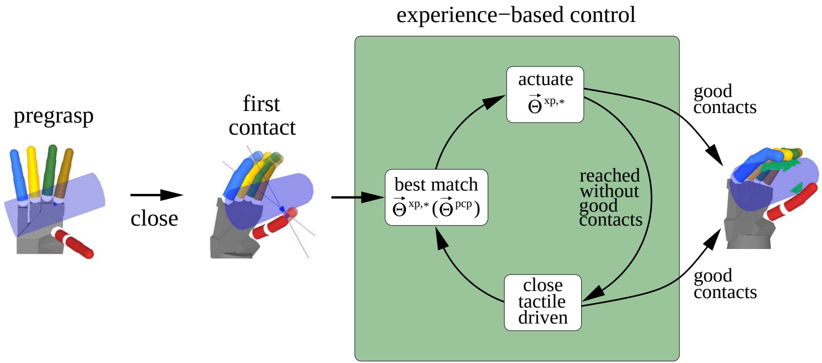


A more complex experience representation

Grasp Manifold

Assumption:
grasp postures form smooth manifold in hand posture space

SOM Grasp Manifold

use SOM as discrete approximation of such *Grasp Manifold*

SOM PCP best-match search: *associative completion*

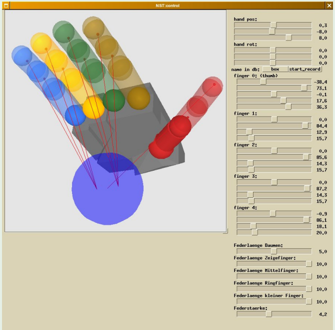
$$dist(\Theta^{\vec{xp}}, \Theta^{\vec{pcp}}) = \sum_{i,j} s_{i,j} \cdot (\Theta^{xp}_{i,j} - \Theta^{pcp}_{i,j})^2 \quad , \quad s_{i,j} \in \{0, 1\}$$

$\Rightarrow$ execution of algorithm *pulls hand posture onto manifold*.

Training data

Training data from simulation

- object fixed
- fingertips on object surface
- springs between fingertips/object
- move hand relative to object
  $\Rightarrow$ jitter around starting positions
- record "5-fingertip-contacts"
- cylinder: 4220 postures
  box: 4079 postures
  sphere: 1885 postures



SOM training and test

Training

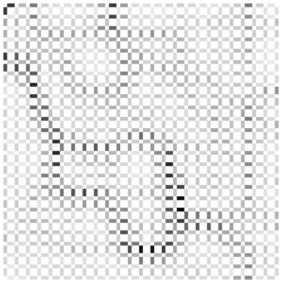
- object-specific 25x25 SOMs
- 300 learning epochs
- random data presentation, $\varepsilon(t) : 0.95 \searrow 0.05$, $\sigma(t) : 6 \searrow 0.7$

Test data from grasp evaluation

- execute experience-based algorithm
- trained SOM as experience base
- regular object position/orientation grid
- cover most of meaningful grasp space

Inter-node distance structure and data support

Inter-node dist's



: small node distance, : large node distance, : data support

Inter-node distance structure and data support

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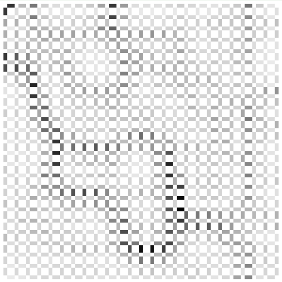
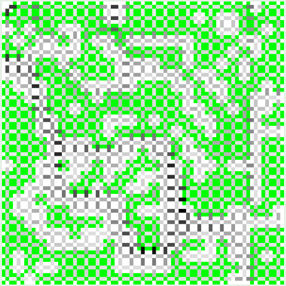


Training data sup.



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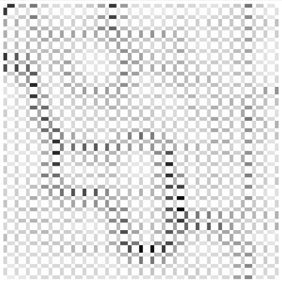

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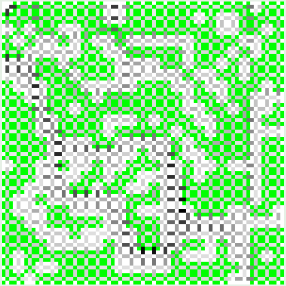
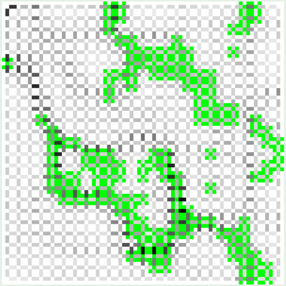


Test data support



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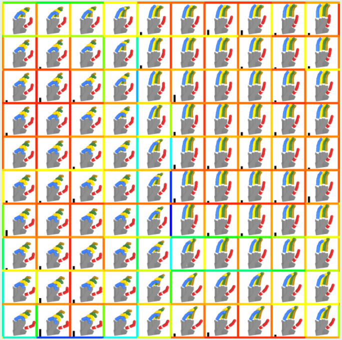
Cluster borders and inter-cluster nodes

Cylinder SOM (10x10 extract)



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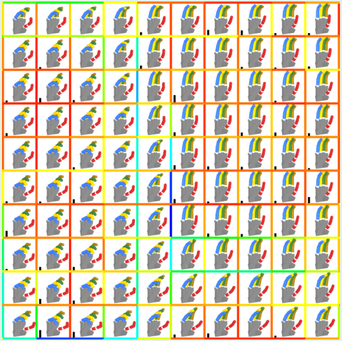

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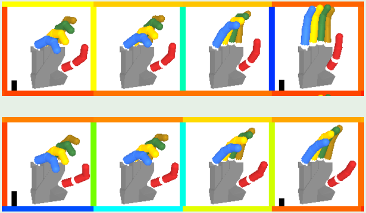

- meaningful inter-cluster nodes
- interpolate between clusters
- supports manifold assumption

Resume training

Conclusion

1. clustered training data
2. discovered more grasping situations in evaluation
3. need higher resolution between clusters

↓

resume training with successful grasp postures from evaluation

Resume training

Conclusion

1. clustered training data
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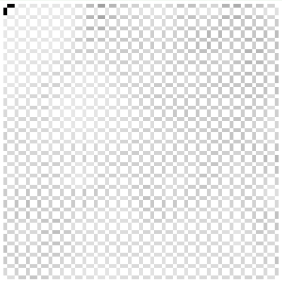
resume training with successful grasp postures from evaluation

Smoothed Grasp Manifold

Structure of the smoothed manifold

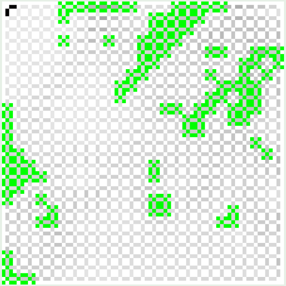
Inter-node dist's

- very smooth



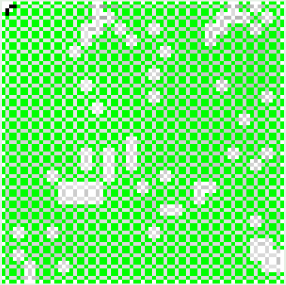
Training data sup.

- loss of resolution



Test data support

- higher resolution



: small node distance, : large node distance, : data support

Conclusion and future work

Conclusion

- new approach to dextrous robot grasping
- smooth SOM-based Grasp Manifold approximation
- resumed training provided homogenised distance structure
- algorithm ”pulls hand posture onto Grasp Manifold”

Future work will address..

- more objects & realisation on the real robot hand
- continuous manifold representations
- object manipulation by navigating through the manifold

Thank you for your interest!

Jan Steffen
(jsteffen@techfak.uni-bielefeld.de)