Understanding Manifolds of Grasping Actions



Javier Romero Thomas Feix¹ Hedvig Kjellström

Danica Kragic

May 3, 2010

 $\mathsf{CAS}\text{-}\mathsf{CVAP}/\mathsf{KTH}$

¹Otto Bock HealthCare





Grasp Dimensionality

- Effective dimensionality of grasping hand poses is low [1]
- Using a low dimensional representation of grasps sequences is useful
 - Measuring similarities is simpler
 - Modeling hand dynamics in a lower dimensional space is simpler
 - Such a dense representation avoids unnatural/impossible poses







Data acquisition Methodology

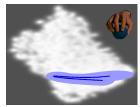
- Record data from different subjects performing a wide range of grasps [1]
- 2 Map the data to a lower dimensional space
- Ose it!
 - Model different grasp types in the low dimensional space
 - Create a data-driven grasp taxonomy
 - Compute dynamic models
 - Generate new grasps



T. Feix et al. A comprehensive grasp taxonomy.

In RSS Workshop on Understanding the Human Hand for Advancing Robotic Manipulation, Poster Presentation, 2009.







Data acquisition

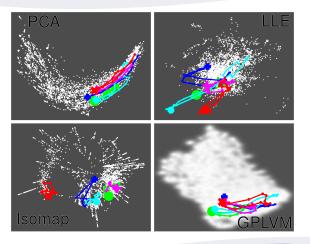
Data

• Polhemus magnetic tracker with 6 sensors ²

- Orientation (quaternion 4D) and position (xyz 3D) for each sensor
- 5 subjects, 31 grasps with 2 trials per grasp (first used for testing and second for training)
- 30 samples per grasp used
- Data used: relative position/orientation of fingertips wrt the wrist



Data acquisition Dimensionality reduction methods





Gaussian Process Latent Variable Models

- Each dimension in the high dimensional space is mapped by a non-linear Gaussian Process
- GPLVM optimizes the mapping parameters and the latent space iteratively to minimize the reconstruction error
- Additional priors can be introduced in the optimization process
 - Discriminative priors favor interclass separation
 - Dynamic priors favor coherent sequential data
- However, none of these priors were used here in order to explore the natural separability and time continuity of the data

7 / 13



GMM/GMR grasp model

- Goal: Grasp type model that contains temporal information
- Method [1]:
 - Fit a mixture of gaussians (GMM) to each grasp type
 - Apply Gaussian mixture regression (GMR) taking into account the timestamp of each data point





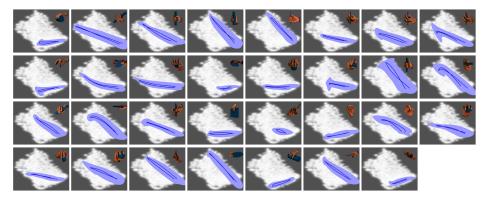




8 / 13



GPLVM GMR results

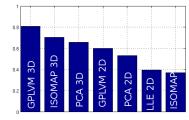


Javier Romero / CAS-CVAP/KTH



Results Quantitative evaluation

- Evaluation of the discriminative power of the latent space
- Each GMR model is used to classify grasping sequences not included in the training set
- GPLVM outperforms the rest of dimensionality reduction methods with same dimensionality
- Classification error is lower for 3D latent spaces than for 2D

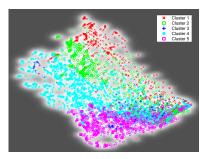


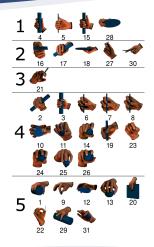
Javier Romero / CAS-CVAP/KTH



Data-Driven Taxonomy

- Create a similarity matrix based on the GMR grasp models
- Cluster the grasp types based on that similarity matrix







Results Current Work

- For our Hand Pose Estimation system [1]
 - Replace Euclidean distance in joint space by distance in low dimensional space
 - Extract dynamic hand behaviour from the low dimensional space
- Generate grasp behaviour subject to kinematic constraints
- Improve Data-driven Grasp Taxonomy

J. Romero et al. Hands in action, real-time 3d reconstruction of hands in interaction with objects. In *ICRA 09:00-09:15, Paper TuA12.3,* 2010.

Javier Romero / CAS-CVAP/KTH

12 / 13



Conclusions

- Modeling grasping actions in latent spaces is useful
- The best results were achieved with GPLVM







