

# Analysis of Human Pivoting Operations Using Hidden Markov Models

Yusuke MAEDA and Tatsuya USHIODA, Yokohama National University

## Abstract

In this paper, human pivoting operations, a typical grasplless manipulation, are studied. We model data of finger motions in pivoting operations using Hidden Markov Models (HMM). The “optimal” HMM with an appropriate number of states is determined based on the MDL (Minimum Description Length) criterion. The obtained HMMs are analyzed by metric MDS (Multidimensional Scaling) to reveal individual characteristics in the operations. This dissimilarity analysis can be used for the validation of models of tacit skills of human manipulation.

## Introduction

### Human manual dexterity

- Mechanism behind it is not yet well-understood
- Models of human skill must be investigated
- Validity of a model should be evaluated: how well does it model the mechanism behind human dexterity?

### HMM-based skill modeling

([Hannaford 91] [Yang 94] [Nechyba 98] [Itabashi 98] ...)

- A powerful tool for modeling human manipulation, which has considerable variations
- Dissimilarity analysis is possible ([Nechyba 98] [Itabashi 98])

### HMM topology

- model accuracy (complex topology) v.s. model simplicity (simple topology)
- empirically determined in most robotics literatures

## Objective

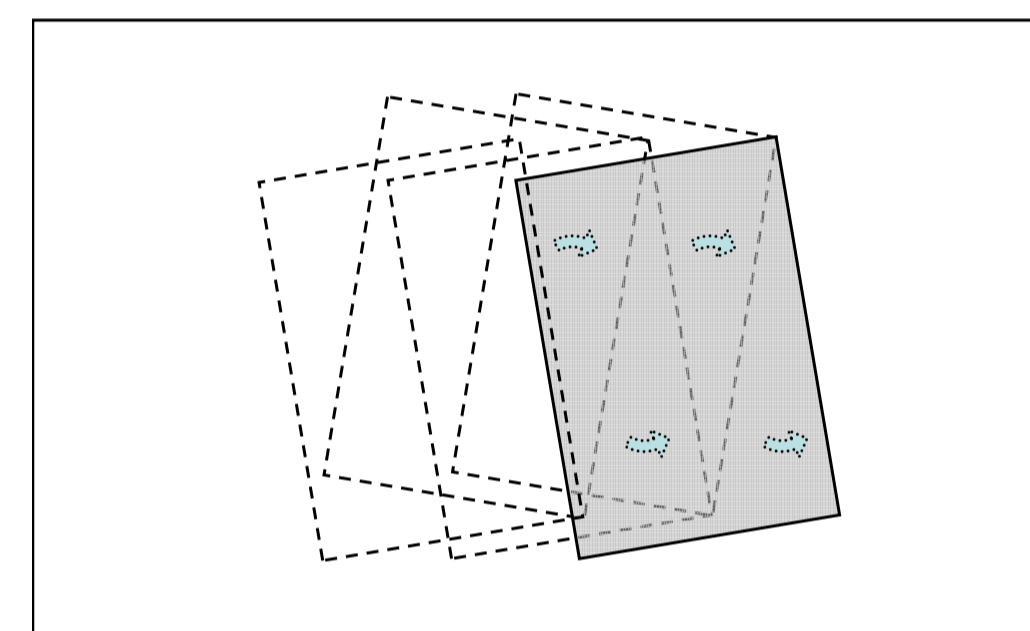
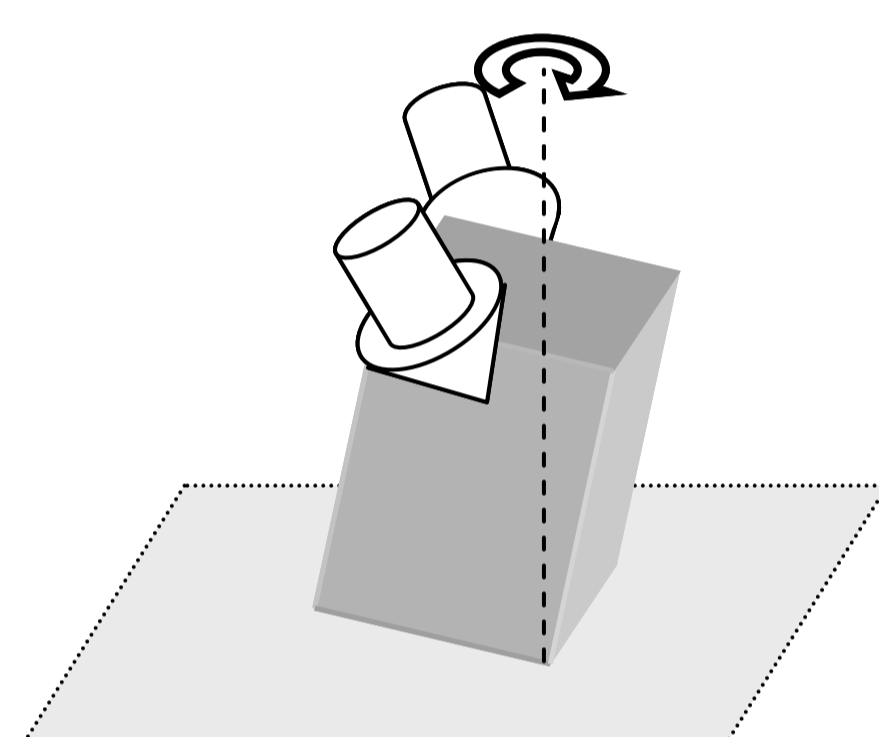
### Objective

to present a method to validate models of human skill

### Approach

- MDL-based hidden Markov modeling: objective determination of HMM topology
- Dissimilarity analysis based on MDS: can be used to validate models of human skill

### Example task: pivoting

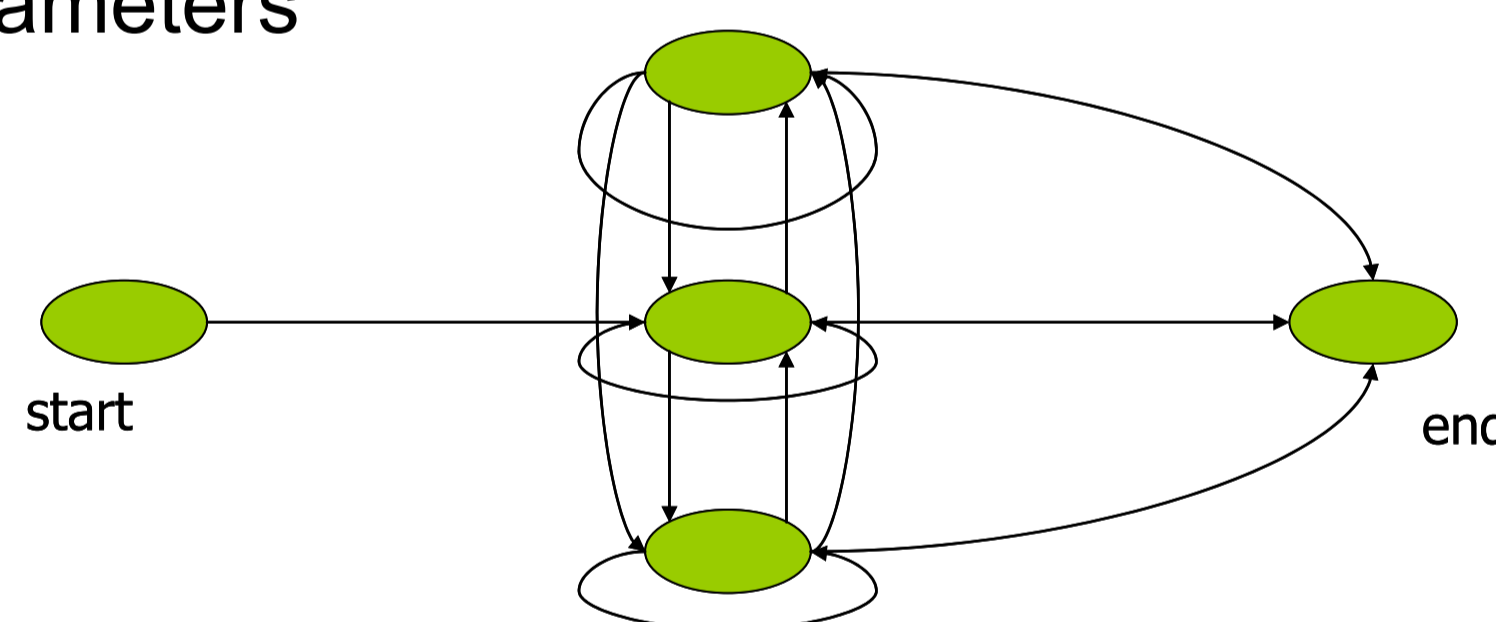


- typical grasplless manipulation
- suitable to manipulate heavy objects
- dexterous manipulation as an outcome of appropriate interaction between human and environment

## MDL Application to HMM

### Hidden Markov Modeling

- HMM (Hidden Markov Models)
  - Markov process with hidden parameters
  - The state is not directly visible
- Continuous HMM
  - Output pdf: Gaussian mixture
  - Ergodic-like topology
  - Number of states: unknown



### HMM Parameters

$$\lambda = (A, w, \mu, \Sigma, \pi)$$

state transition matrix  $A$ , weights  $w$ , means  $\mu$ , covariances  $\Sigma$  (for Gaussian mixture pdf), initial state probabilities  $\pi$

- Estimated using Baum-Welch algorithm

### Minimum Description Length (MDL) Criterion

- An objective measure for accuracy/complexity balance
- A model that minimizes MDL criterion is considered as “best”

$$\text{Model accuracy: } -\log p_{\theta^{(i)}}^T(O) + \frac{L_i}{2} \log T + \log M_c \quad \text{constant (ignored)}$$

### Application to HMM

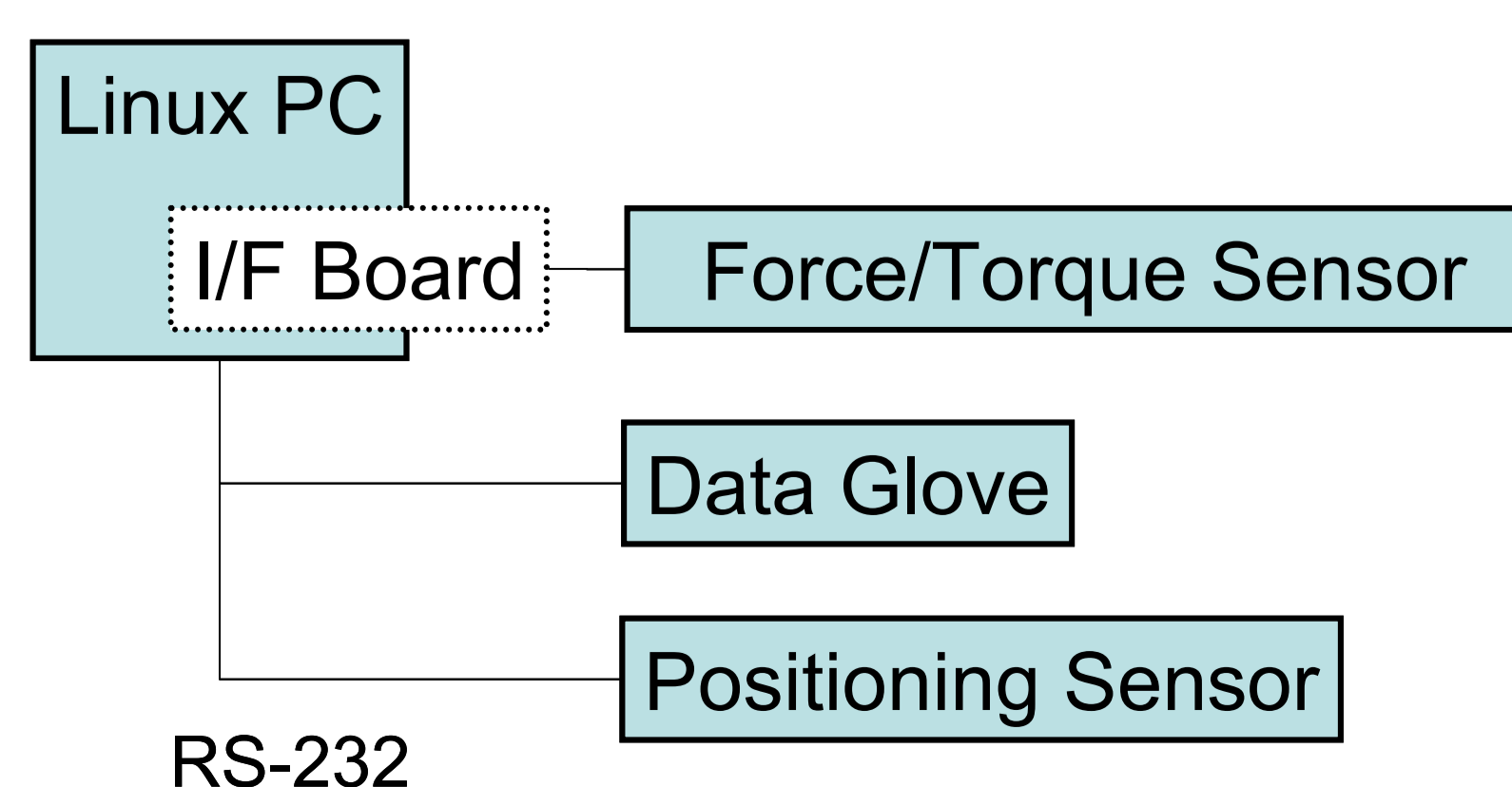
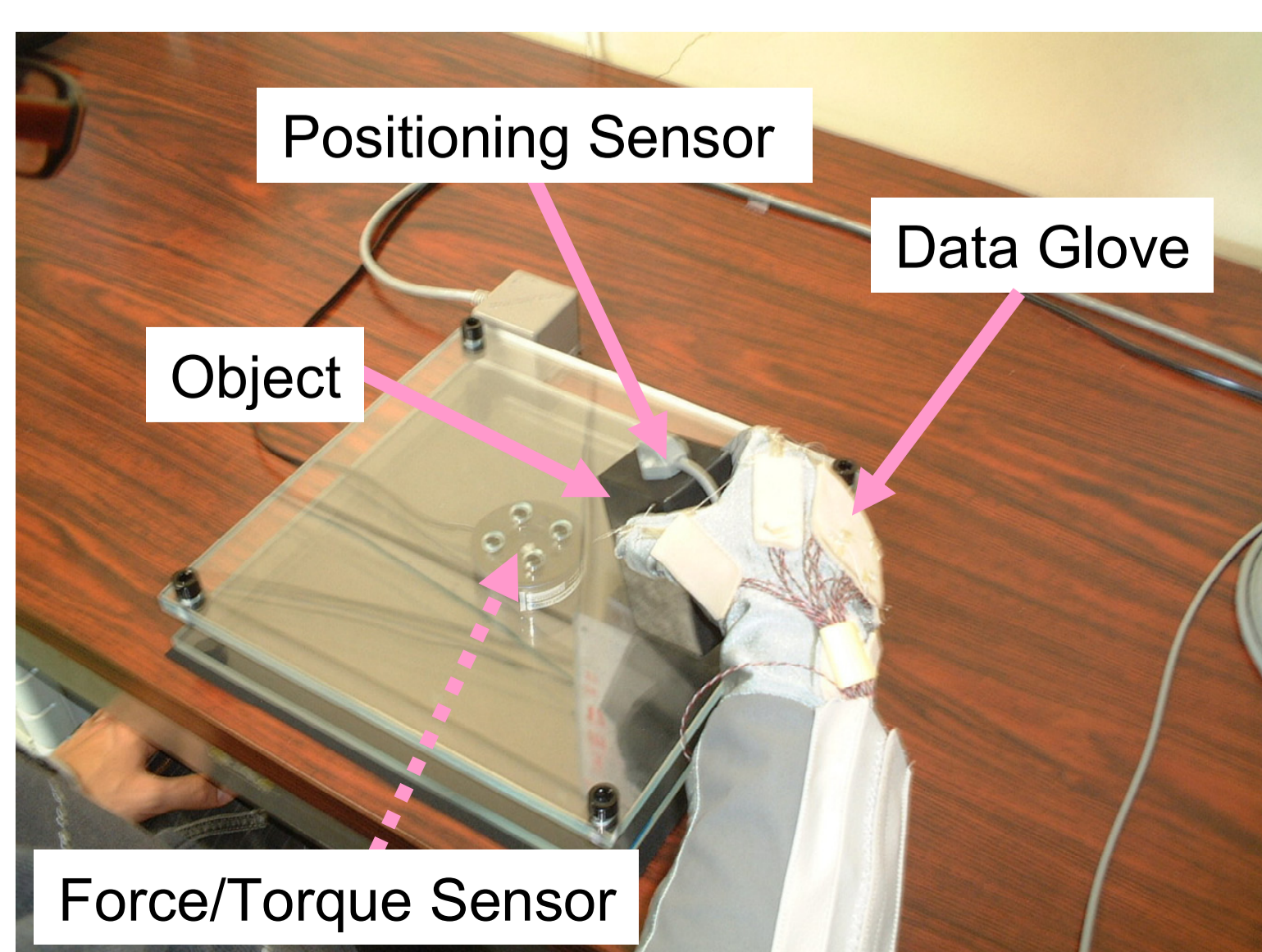
$$-\sum_k \log p(O^{(k)}|\lambda) + \frac{N^2 + (M-1)N + 2SMN}{2} \log \left( S \sum_k T^{(k)} \right)$$

- “Best” HMM topology can be determined with the MDL criterion

$O$ : observation sequence  
 $p_{\theta^{(i)}}^T(O)$ : maximum likelihood of  $O$  by  $i$ -th model  
 $L_i$ : model dimension of  $i$ -th model  
 $T$ : data length  
 $M_c$ : number of model candidates

$O^{(k)}$ :  $k$ -th observation sequence  
 $p(O^{(k)}|\lambda)$ : likelihood of  $O^{(k)}$  by HMM  $\lambda$   
 $T^{(k)}$ : length of  $k$ -th observation sequence  
 $M$ : number of mixture components of pdf  
 $N$ : number of states  
 $S$ : number of elements of observation vector

## Data Acquisition Setup

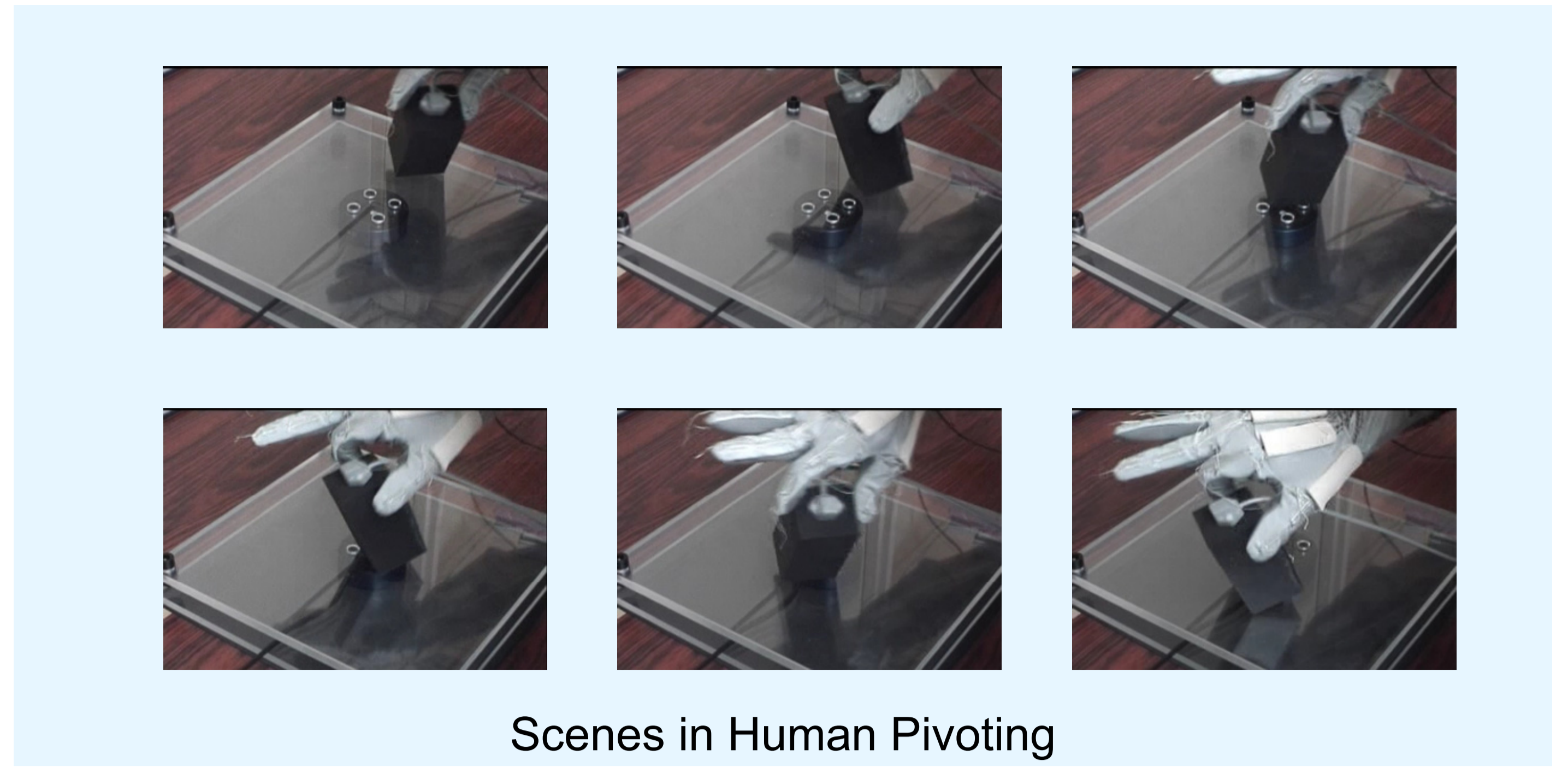
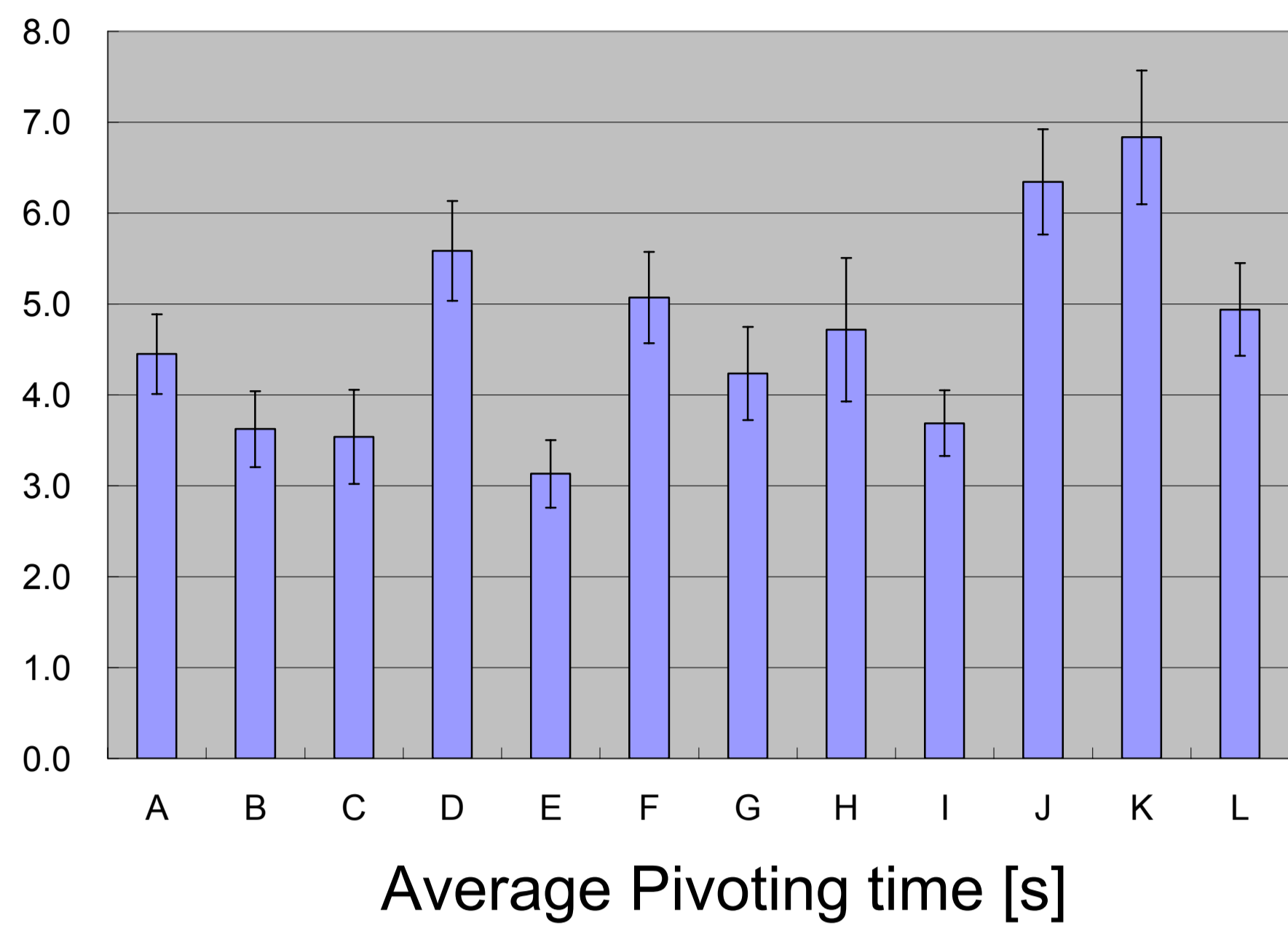


- Object: rubber cuboid
  - 50x50x100 [mm]
  - 0.36 [kg]: heavy to pick up by two fingers
- Sensors:
  - Data glove: Teiken StrinGlove (up to 24DOF)
  - Positioning sensor: Polhemus Fastrak (6DOF)
  - Force/torque sensor: Nitta (6-axis)
  - 120 [Hz] sampling

# Experimental Results

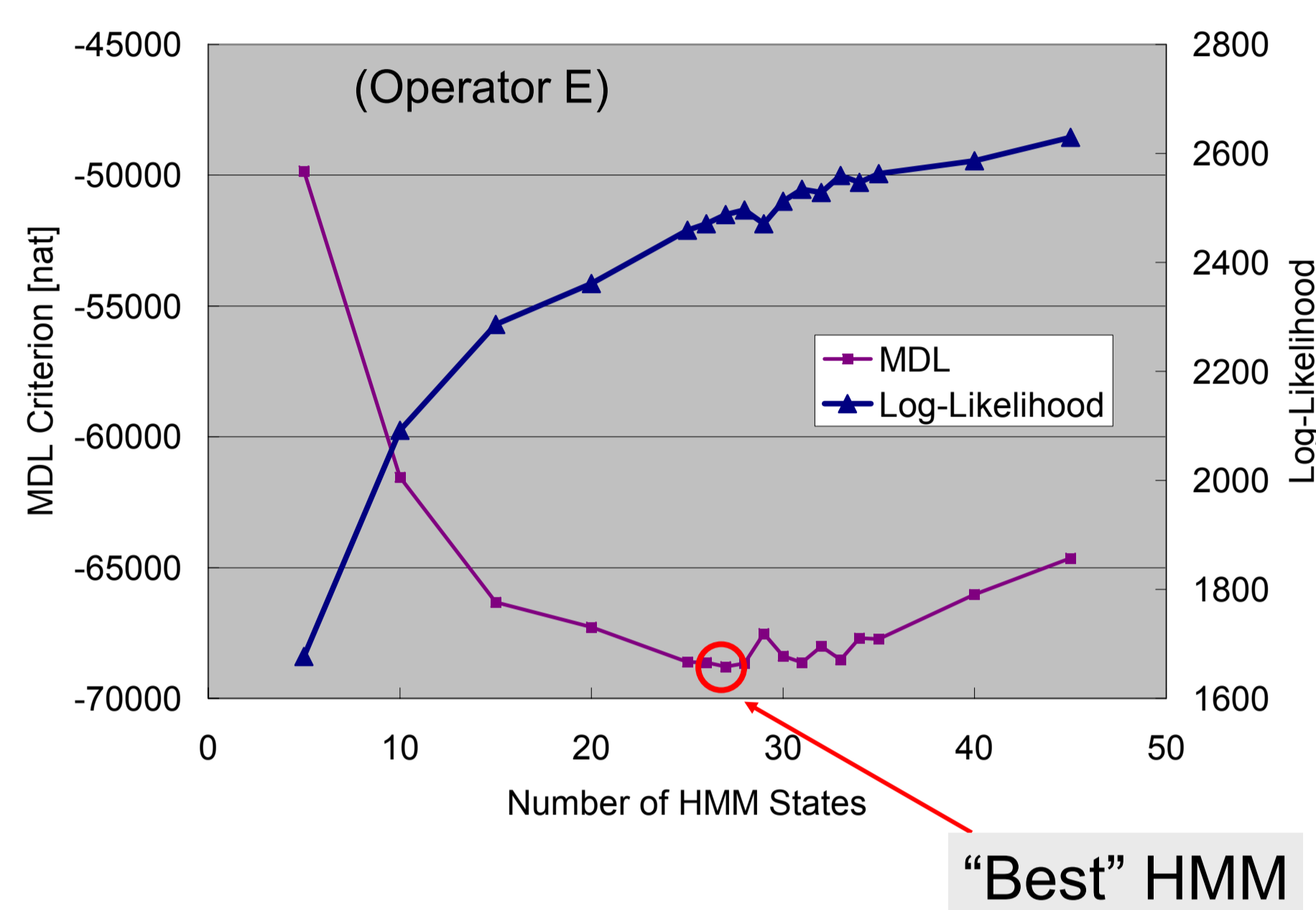
## Task

- 300 [mm] pivoting
  - as fast as possible
  - 12 male subjects (A-L)
  - 30 or more trials for each subject



## MDL-based topology determination

- Optimal number of HMM states is obtained



## Obtained "Best" HMMs

operator	states	MDL [nat]
A	40	$-1.11 \times 10^5$
B	35	$-0.56 \times 10^5$
C	26	$-0.32 \times 10^5$
D	32	$-1.21 \times 10^5$
E	27	$-0.69 \times 10^5$
F	35	$-1.43 \times 10^5$
G	39	$-0.52 \times 10^5$
H	40	$-0.38 \times 10^5$
I	34	$-0.76 \times 10^5$
J	49	$-1.60 \times 10^5$
K	40	$-1.66 \times 10^5$
L	39	$-1.26 \times 10^5$

## HMM symbols

- Thumb: MP and IP flexion/extension
- Index finger: MP, PIP and DIP flexion/extension
- Ground reaction force in vertical axis

## Dissimilarity Analysis

- A stochastic dissimilarity measure for HMMs [Rabiner 89]

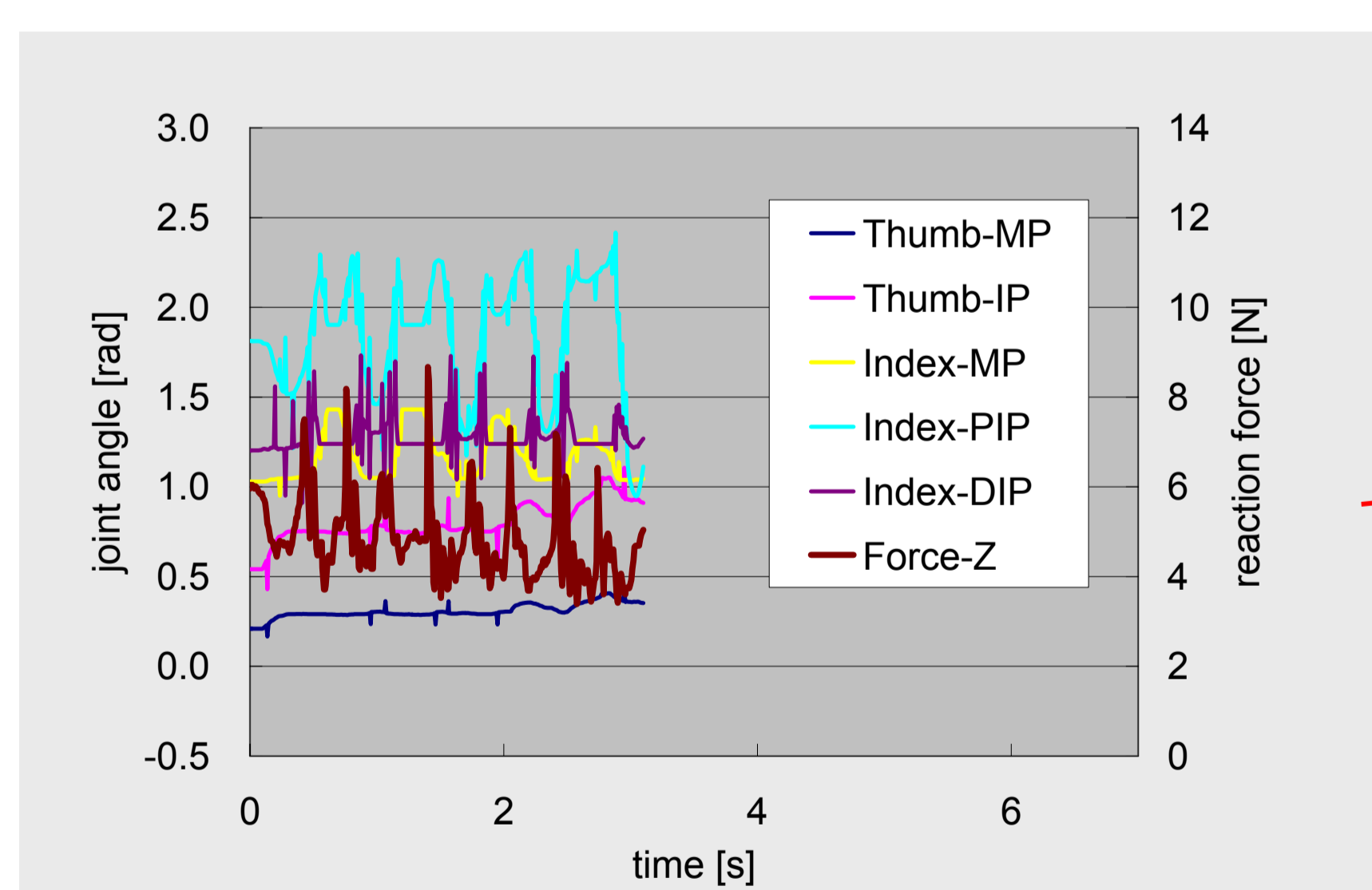
$$D(\lambda_i, \lambda_j) = \frac{1}{K} \sum_{k=1}^K \frac{\log p(O_i^{(k)} | \lambda_i) - \log p(O_i^{(k)} | \lambda_j)}{T_i^{(k)}}$$

$$D_s(\lambda_1, \lambda_2) = \frac{1}{2} \{D(\lambda_1, \lambda_2) + D(\lambda_2, \lambda_1)\}$$

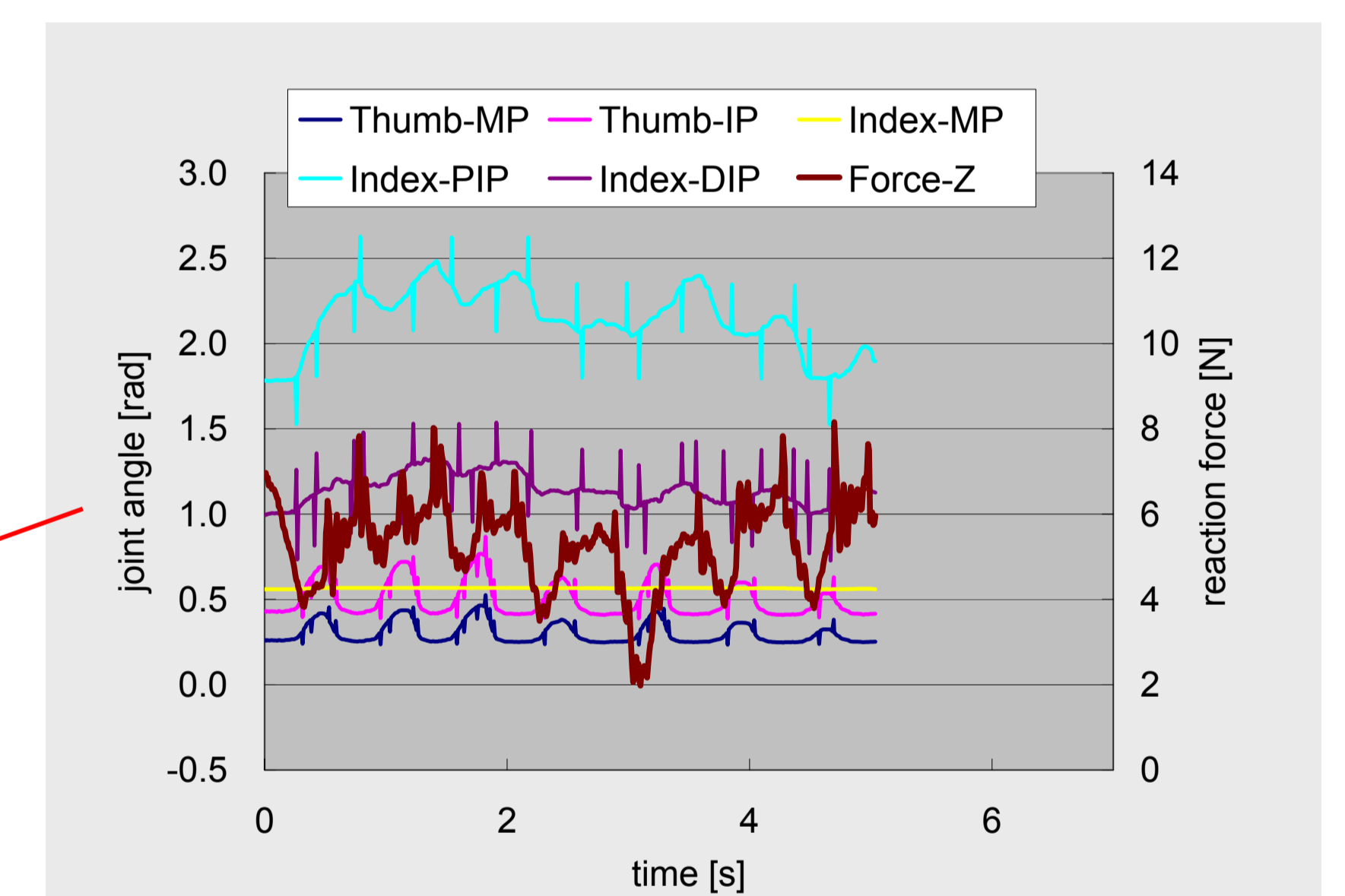
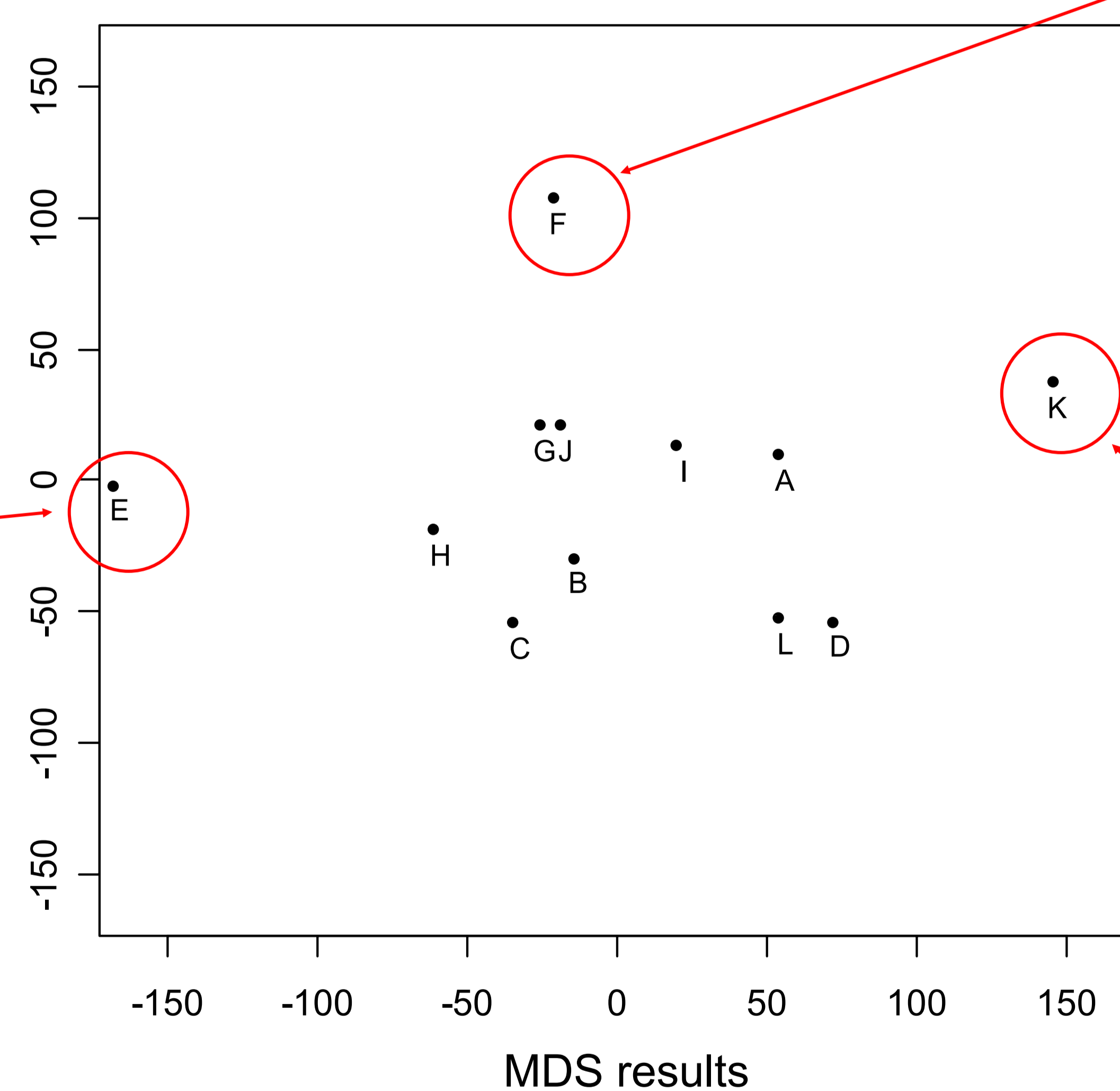
$O_i^{(k)}$ :  $k$ -th observation sequence of  $i$ -th operator  
 $p(O_i^{(k)} | \lambda_j)$ : likelihood of  $O_i^{(k)}$  by HMM  $\lambda_j$   
 $T_i^{(k)}$ : length of  $O_i^{(k)}$   
 $K$ : number of observation sequences

## Metric multidimensional scaling (MDS)

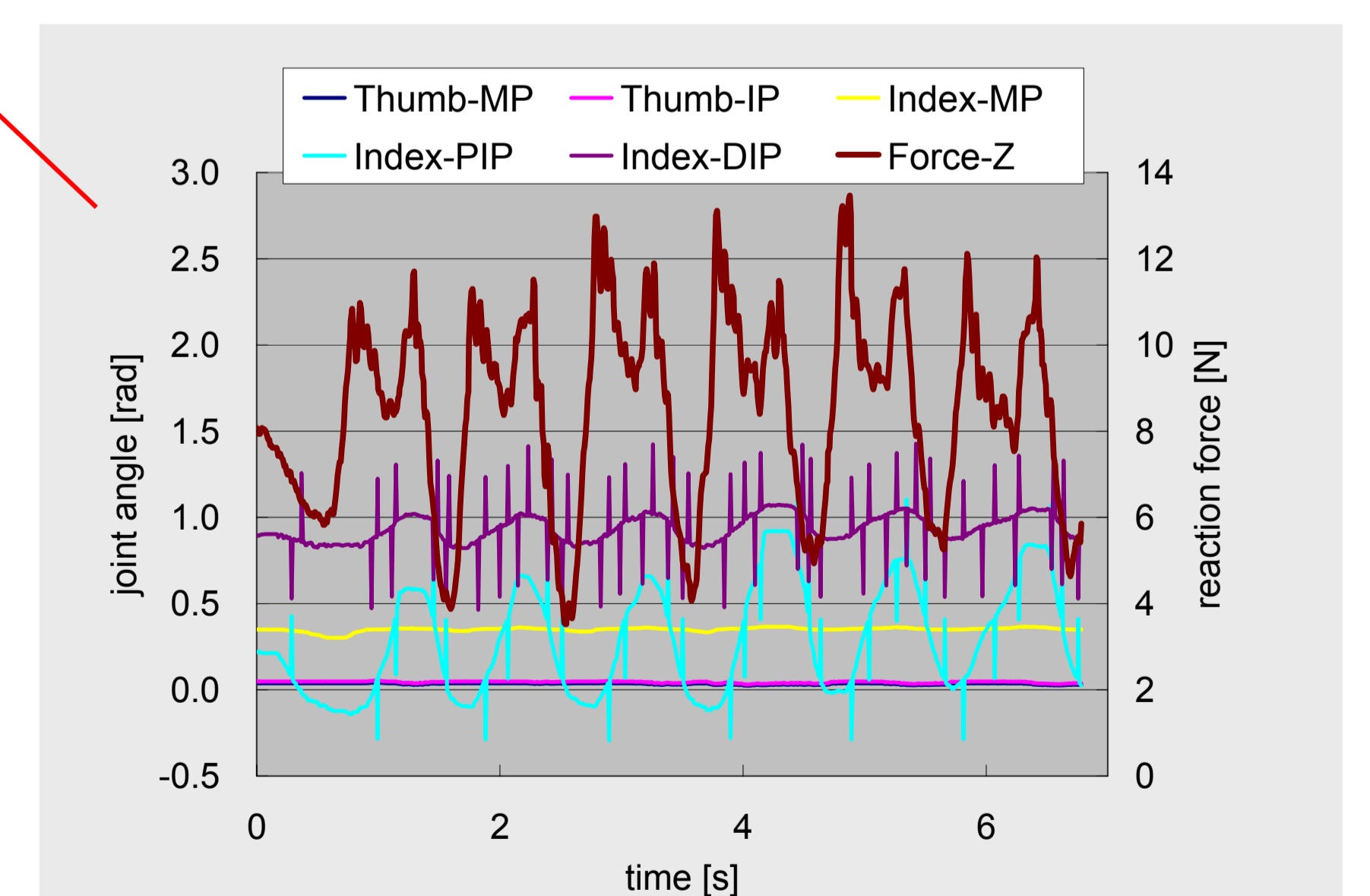
- Plot HMMs on a plane to grasp dissimilarities easily
- Features of individual manipulation are reflected in the plot



Operator E (typical)  
• fastest manipulation



Operator F (typical)  
• minimal use of MP flexion/extension of index finger



Operator K (typical)  
• slowest manipulation

# Conclusion

## Summary

- An MDL-based hidden Markov modeling of human dexterous manipulation
  - applied to human pivoting operations
- Dissimilarity analysis that can be used to validate models of the internal mechanism behind human dexterity

## Future work

- CPG-based modeling of human pivoting operations and its validation

