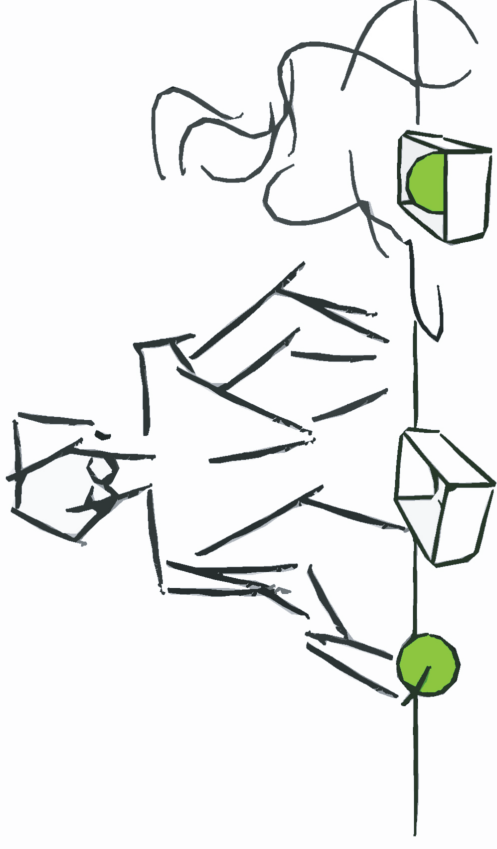# Incremental Learning of Full Body Motions

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Learning from Observation for Humanoids

- Learn to accomplish tasks by observing a human teacher, rather than programming or trajectory planning

- Take advantage of similar structure between human and robot

- Suitable for non-expert demonstrators

Related Work

[Ikeuchi et al. 2004] HRP-2 at AIST

[Calinon and Billard 2007] HOAP at EPFL

Limitations of the current approaches

- Motions are specified manually by the designer

- In learning systems, motions are segmented and clustered a-priori

- Off-line, one-shot training

- No further learning during the execution stage

Desired System

- A robot that cohabits with humans, and learns incrementally over a lifetime of observations

- A robot that accumulates knowledge and improves performance over time

- Fully autonomous, on-line, continuous learning

System Requirements:

- Autonomous Motion Segmentation

- Autonomous, On-line Motion Clustering

- Autonomous Knowledge Management with fast Retrieval

Talk Outline

- Robot Learning from Observation

- Representing full-body Motion

  - On-line Segmentation

  - On-line Clustering and Organization

  - Combining Segmentation and Clustering

  - Learning the sequencing of motion primitives

  - On-line correction of clustering errors

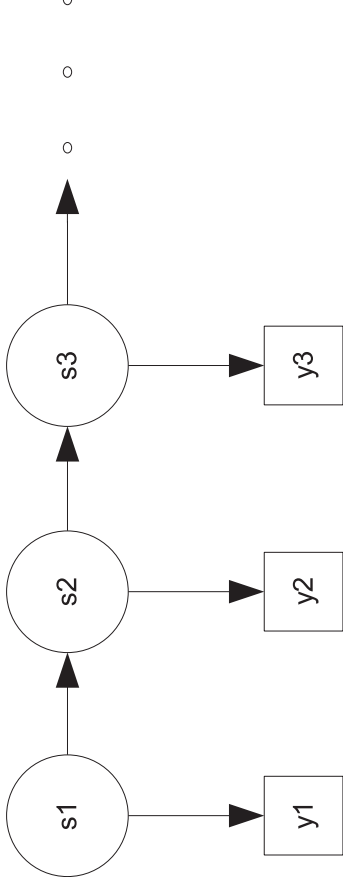- Conclusions and Directions for Future Work

Learning from Observation - *Mirror Neurons*

The same neural structure is used for both recognition and generation [Rizzolatti et al. 2001]
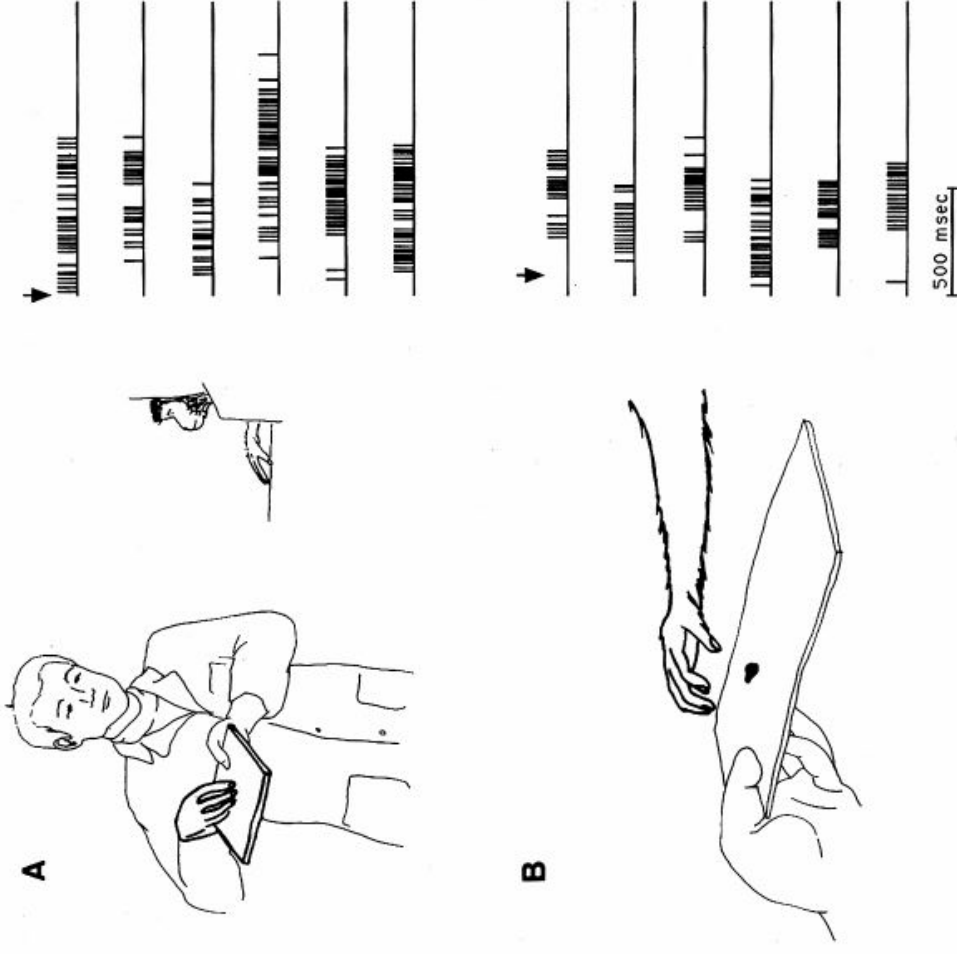
Motion Representation by Hidden Markov Models
[Inamura et al. 2004]

s1 → s2 → s3

s1 → y1
s2 → y2
s3 → y3

- Stochastic model capturing both spatial and temporal variability

- Model training (learning) is implemented with the Baum-Welch Algorithm

- Once the model is trained, the same model can be used for both
  - Recognition (Forward Procedure)
  - Generation (either stochastic or deterministic)

- Factorial HMMs also used for representing motions with greater accuracy [Kulic et al. 2007]

Stochastic Segmentation

[Kohlmorgen and Lemm, 2001]
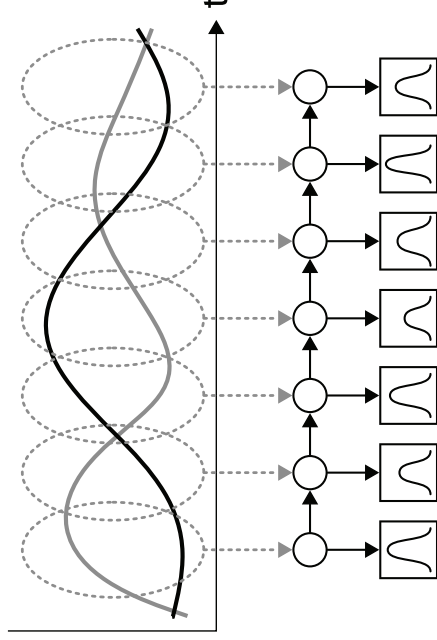
- Layout a set of windows over recently observed data

- Estimate the density distribution in each window

- Compute the distance between windows based on integrated square error

- Define an HMM over the set of windows

- Use Viterbi algorithm to generate the optimum state sequence representing the segmentation result

- If known motions are available, generate known states and bias the model towards them [Kulić and Nakamura, 2008]

On-line clustering and hierarchy formation

- Use HMM representation to abstract motion patterns as they are perceived

- Cluster individual motion patterns incrementally, based on intra-model distances

- Use formed clusters to form group models

- Autonomously select appropriate model type, based on model distances in the considered region of the motion space
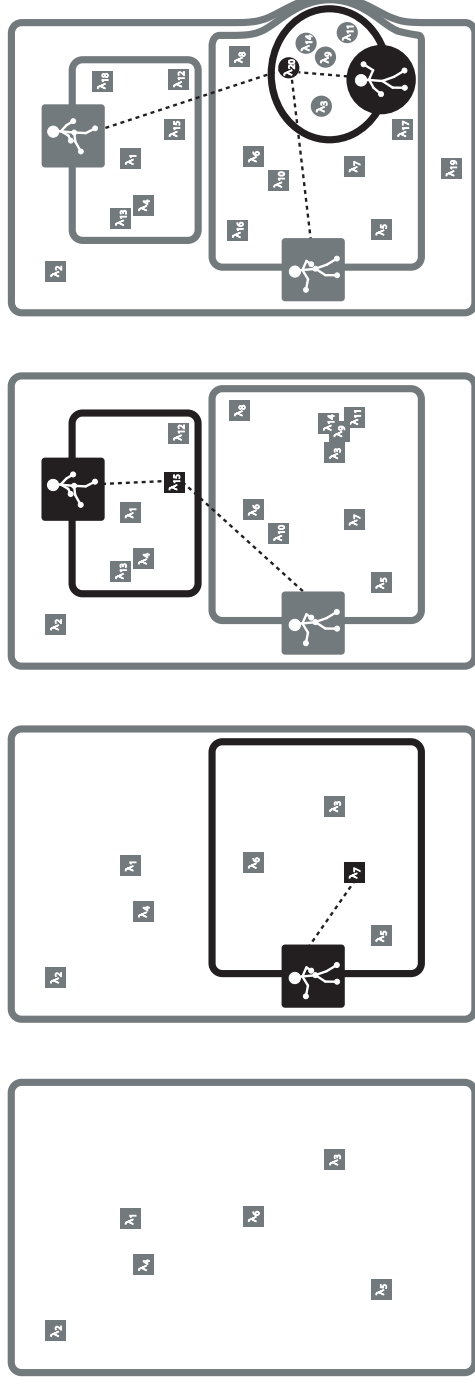
Algorithm Pseudo-Code

Following observation of each motion sequence:
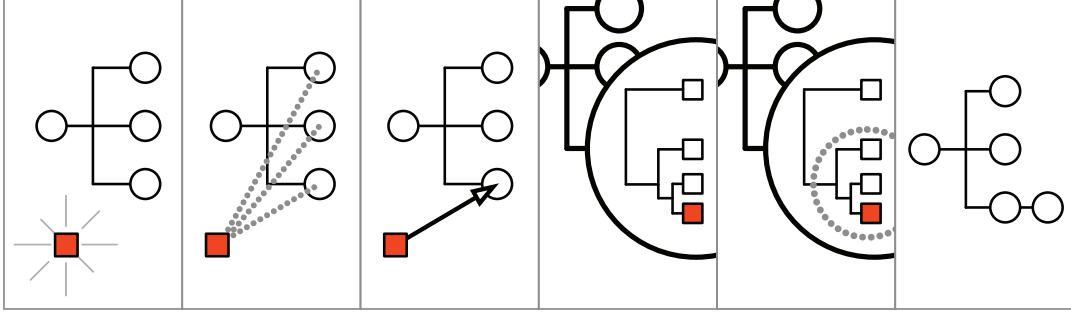
Step1 Encode observation sequence O_i into an HMM λ_i

Step2 Calculate the distance between λ_i and each existing behavior group model λ_{Gj}

Step3 Place λ_i into the closest group G_c

**Step4** Cluster all exemplars within G_c

Step5 If a sub-group forms, form a new node G_n, containing the exemplars of the cluster

Step6 Using the observation sequences from the exemplars in G_n, form the new sub-group model λ_{Gn}

Combining segmentation and Clustering

```
1: procedure COMBINEDSEGMENTATIONANDCLUSTERING
2:     while 1 do
3:         Observe Data Point
4:         call ONLINEVITERBISCAFFOLDED
5:         if SegPoint then
6:             if ISVALID(Segment) then
7:                 call INCREMENTALCLUSTER
8:                 if ISVALID(NewMotion) then
9:                     Add/Replace new motion as permanent state
10:                 end if
11:             end if
12:         end if
13:     end while
14: end procedure
```

Experiments
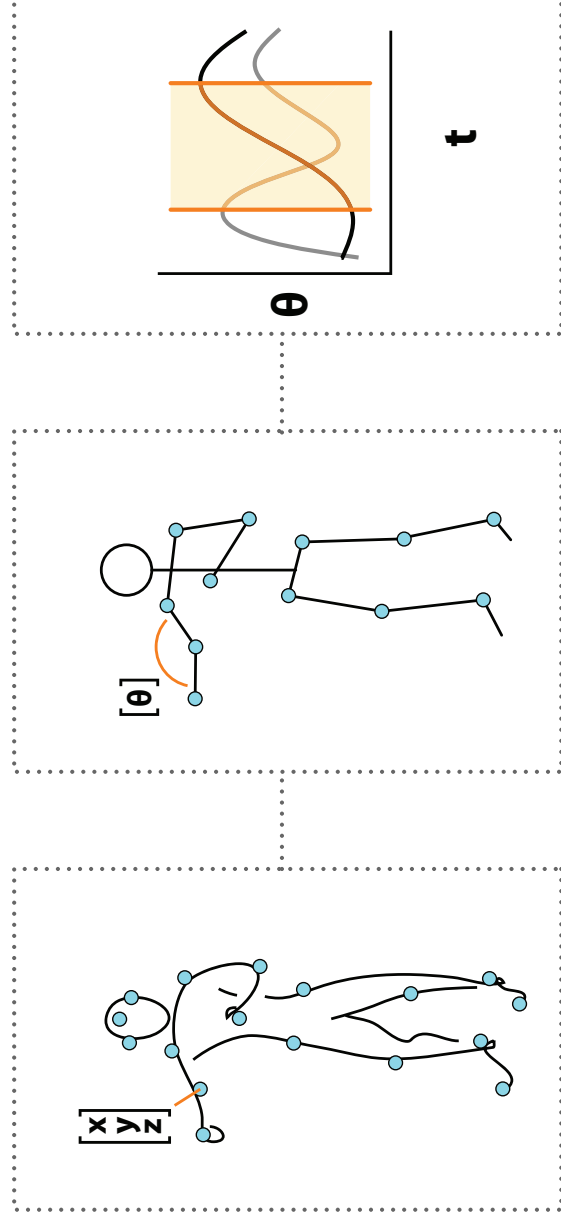
- 4 minutes of continuous whole body motion data of a single subject from motion capture data

- data is converted to a 20DoF humanoid model by online inverse kinematics

- First, test the basic segmentation algorithm, with no known states, and compare with manual segmentation

Testing the Segmentation
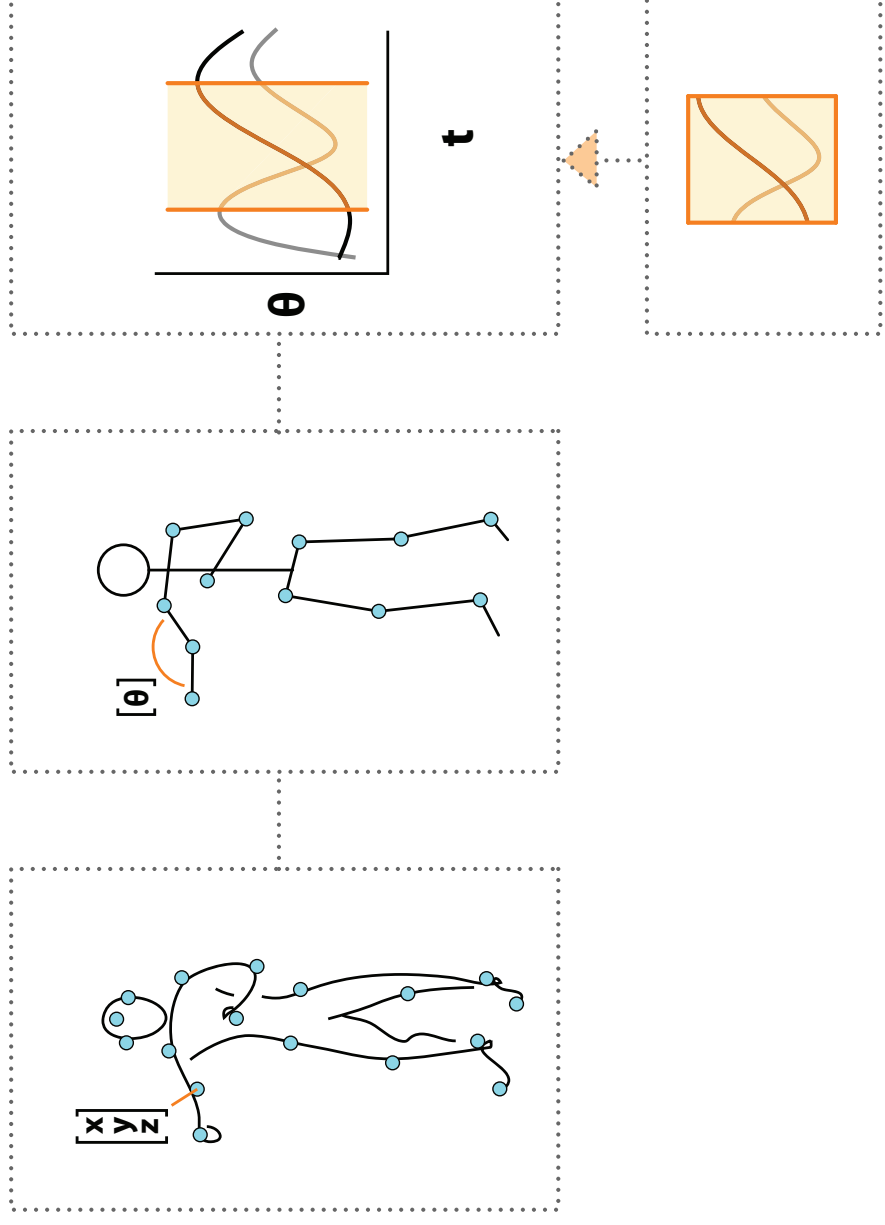
- Next, test the improvements obtained through adding known motions
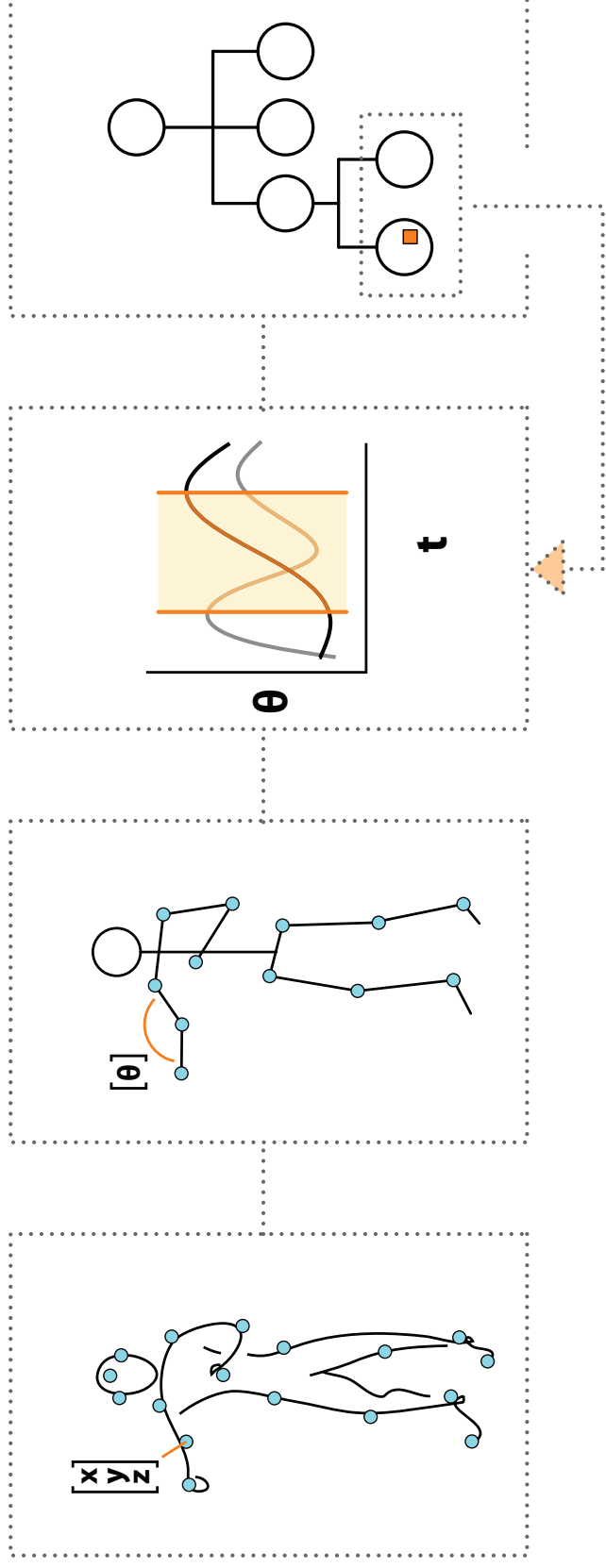- Provide manually extracted primitives as exemplars

Segmentation Results
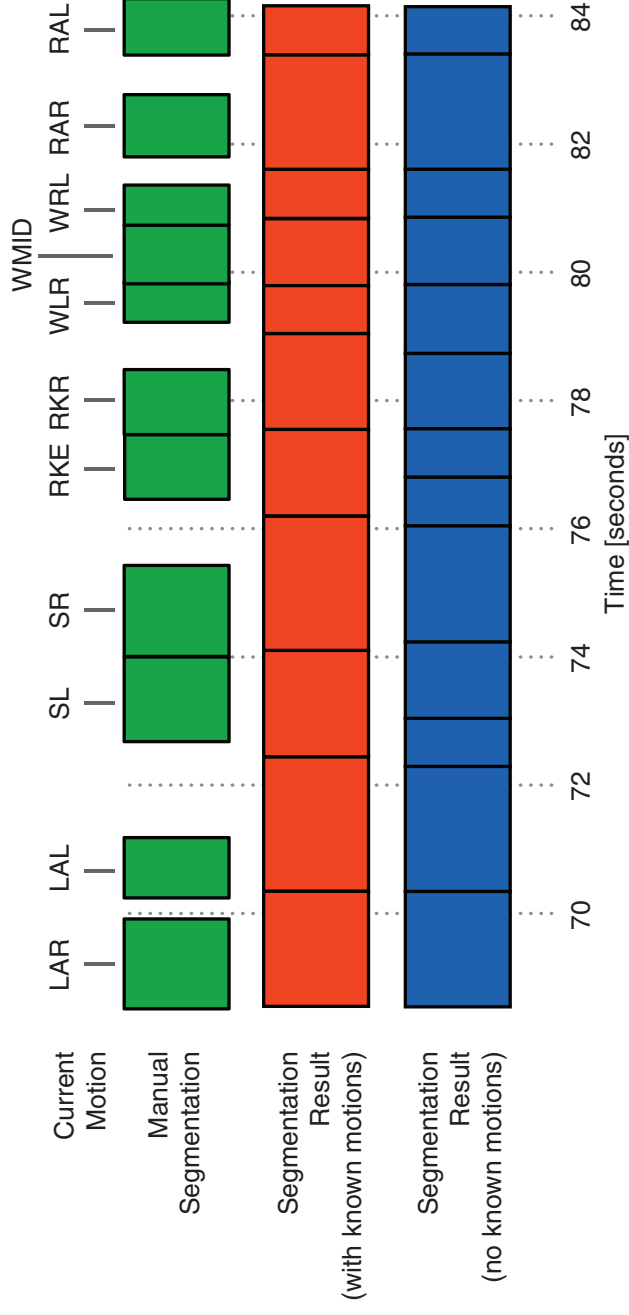
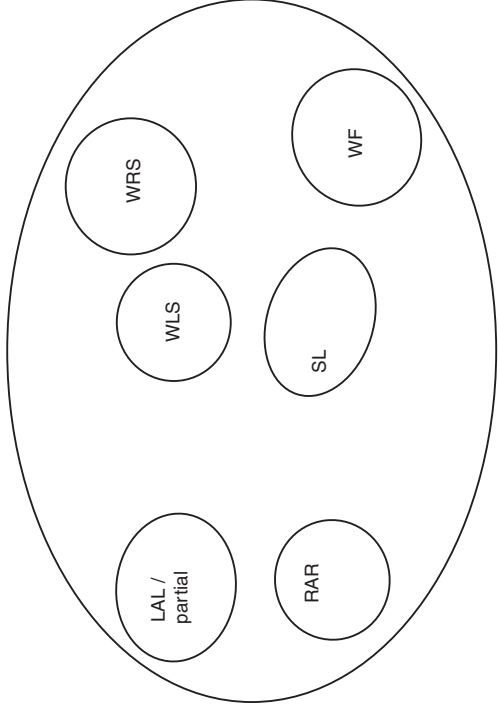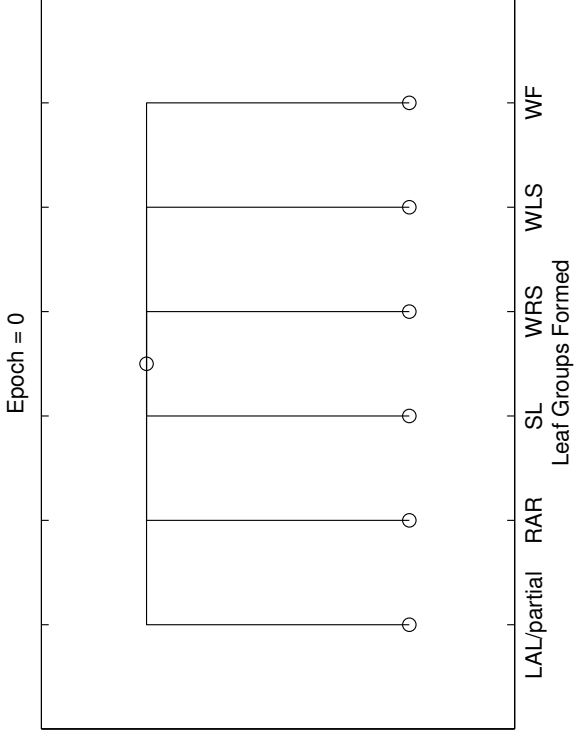| Algorithm	Correct	False Pos	False Neg
Basic	128	65	43
Scaffolded (with Squat and Kick)	139	59	32

■ Worst performance occurs at switching points where few joints are moving

Sample Video
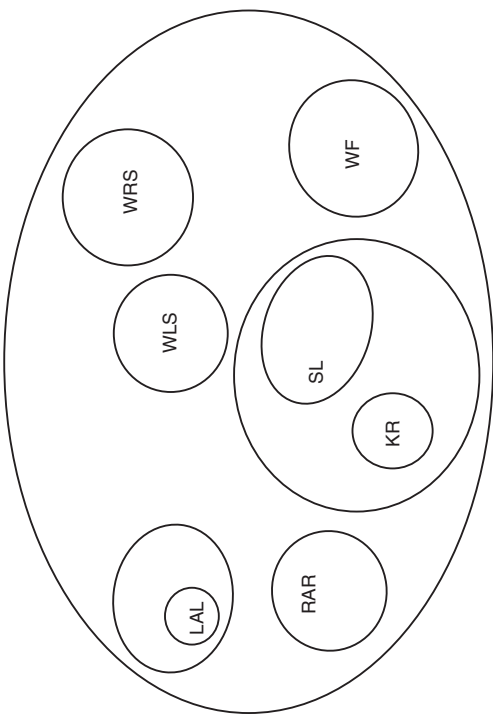
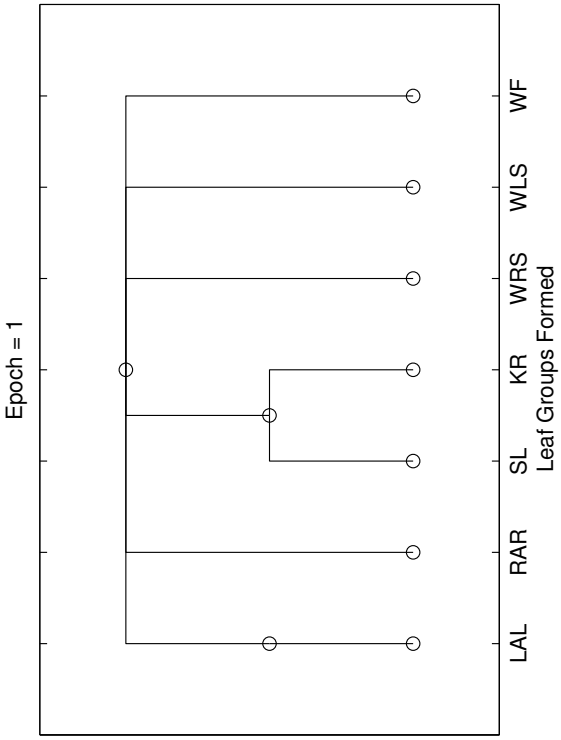# *Testing the Combined Segmentation and Clustering*

- Present the complete 4min sequence and apply segmentation

- The leaf nodes of the resulting tree are used to scaffold the segmentation

- To facilitate analysis, 4min sequence is presented repeatedly (epochs), and new exemplars are added to the segmentation module at the end of each epoch
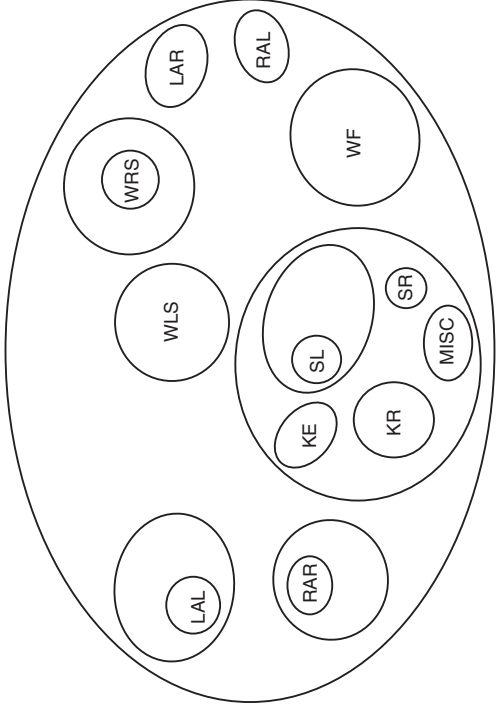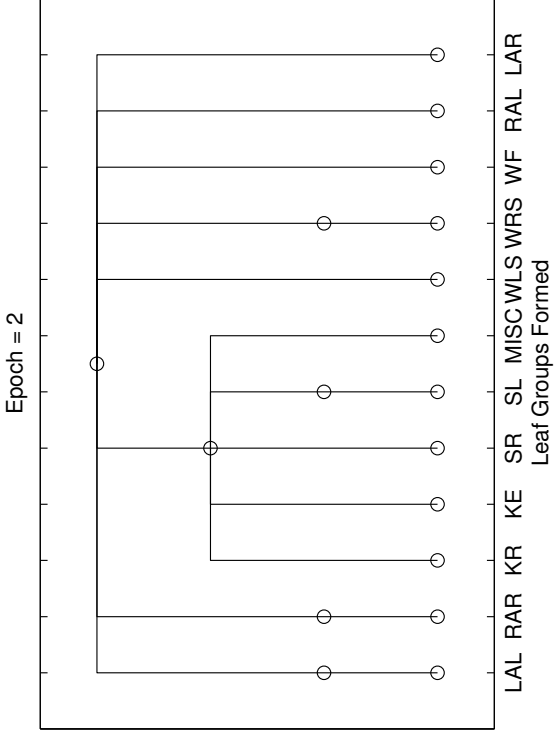
After Epoch 1

Epoch = 0

LAL/partial   RAR   SL   WRS   WLS   WF
Leaf Groups Formed

WRS   WLS   WF   SL   LAL / partial   RAR

Example Extracted Motion: Right Arm Raise

After Epoch 2

Epoch = 1

LAL RAR SL KR WRS WLS WF

Leaf Groups Formed

WRS WLS WF SL KR LAL RAR

Example Extracted Motion: Left Arm Lower

After Epoch 3

Epoch = 2

LAL RAR KR KE SR SL MISC WLS WRS WF RAL LAR
Leaf Groups Formed

Example Extracted Motion: Kick Extend, Squat Raise
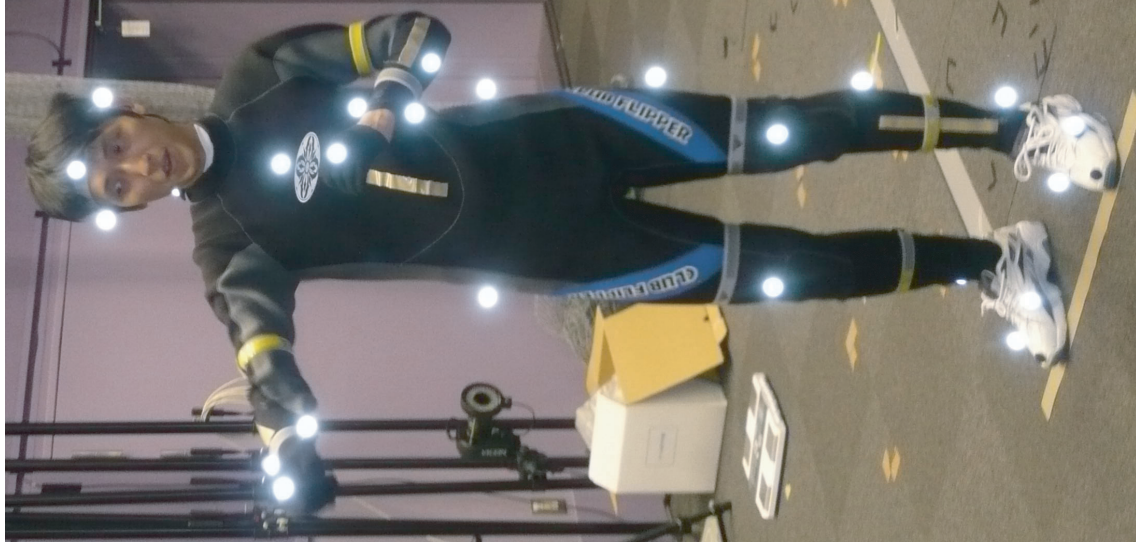
Motion Primitive Graph
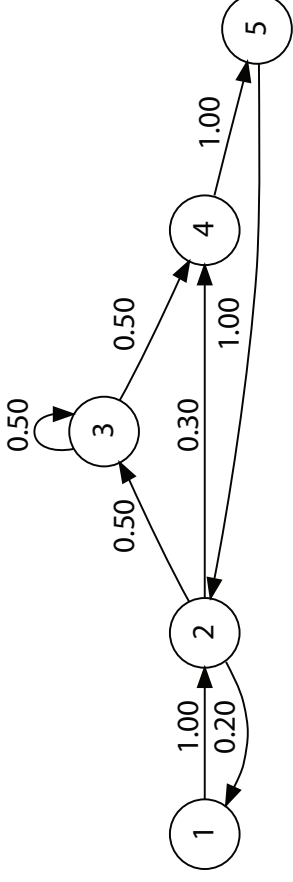
- At the same time as learning the motion primitives, learn the transition rules between primitives

- Each node in the motion primitive graph represents a motion primitive, while each edge represents an observed transition between two motion primitives

- Each time a new motion primitive is abstracted by the clustering algorithm as a leaf node, a corresponding node is added to the motion primitive graph.

- Each time a transition is observed between two known motions, the edge count is updated
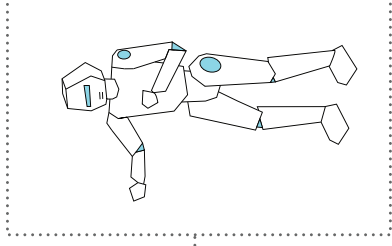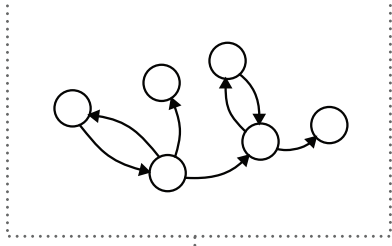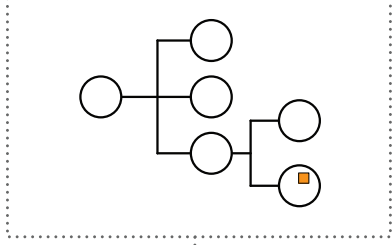
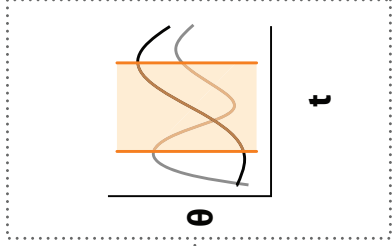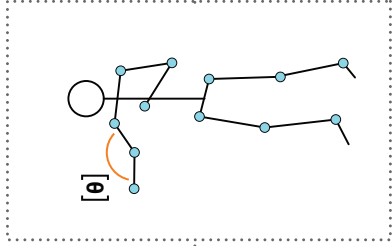# *Experiments with a Humanoid Robot*

Collected 16 min of continuous whole body motion data (26 different motion types) of a single subject from motion capture data

data is converted to a 32DoF humanoid model by online inverse kinematics

online feed to automated segmentation, clustering and motion graph extraction

Data Flow Diagram
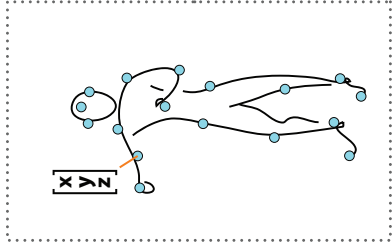
Robot Hardware and Control System

upper body   desired   base link   des. base link
joint angles   COG   height   orientation

Body orientation
optimization

COG
optimization

base link
angular velocity

cog vel.

COG Jacobian
based IK

right leg joint
velocity

$\int$

right leg joint angles

computation of
left leg joint angles

The Extracted Motion Primitive Tree

SQR MLR SQD LPR RKR AR BAL RAL LAL LAR RAR BAU BAD BAR MRL MMID LKR

Leaf Groups Formed
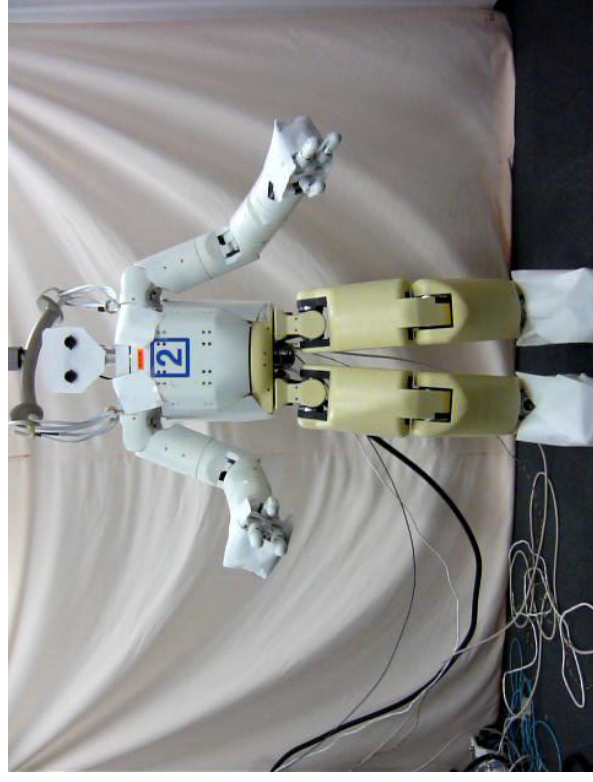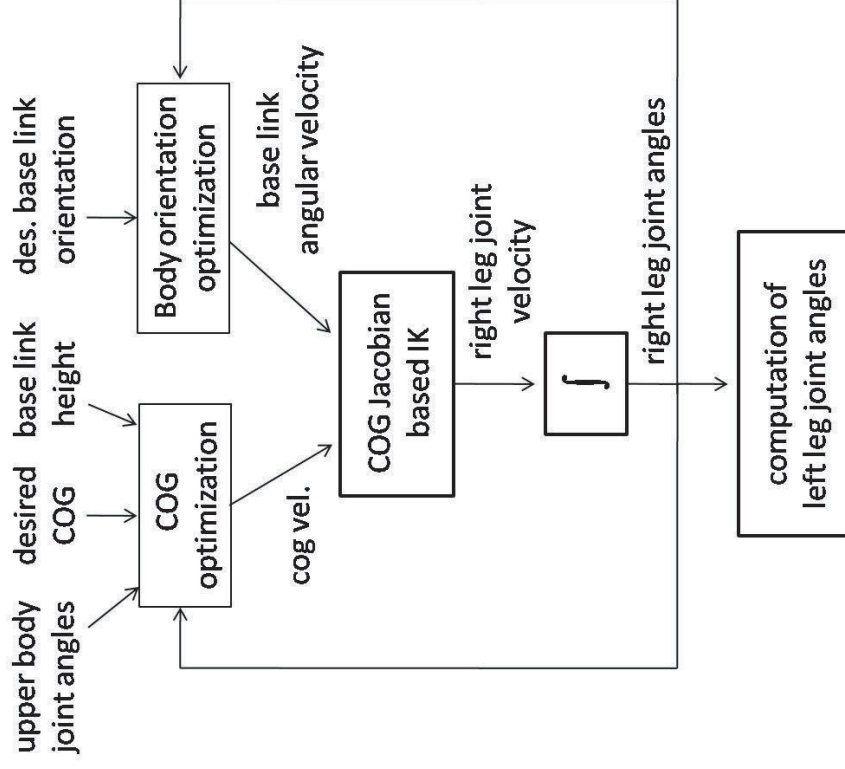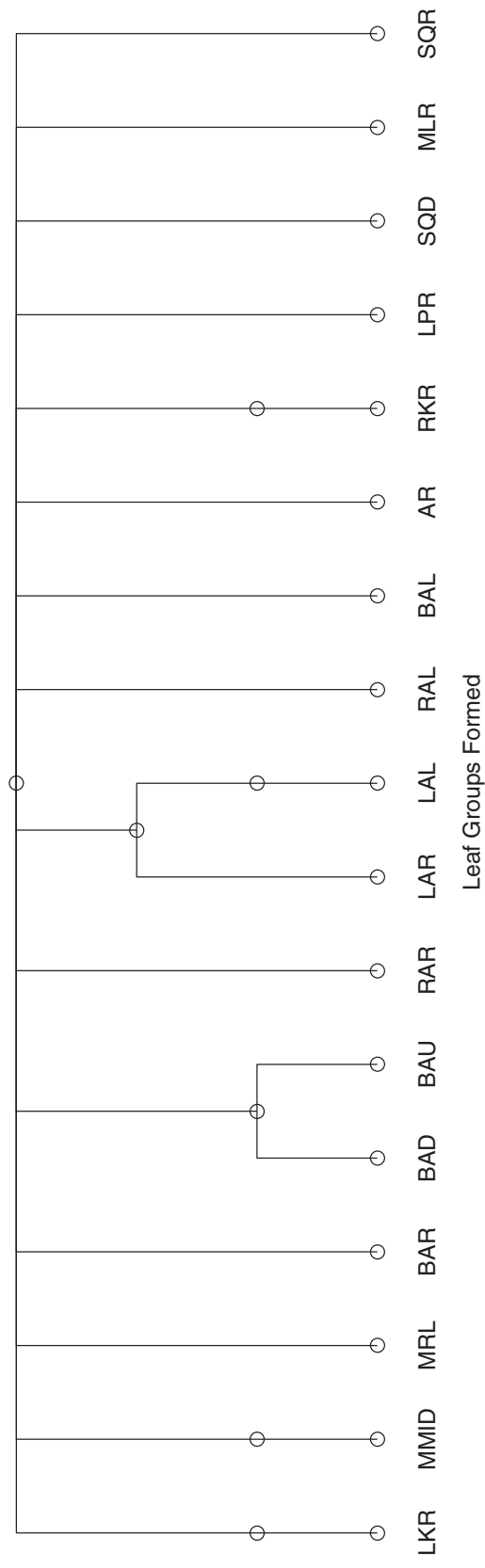
The Extracted Motion Primitive Graph
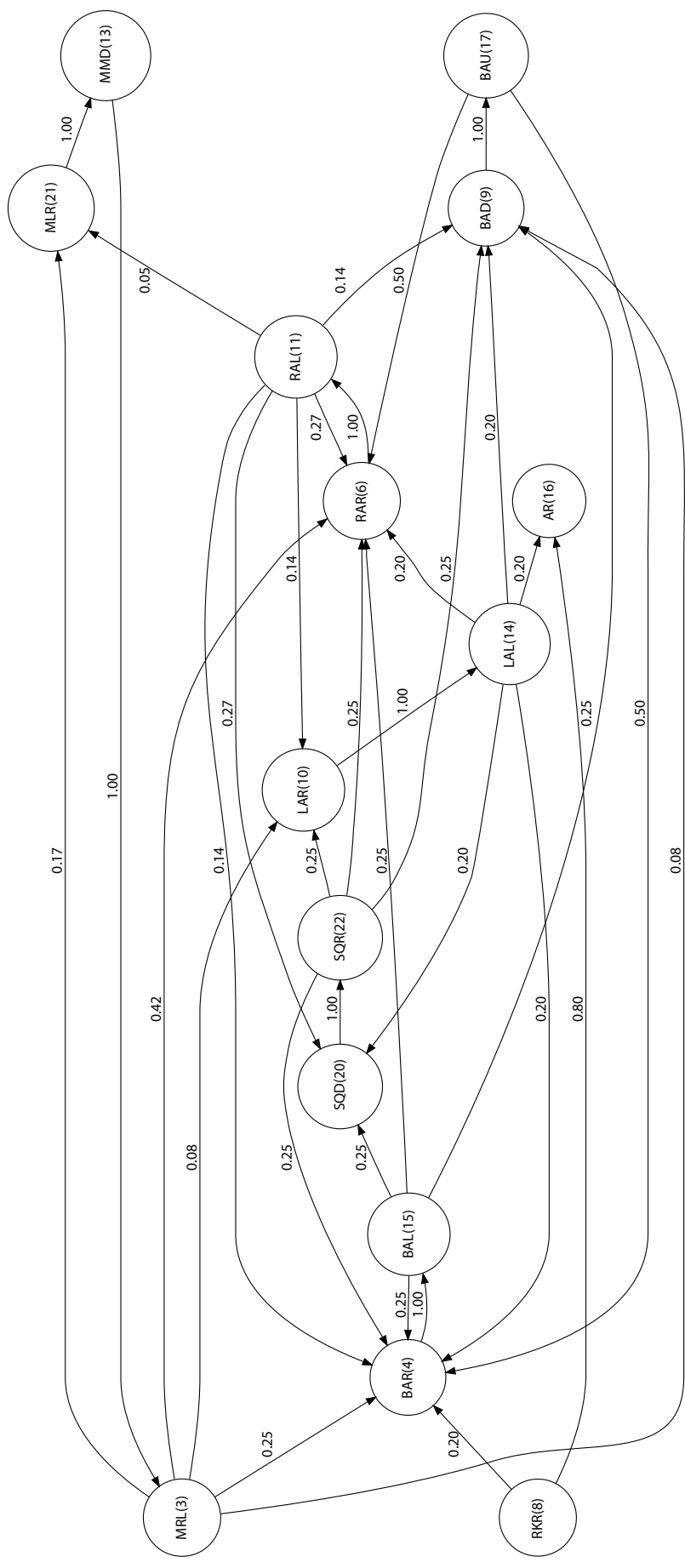
- Due to current hardware limitations of the robot, motions involving foot raising are manually removed from the graph

Robot Motion Generation

Video of Experiment

Summary on Automated Segmentation

- Autonomous, on-line segmentation of full body motion data, by building an HMM over a window of previous observations, and finding the optimum state sequence [Kohlmorgen and Lemm]

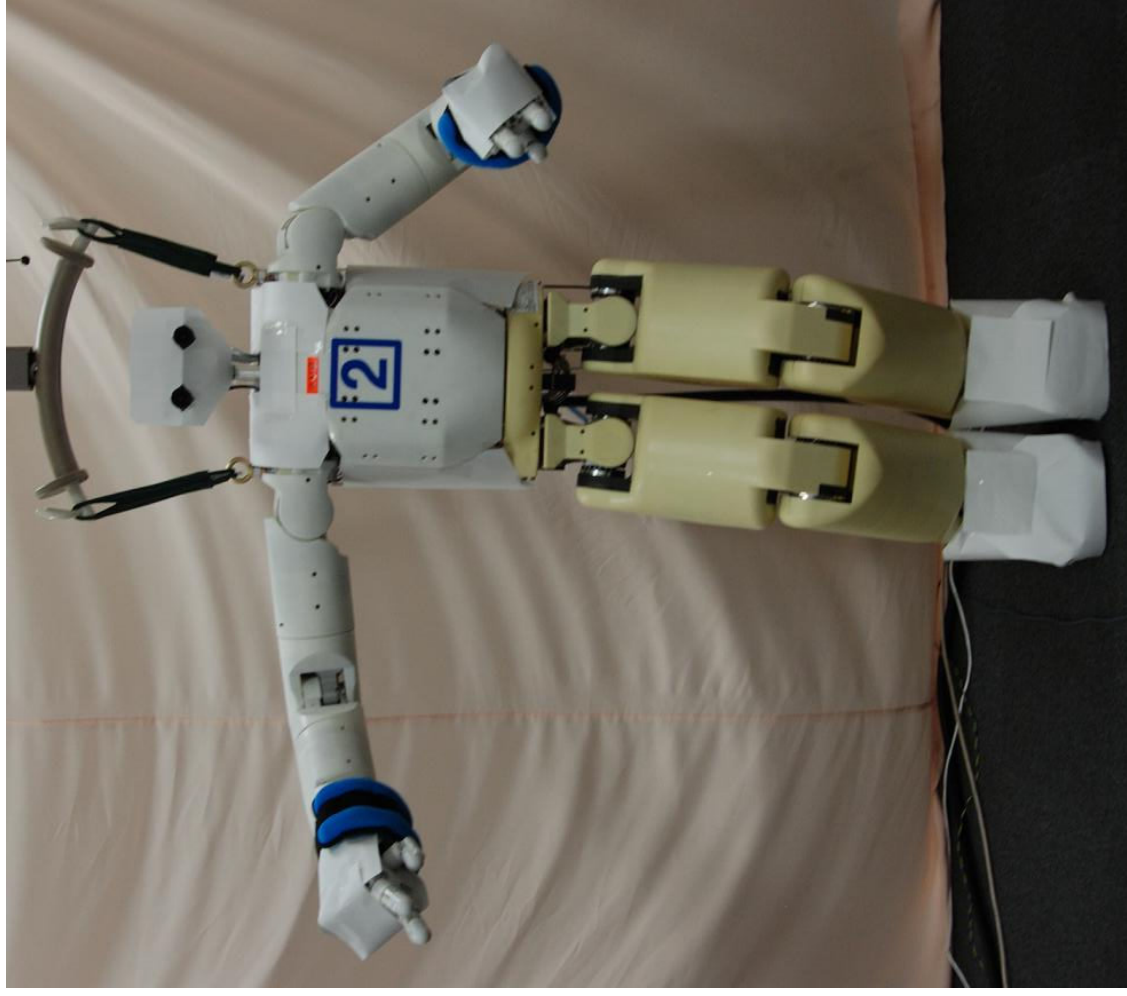- Input segments into automated incremental clustering algorithm for motion primitive extractions

- Improve segmentation results by scaffolding with known motion primitives obtained from the clustering

- As more motions become known, motion model and segmentation results become more accurate

- At the same time, learn the transition model of the motion primitives by constructing a motion primitive graph

Future Work

- Incorporating interaction with the environment

- Selecting the correct task representation

- Including additional learning modalities: learning from practice and interaction with the teacher

- Learning complex behaviors from the motion primitives

- Long term autonomous motor skill memory organization

References

D. Kulić, W. Takano and Y. Nakamura, Incremental Learning, Clustering and Hierarchy Formation of Whole Body Motion Patterns using Adaptive Hidden Markov Chains, International Journal of Robotics Research, Vol. 27, No. 7, pp. 761 - 784, 2008.

D. Kulić, D. Lee, C. Ott and Y. Nakamura, Incremental Learning of Full Body Motion Primitives for Humanoid Robots, IEEE International Conference on Humanoid Robots, 2008, Accepted for Publication.

D. Kulić and Y. Nakamura, Scaffolding On-line Segmentation of Fully Body Human Motion Patterns, IEEE International Conference on Intelligent Robots and Systems, pp. 2860 - 2866, 2008.

D. Kulić and Y. Nakamura, Incremental Learning and Memory Consolidation of Whole Body Motion Patterns, International Conference on Epigenetic Robotics, pp. 61 - 68, 2008.

D. Kulić, W. Takano and Y. Nakamura, Combining Automated On-Line Segmentation and Incremental Clustering for Whole Body Motions, IEEE International Conference on Robotics and Automation, pp. 2591 - 2598, 2008.

D. Kulić, W. Takano and Y. Nakamura, Towards Lifelong Learning and Organization of Whole Body Motion Patterns, International Symposium of Robotics Research, pp. 113 - 124, 2007.

D. Kulić, W. Takano and Y. Nakamura, Incremental Learning of Full Body Motions via Adaptive Factorial Hidden Markov Models, International Conference on Epigenetic Robotics, pp. 69 - 76, 2007.

D. Kulić, W. Takano and Y. Nakamura, Representability of Human Motions by Factorial Hidden Markov Models, IEEE International Conference on Intelligent Robots and Systems, pp. 2388 - 2393, 2007.

D. Kulić, W. Takano and Y. Nakamura, Incremental On-line Hierarchical Clustering of Whole Body Motion Patterns, IEEE International Symposium on Robot and Human Interactive Communication, pp. 1016 - 1021, 2007.

The End

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