Incremental learning of full-body human motion primitives for humanoid robots

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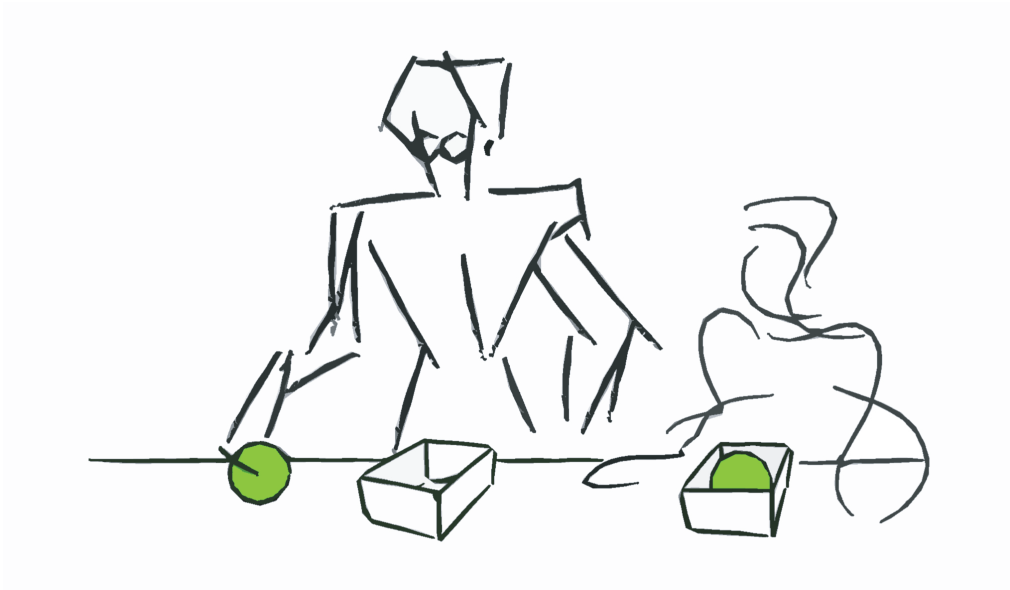
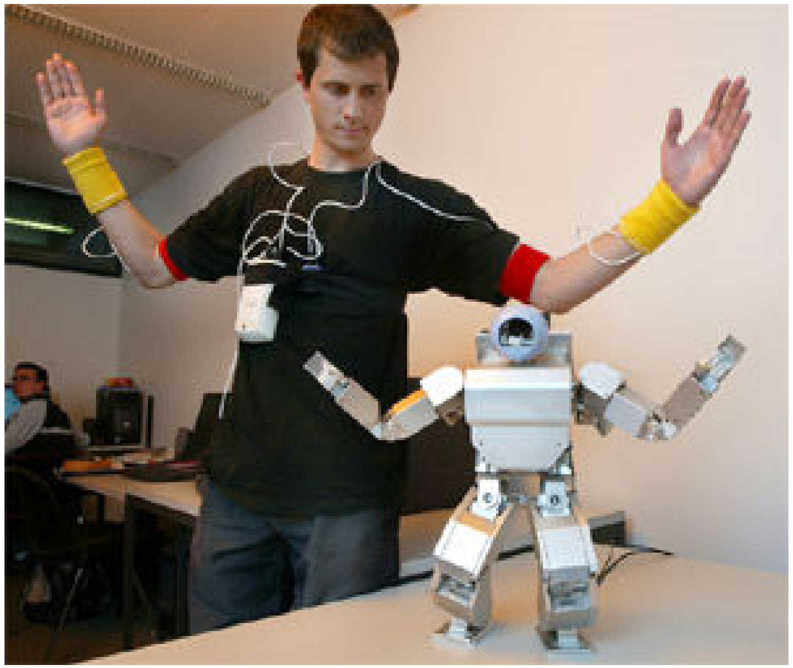
Learning from Observation for Humanoids



- 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



[Calinon and Billard 2007] HOAP at EPFL

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

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:

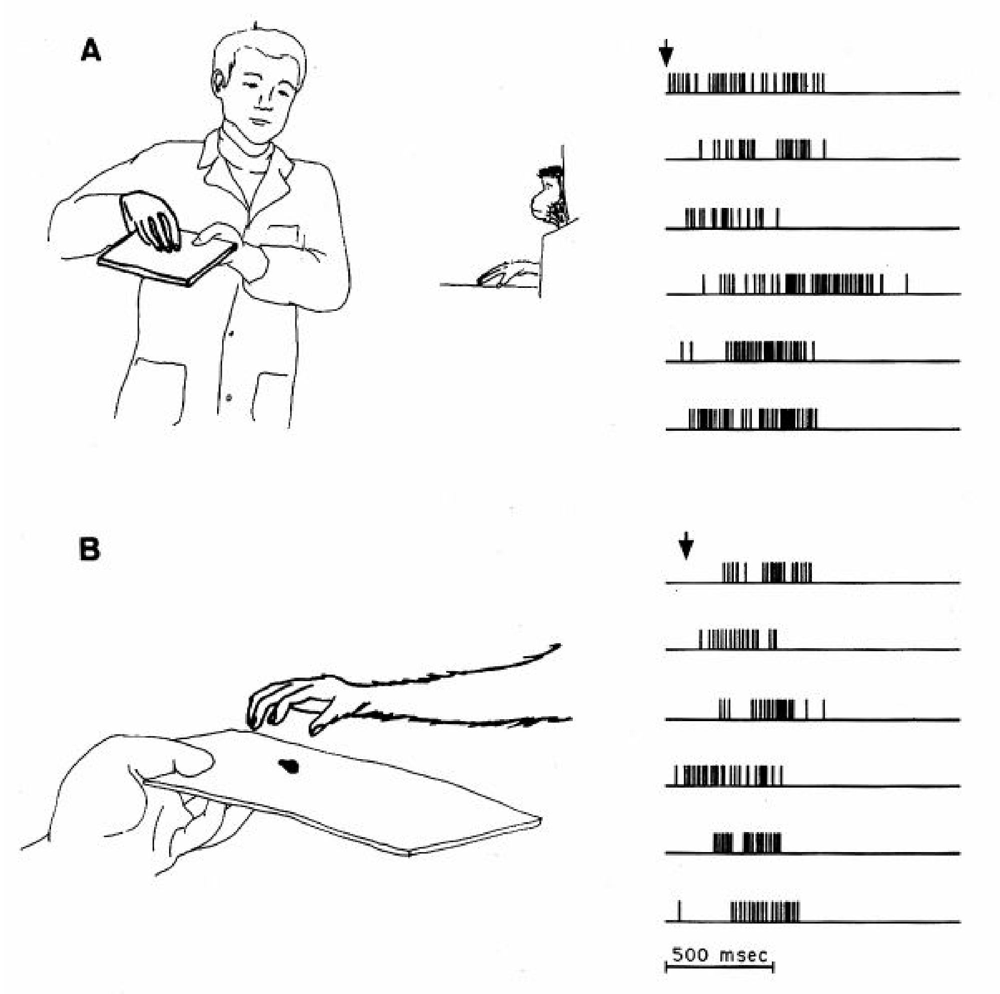
- Autonomous Motion Segmentation
- Autonomous, On-line Motion Clustering
- Autonomous Knowledge Management with fast Retrieval

Talk Outline

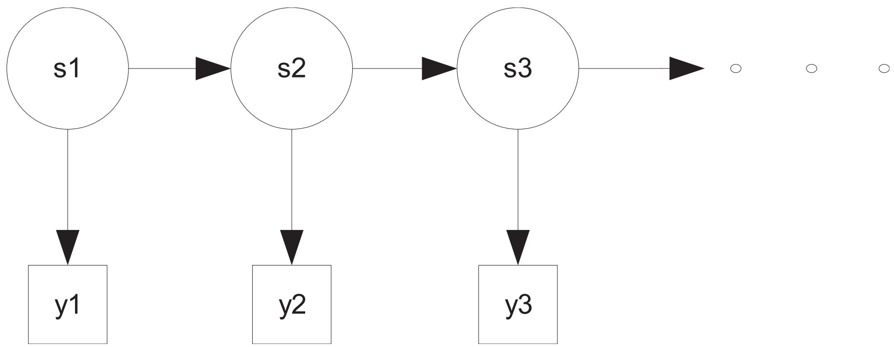
- Robot Learning from Observation
  - Representing full-body Motion
  - On-line Segmentation
  - On-line Clustering and Organization
  - Combining Segmentation and Clustering
  - Learning the sequencing of motion primitives
- Conclusions and Directions for Future Work

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]

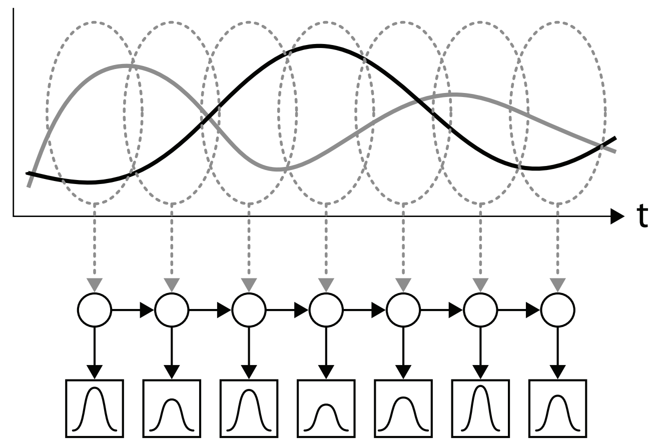


- Stochastic model capturing both spatial and temporal variability
- Model training (learning) is implemented with the Baum-Welch Algorithm
- Once the model is trained, the same model can be used for both
  - Recognition (Forward Procedure)
  - Generation (either stochastic or deterministic)
- Factorial HMMs also used for representing motions with greater accuracy [Kulić et al. 2007]

On-line Segmentation

- Want to segment with no a-priori knowledge of the motions
- Must make some assumption about the structure of the data
  - Mean velocity falls below a certain value [Pomplun and Matarić, 2000]
  - Zero velocity crossing in some dimensions [Fod et al., 2002]
  - Minimize variance [Koenig and Matarić, 2006]
  - Same motion will belong to same underlying distribution [Kohlmorgen and Lemm, 2001] [Janus and Nakamura, 2005]

Stochastic Segmentation [Kohlmorgen and Lemm, 2001]



Embed the data into a higher-dimensional space

$$\vec{x_t} = (\vec{y_t}, \vec{y_{t-1}}, \ldots, \vec{y_{t-(m-1)\tau}})$$

Estimate the density distribution over a sliding window of length W

$$p_t(\mathbf{x}) = \frac{1}{W}\sum_{w=0}^{W-1}\frac{1}{(2\pi\sigma^2)^{d/2}}exp(-\frac{(\mathbf{x}-\vec{x_{t-w}})^2}{2\sigma^2})$$

Computing the distance between states

Can compute the distance between windows based on integrated square error between two pdfs

$$
\begin{aligned}
d(p_{t1}(\mathbf{x}), p_{t2}(\mathbf{x})) = {} & \frac{1}{W^2(4\pi\sigma^2)^{d/2}} \\
& \sum_{w,v=0}^{W-1} [exp(-\frac{(x_{\vec{t1-w}} - x_{\vec{t1-v}})^2}{4\sigma^2}) \\
& - 2exp(-\frac{(x_{\vec{t1-w}} - x_{\vec{t2-v}})^2}{4\sigma^2}) \\
& + exp(-\frac{(x_{\vec{t2-w}} - x_{\vec{t2-v}})^2}{4\sigma^2})
\end{aligned} \tag{1}
$$

Segmentation based on Viterbi Algorithm

Define an HMM over a set of sliding windows.

Observation Function:

$$p(p_t(\mathbf{x})|s) = \frac{1}{\sqrt{2\pi}\varsigma} exp(-\frac{d(p_s(\mathbf{x}), p_t(\mathbf{x}))}{2\varsigma^2})$$

State Transition Model:

$$a_{ij} = \begin{cases} \frac{k}{k+N-1} & \text{if } i = j; \\ \frac{1}{k+N-1} & \text{if } i \neq j. \end{cases}$$

Optimum state sequence (obtained via on-line Viterbi) represents the segmentation result

Improving the Segmentation

Bias state transition model towards known states

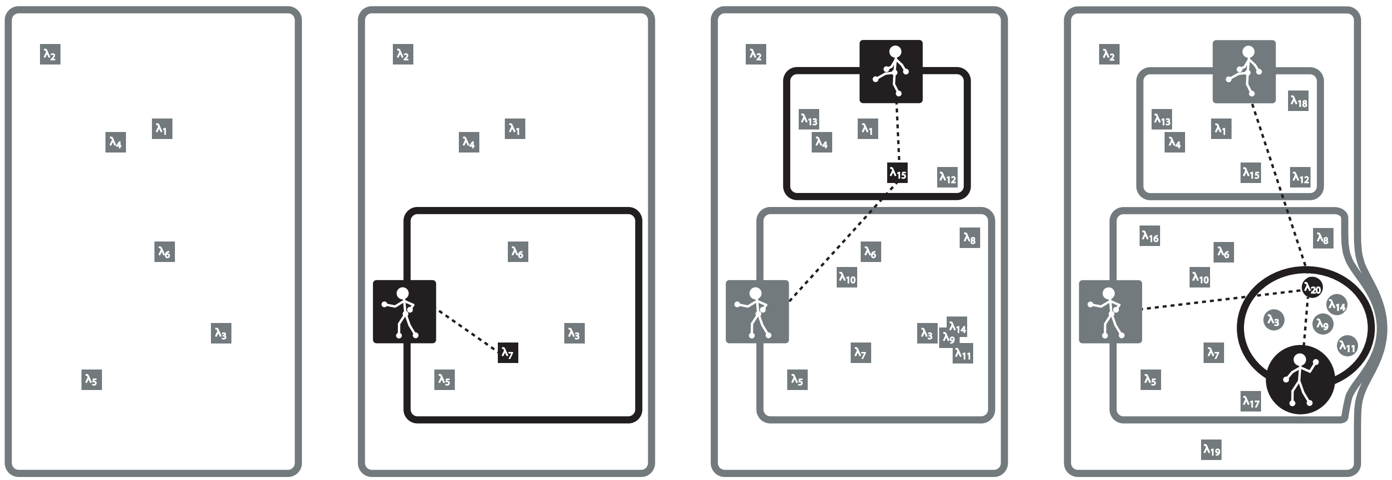
$$a_{ij} = \begin{cases} \frac{k}{C} & \text{if } i = j; \\ \frac{1}{C} & \text{if } i \neq j \text{ and } i \in \mathcal{S}_t; \\ \frac{K_s}{C} & \text{if } i \neq j \text{ and } i \in \mathcal{S}_p. \end{cases}$$

Modify pdf based on active joints in the known state

$$\begin{aligned} D_w(p_{t1}(\mathbf{x}), p_{t2}(\mathbf{x})) = & \frac{1}{L^2(4\pi\sigma_k^2)^{d/2}} \\ & \sum_{i,j=0}^{L-1} [exp(-\frac{W(\vec{x_{t1-i}} - \vec{x_{t1-j}})^2}{4\sigma_k^2}) \\ & - 2exp(-\frac{W(\vec{x_{t1-i}} - \vec{x_{t2-j}})^2}{4\sigma_k^2}) \\ & + exp(-\frac{W(\vec{x_{t2-i}} - \vec{x_{t2-j}})^2}{4\sigma_k^2}) \end{aligned} \quad (2)$$

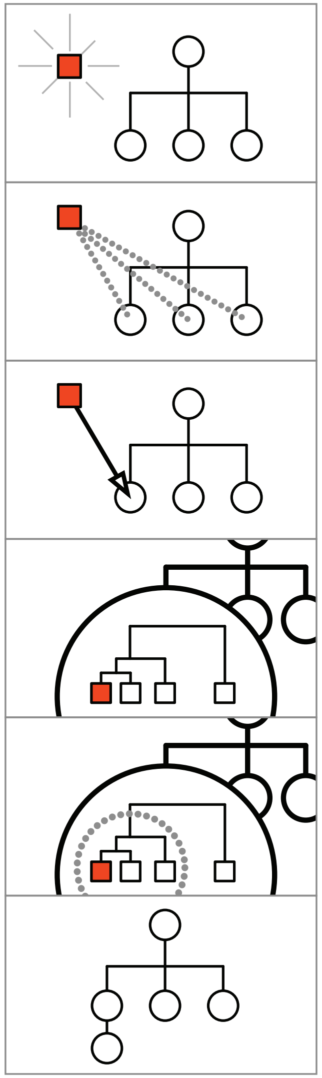
On-line clustering and hierarchy formation

- 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

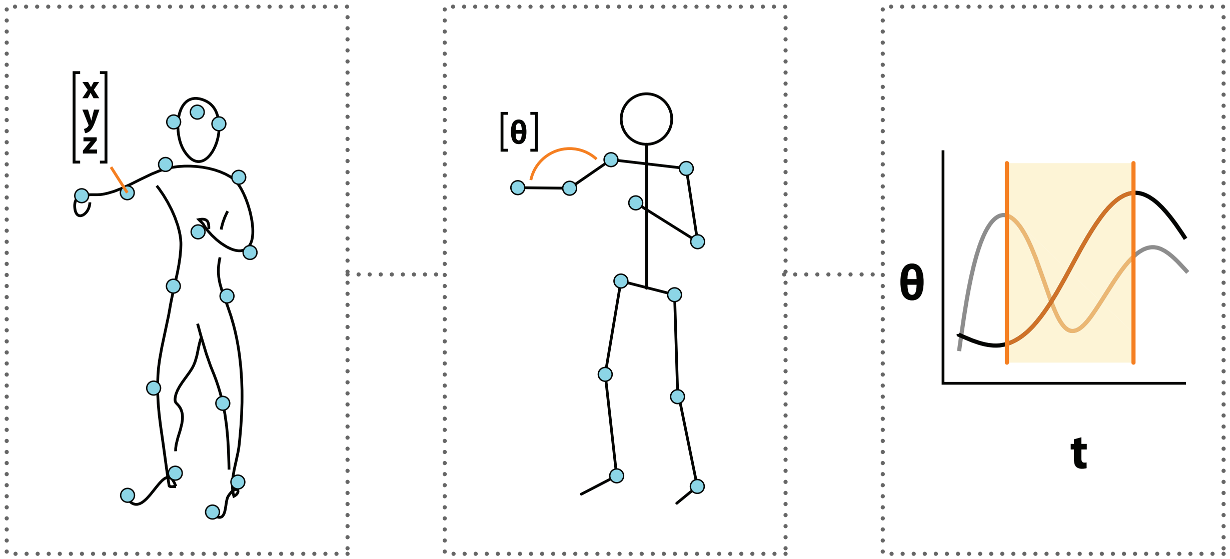
Step5 If a sub-group forms, form a new node G_n, containing the exemplars of the cluster

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

Combining segmentation and Clustering

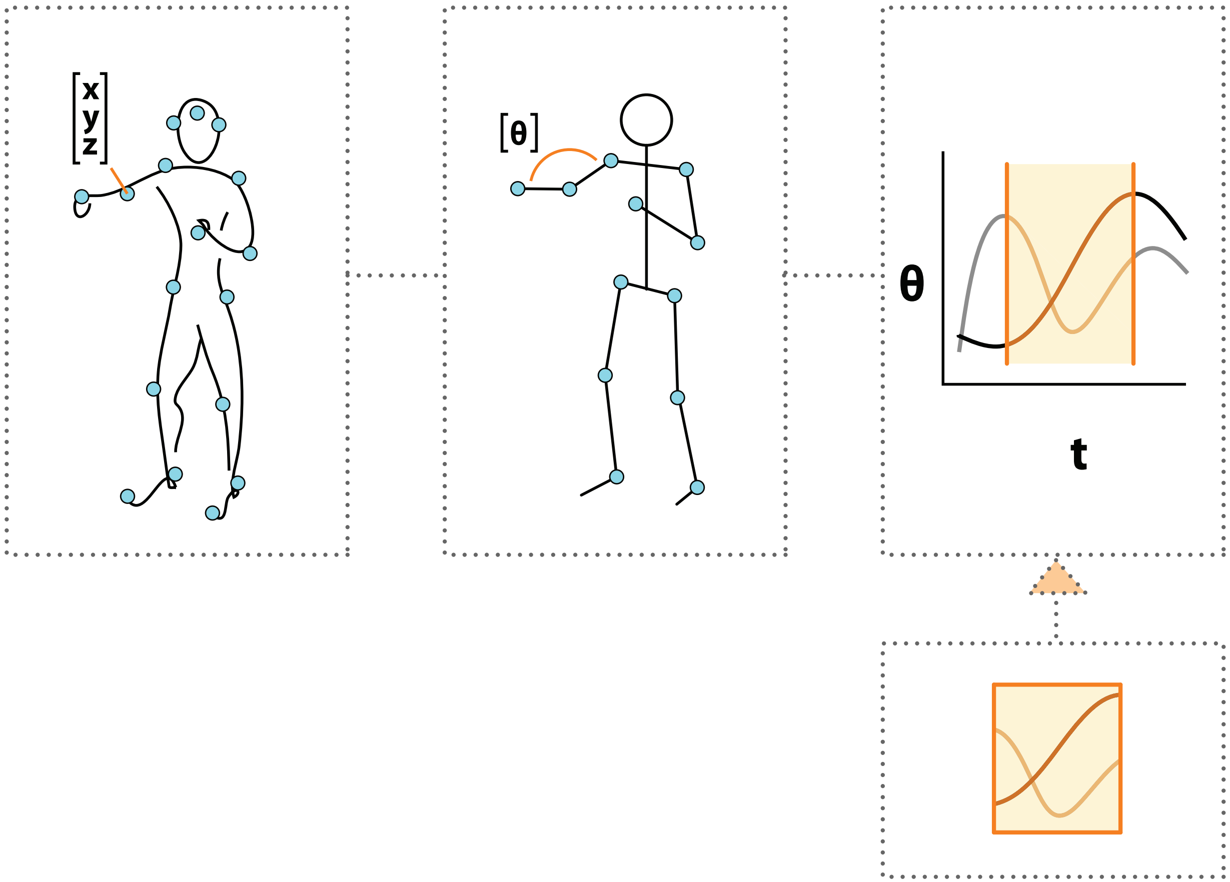
```
procedure CombinedSegmentationAndClustering
    while 1 do
        Observe Data Point
        call OnLineViterbiScaffolded
        if SegPoint then
            if IsValid(Segment) then
                call IncrementalCluster
                if IsValid(NewMotion) then
                    Add/Replace new motion as permanent state
                end if
            end if
        end if
    end while
end procedure
```

Experiments



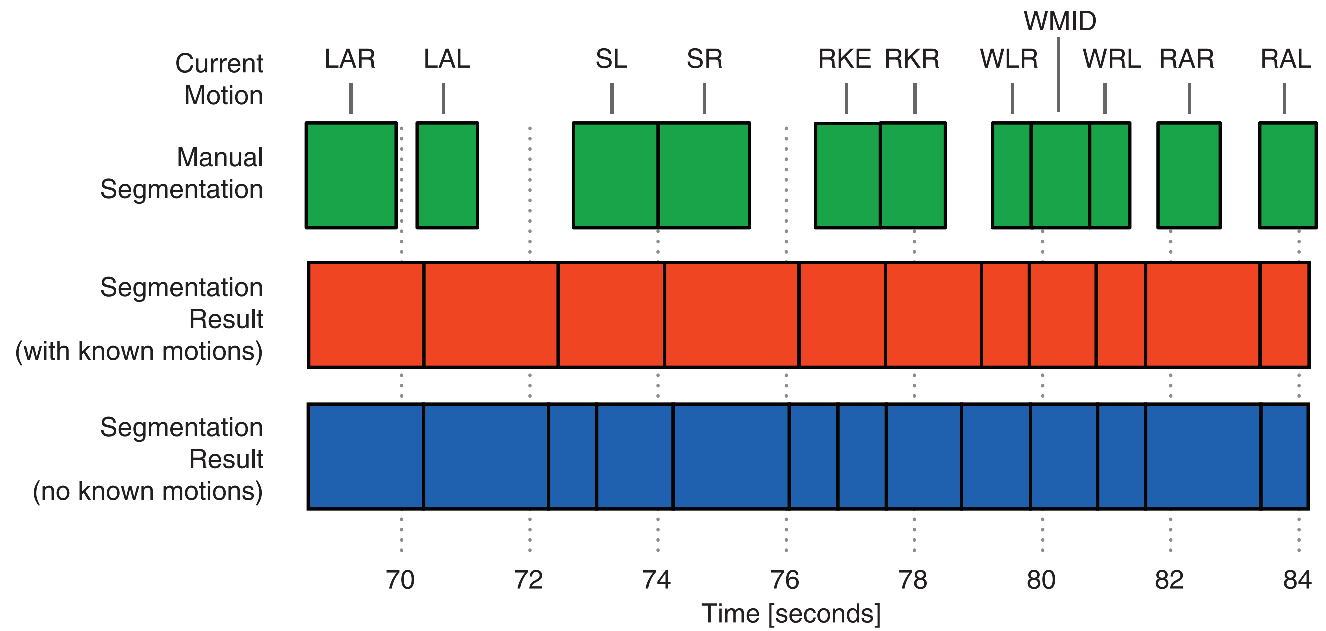
- 4 minutes of continuous whole body motion data of a single subject from motion capture data
- data is converted to a 20DoF humanoid model by online inverse kinematics
- First, test the basic segmentation algorithm, with no known states, and compare with manual segmentation

Testing the Segmentation



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

Segmentation Results

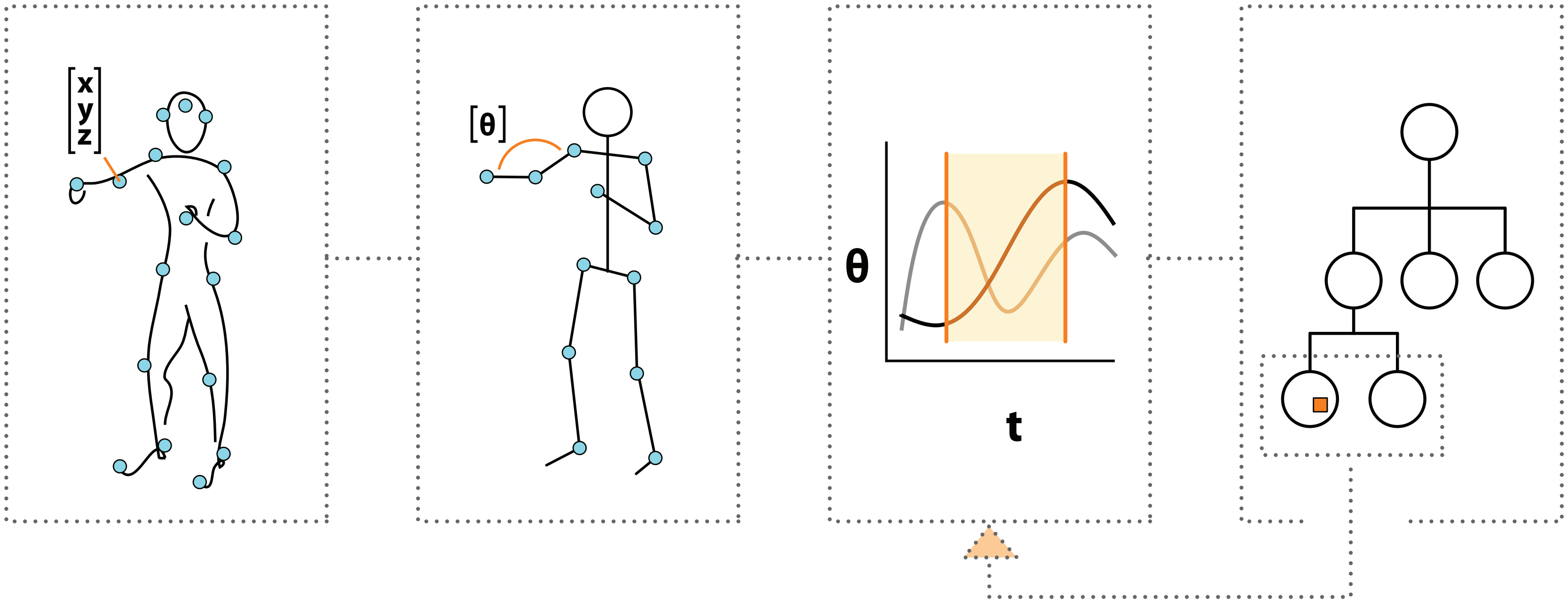


Algorithm	Correct	False Pos	False Neg
Basic	128	65	43
Scaffolded (with Squat and Kick)	139	59	32

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

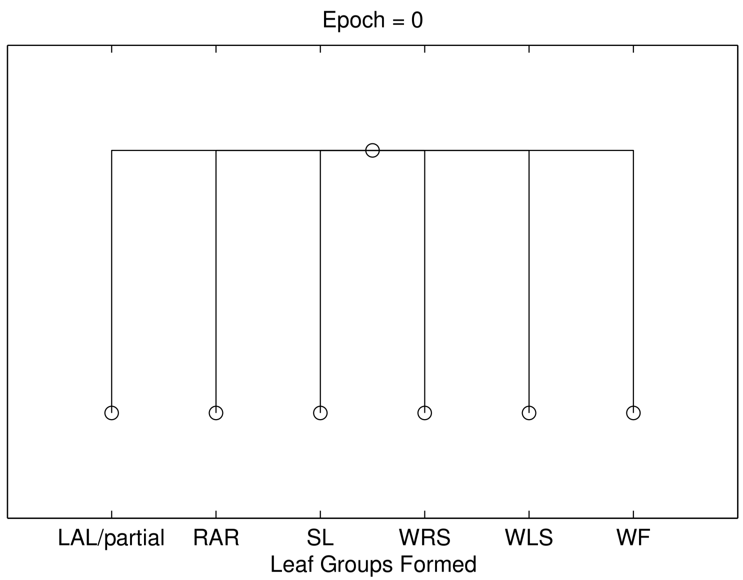
Sample Video

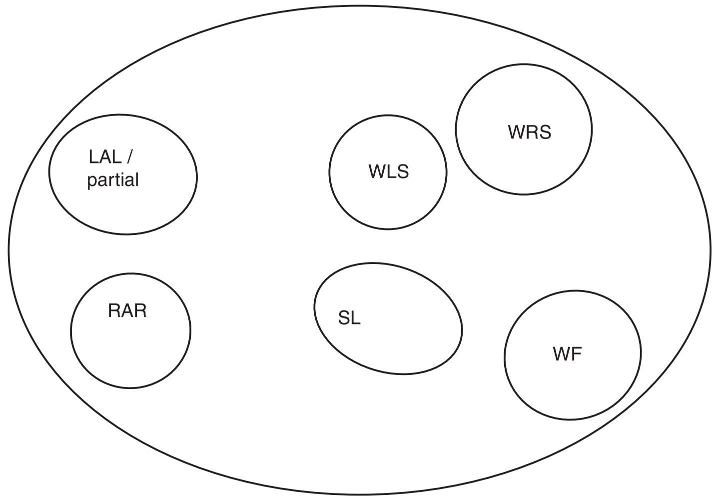
Testing the Combined Segmentation and Clustering



- 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

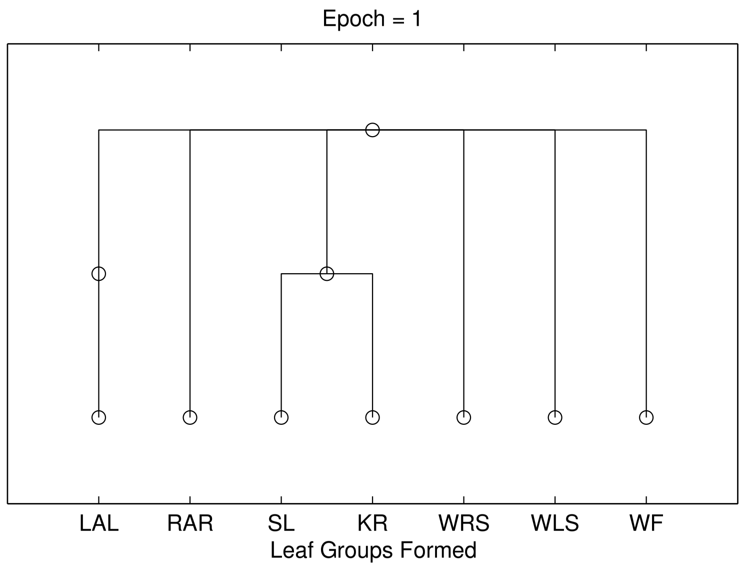
After Epoch 1

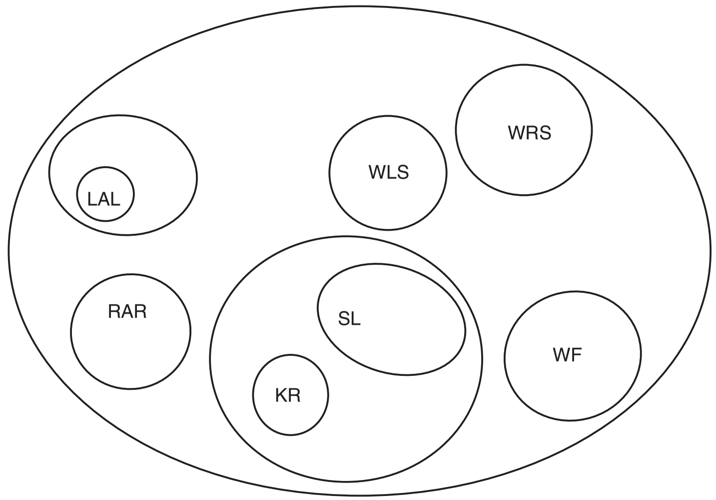




Example Extracted Motion: Right Arm Raise

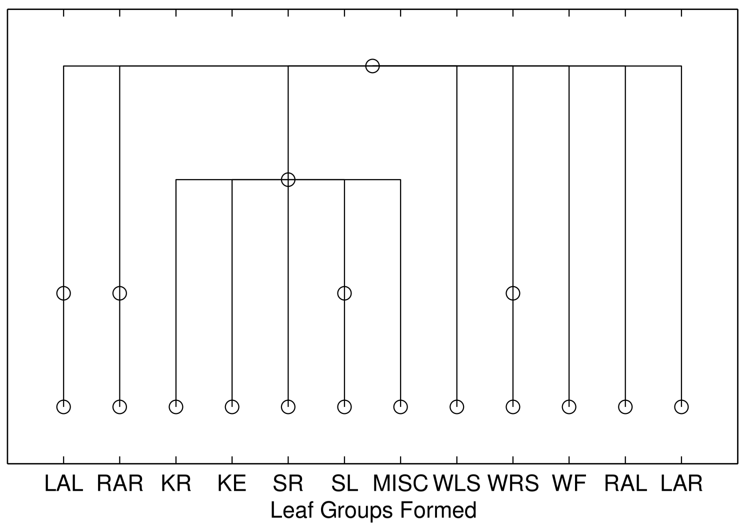
After Epoch 2

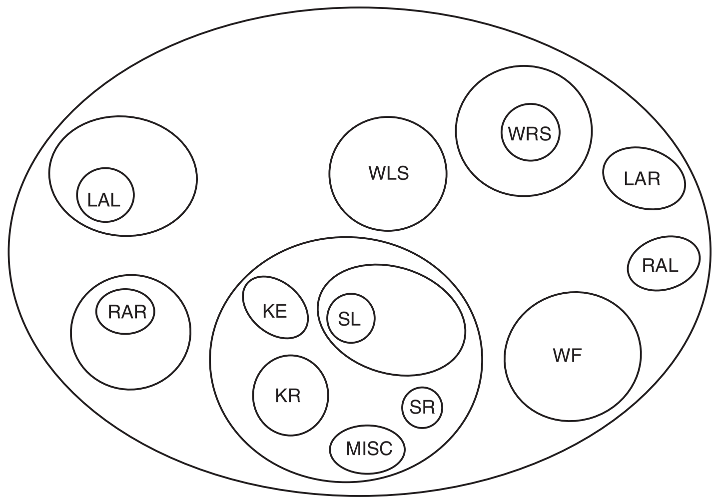




Example Extracted Motion: Left Arm Lower

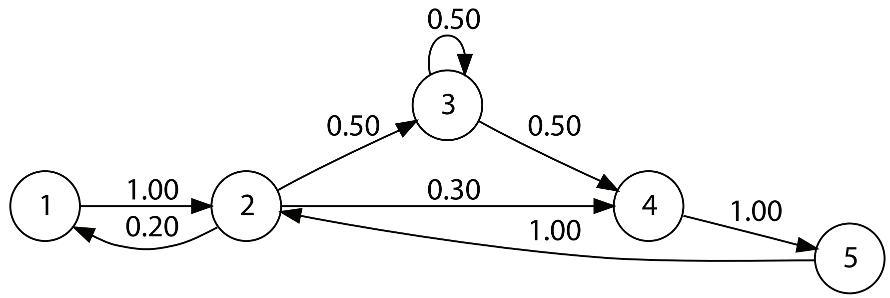
After Epoch 3





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

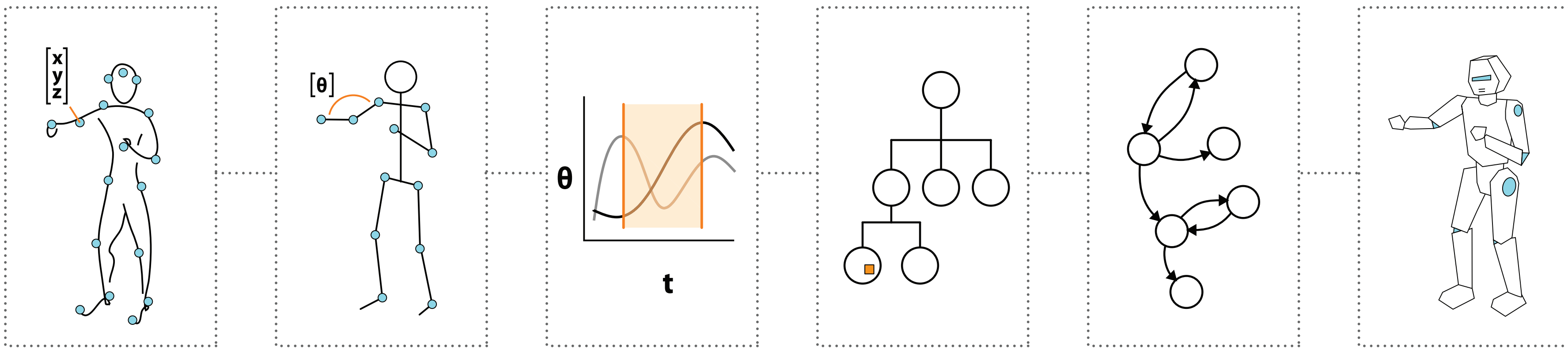
Experiments with a Humanoid Robot

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

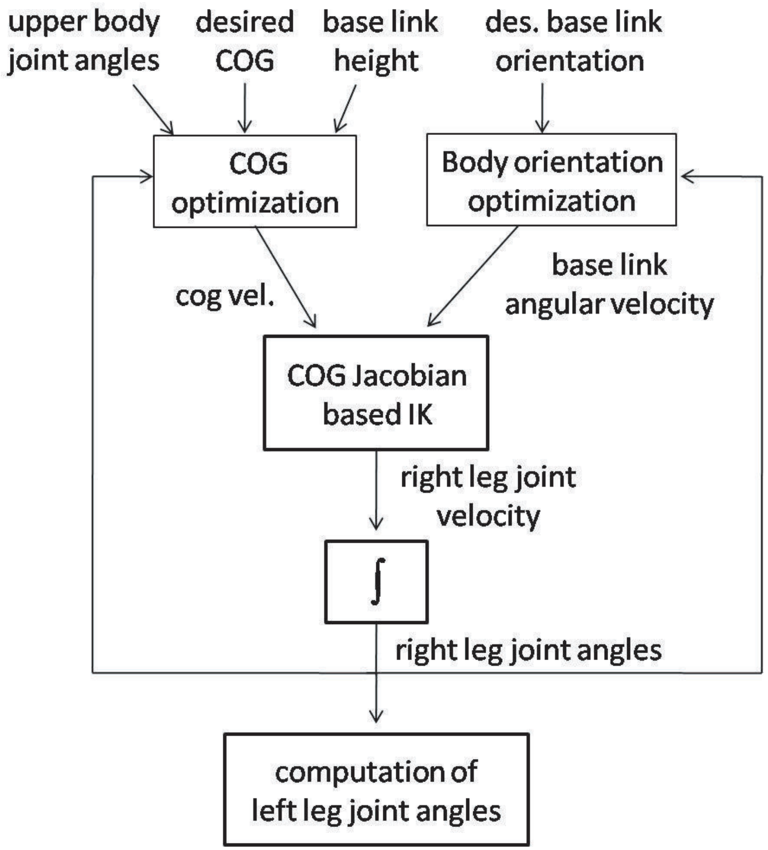
data is converted to a 32DoF humanoid model by online inverse kinematics

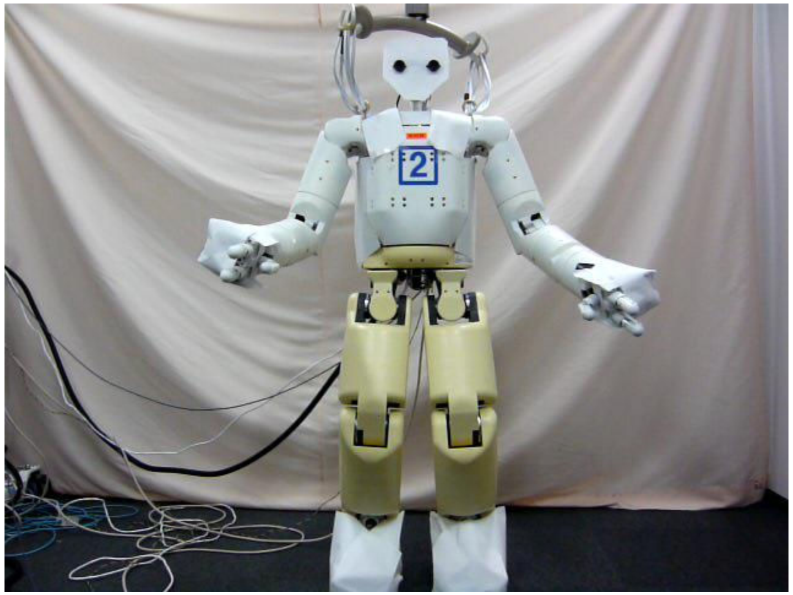
online feed to automated segmentation, clustering and motion graph extraction

Data Flow Diagram

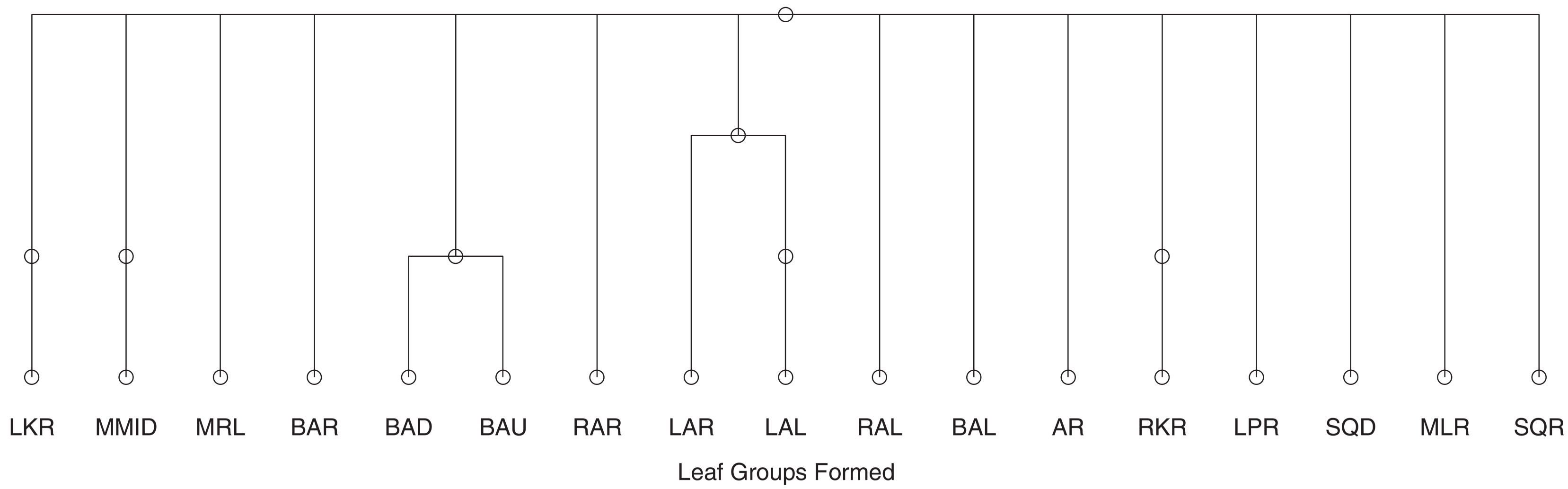


Robot Hardware and Control System

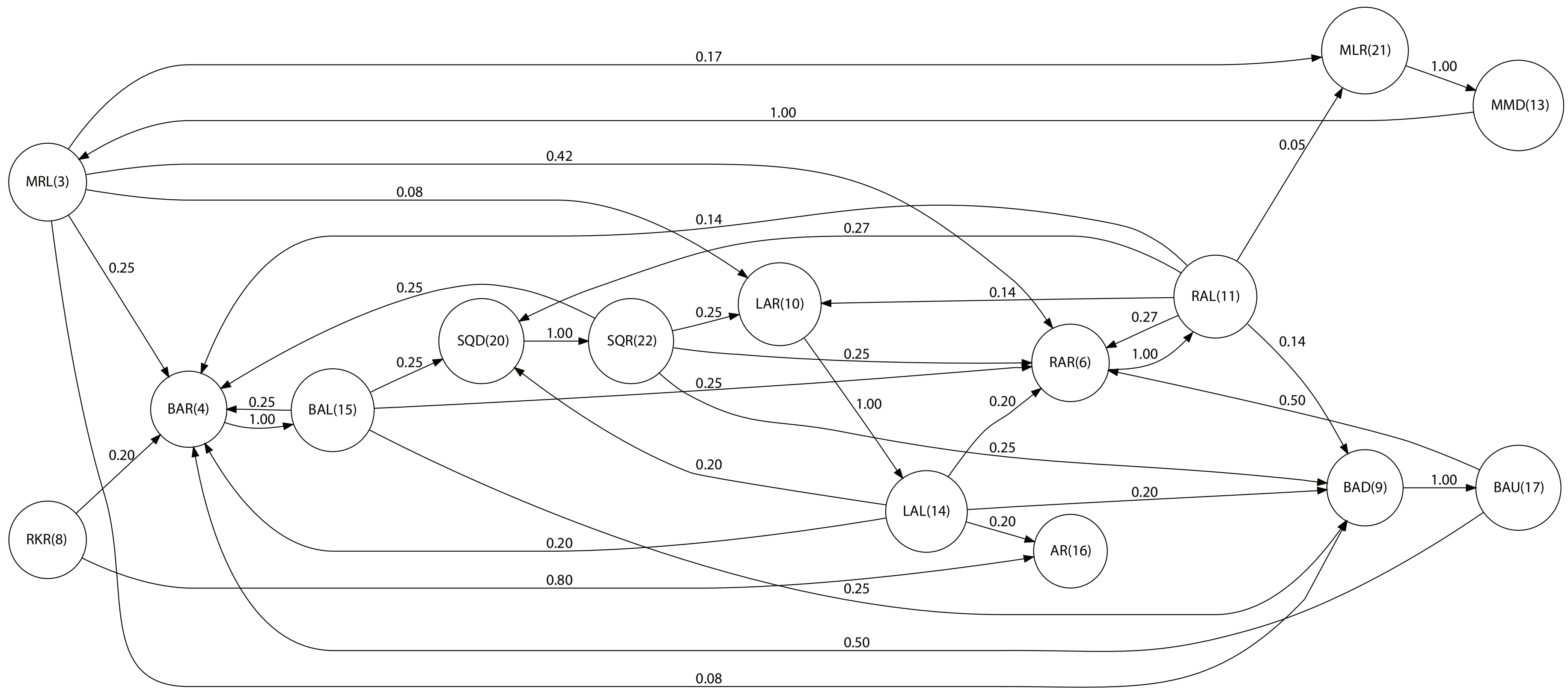




The Extracted Motion Primitive Tree

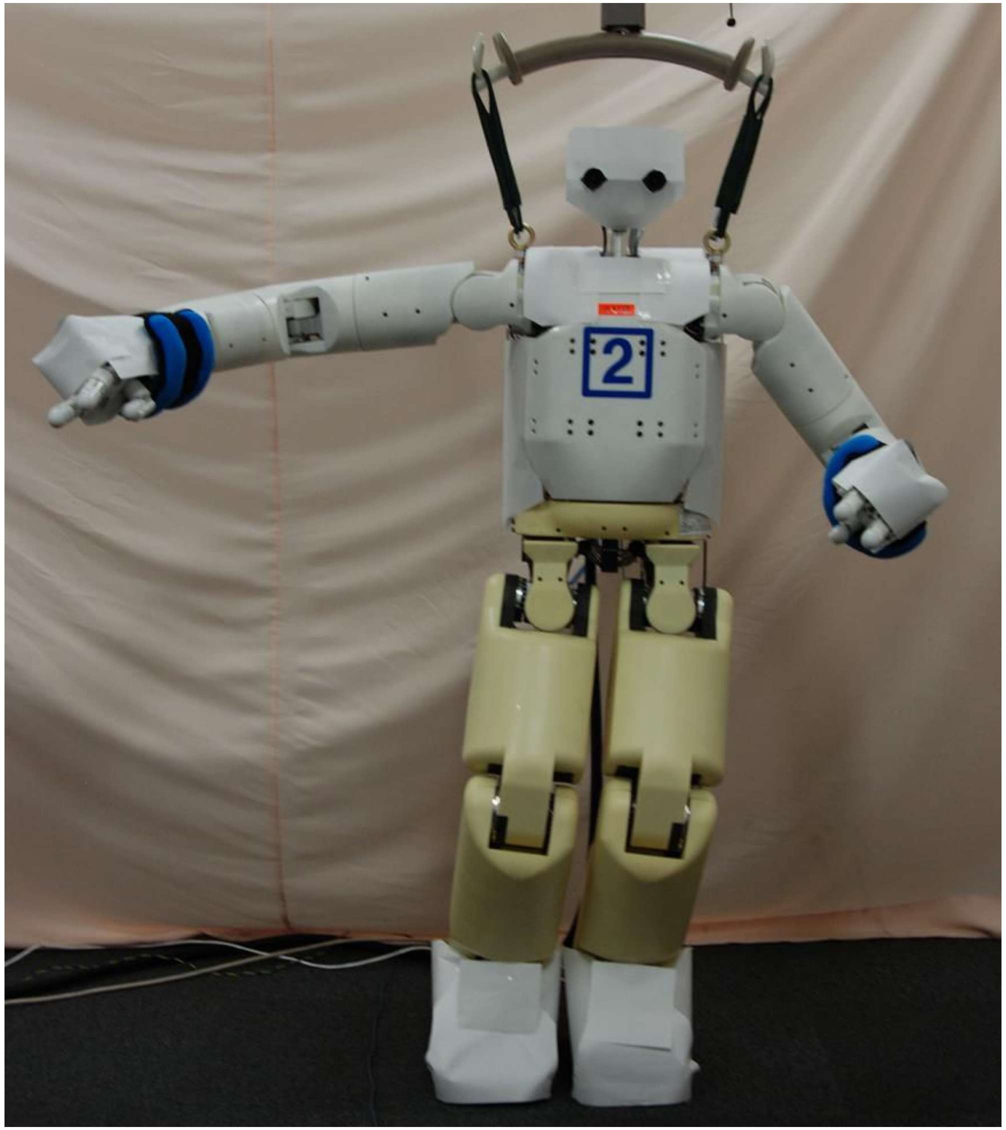


The Extracted Motion Primitive Graph



- 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

The End

Questions?

Additional Questions or Comments?
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Copies of publications can be obtained from:
www.ynl.t.u-tokyo.ac.jp/∼dana