Predictive Assistance for Manufacturing Robotics

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Problem

- Certain assemblies require fine dexterity
- Changing manufacturing processes prevent the use of traditional robotic systems
- Current robotics systems cannot adapt to operator variability
- **Goal:** To recognize human activity for robotic assistance in human-robot collaborative tasks

Sample Scenario: Assembly of a Motor

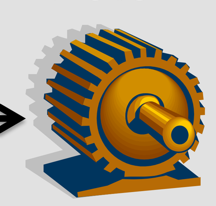
Problem: To assemble a motor consisting of multiple parts

- Labor is divided between a robot assistant and a human agent.
  - Assembly is performed by the human agent
  - Part/tool delivery is performed by a robot assistant
- Different assemblies require different tools and parts
- Tools and parts are transported to the human agent from a storage container
- Work space and tools are limited - Only one tool and part maybe checked out from the storage container at any point in time

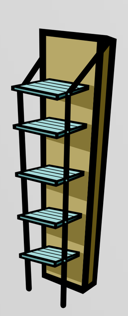
Human Agent

- Fine dexterity motions
- Assemble individual parts
- Limited work space

Motor

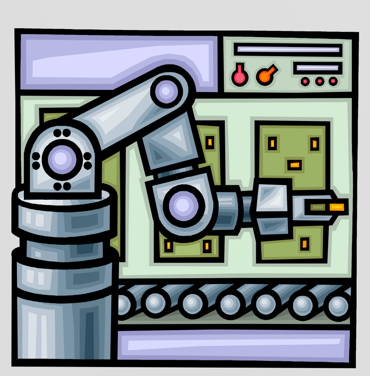


Tools and Parts



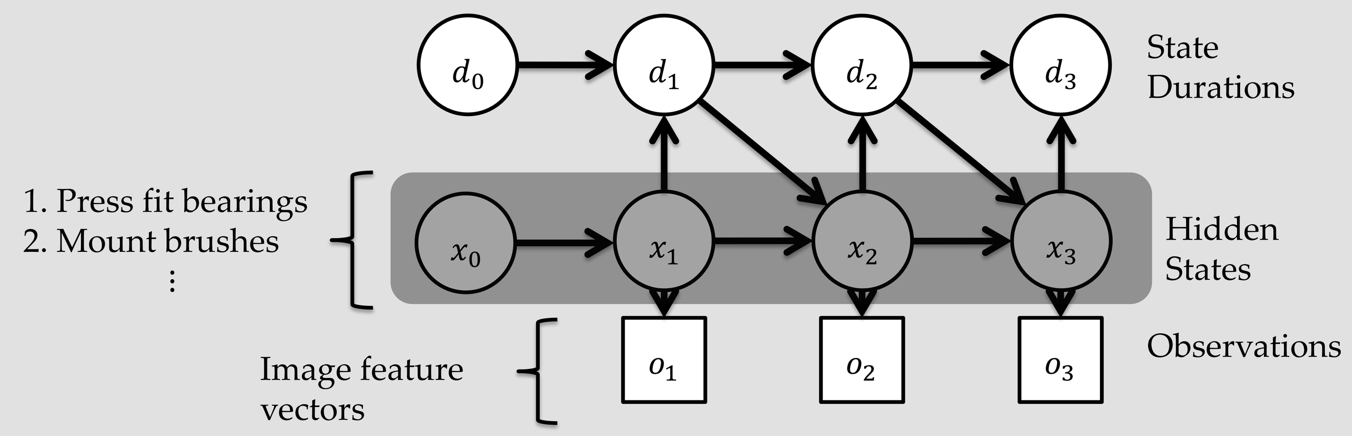
- A maximum of one tool and part may be taken at a time

Robot Assistant

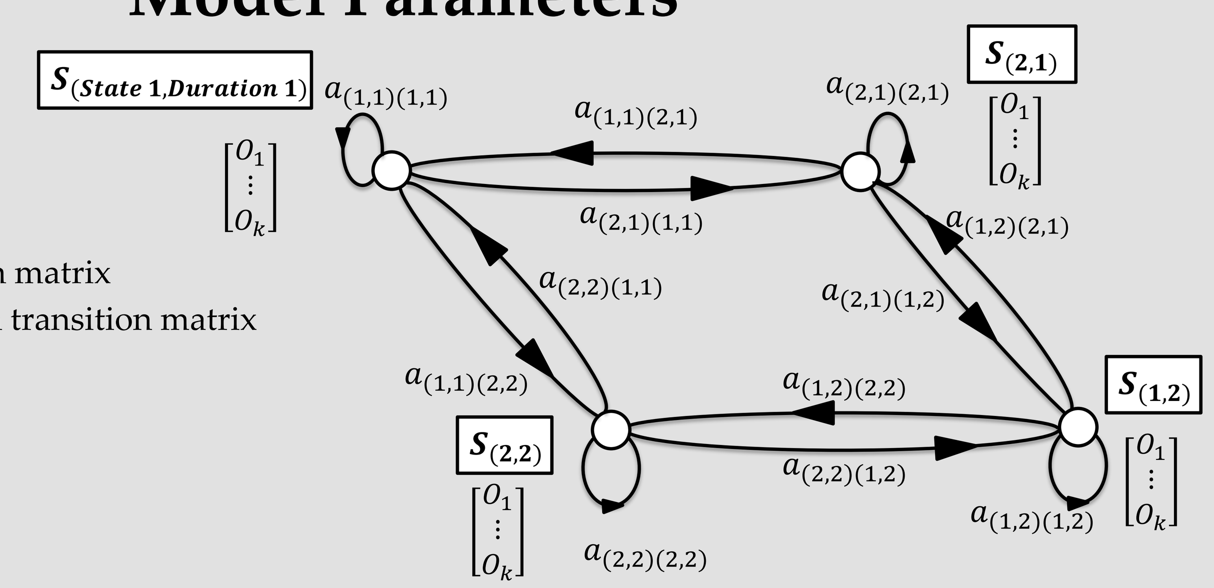


- Delivers and receives tools and parts from human agent

Hidden Semi-Markov Model



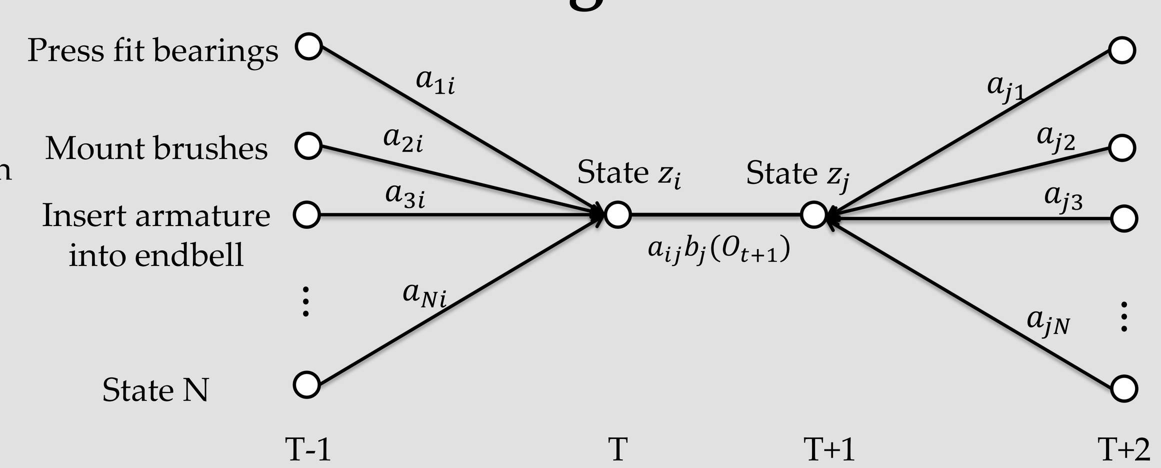
Model Parameters



- $a_{(i,d\prime)(j,d)}$ = State transition matrix
- $b_{j,d}(v_{k_1:k_d})$ = Observation transition matrix
- $S_{(s,d)}$ redefined as S_z

Forward-Backward Algorithm

- Probability of the observation sequence give the parameter model



Parameter Estimation using Baum-Welch

Probablity of being in S_i at t and S_j at $t+1$

$$\xi_t(i,j) = \frac{\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_t(i)a_{ij}b_j(O_{t+1})\beta_{t+1}(j)}$$

Probablity of being in S_i at t given the observation sequence

$$\gamma_t(i) = \sum_{j=1}^{N}\xi_t(i,j)$$

Initial state distribution

$$\bar{\pi}_i = \gamma_1$$

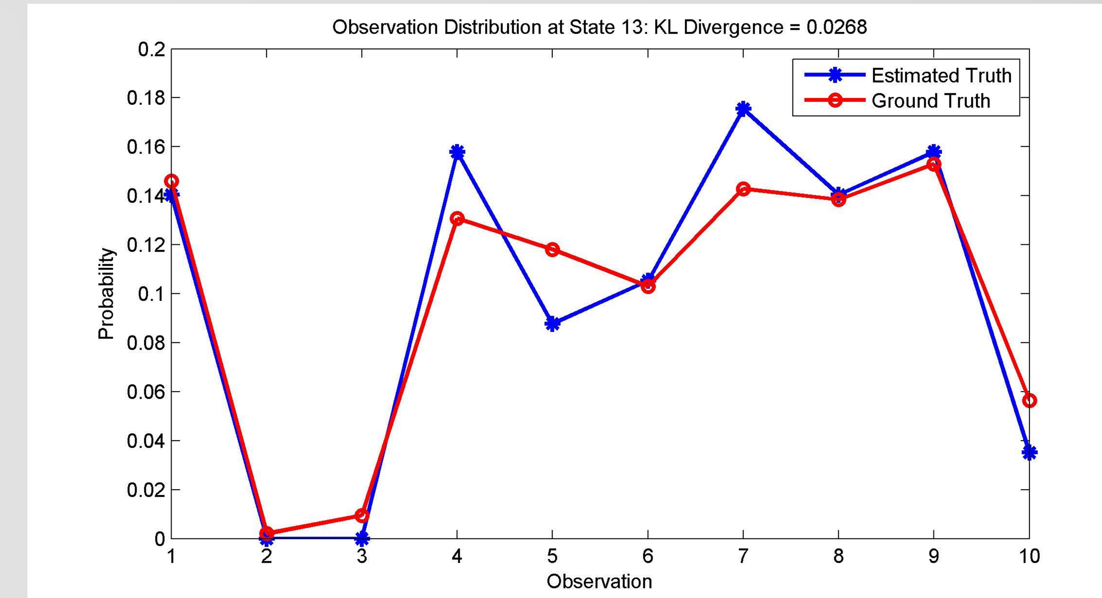
$$\frac{Expected\ \#\ of\ transitions\ from\ state\ S_{z_i}\ to\ S_{z_j}}{Expected\ \#\ of\ transitions\ from\ state\ S_{z_i}} \qquad \overline{a_{ij}} = \frac{\sum_{T=1}^{T-1}\xi_t(i,j)}{\sum_{T=1}^{T-1}\gamma_t(i)}$$

$$\frac{Expected\ \#\ of\ times\ in\ S_{z_j}\ and\ observing\ v_k}{Expected\ \#\ of\ times\ in\ state\ S_{z_j}} \qquad \bar{b}_j(k) = \frac{\sum_{T=1}^{T-1}\gamma_t(i)\ \ s.t.\ O_t = v_k}{\sum_{T=1}^{T-1}\gamma_t(i)}$$

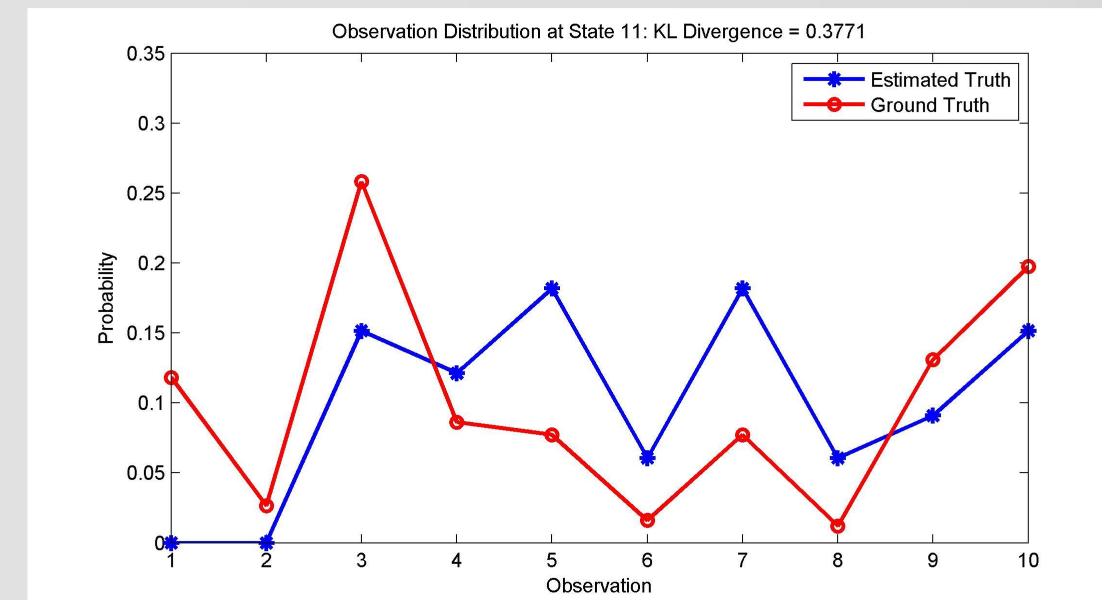
Results

Synthetic data

- Randomly generated N by N state transition matrix
  - Zero self transition
  - Row-wise normalization
  - N = 25 states
  - Duration = {1:4}
  - 1000 Time steps



- Randomly generated M by N observation transition matrix
  - M = 10 observations
  - Column-wise normalization



Future Work

- Explore Explicit Duration Hidden Markov Models
  - The current method of parameter estimation requires a specified duration for all states
  - Implement Beam sampling to limit the number of states considered at each time step.
- Utilize feature vectors from an RGB camera to estimate model parameters.

References

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