

Dynamic Gesture Recognition with Hidden Markov Model

Qing Chen

Discover Lab

University of Ottawa

January 18, 2005

Outline

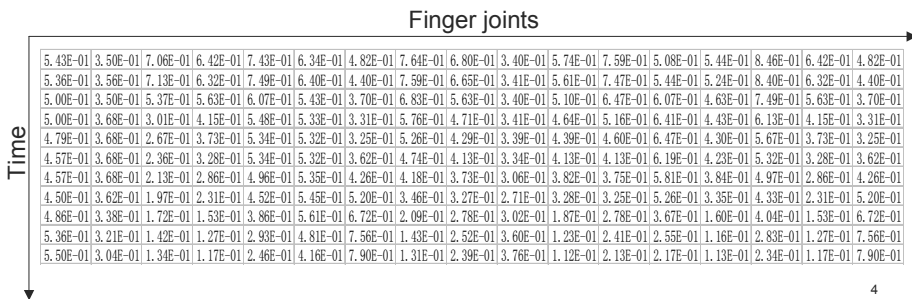
- 1. Introduction
- 2. Dynamic Data
- 3. HMM in a Nutshell
- 4. Data Processing
- 5. Model Training
- 6. Recognition
- 7. Conclusions & Future Work

1.Introduction

- Objective: Classify dynamic gesture with Discrete HMM (DHMM);
- Motivation: VERGINA Project
- Tasks involved:
 - data analysis & process
 - model training
 - classification

2.Dynamic Data

- A group of raw data which varies with time;
- For CyberGlove, data collected from 20 joint angles at about 10Hz;
- Example: (1) Raw data for the 'Grabbing' gesture:



2.Dynamic Data (cont'd)

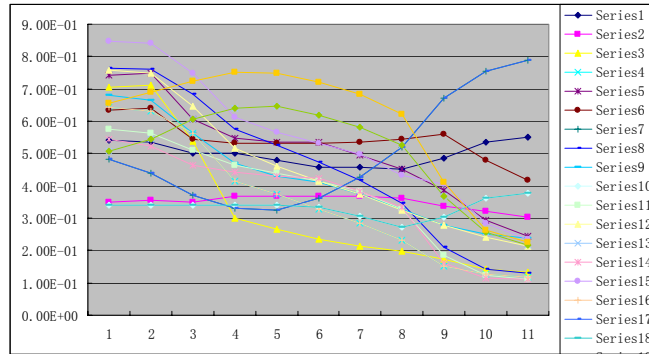
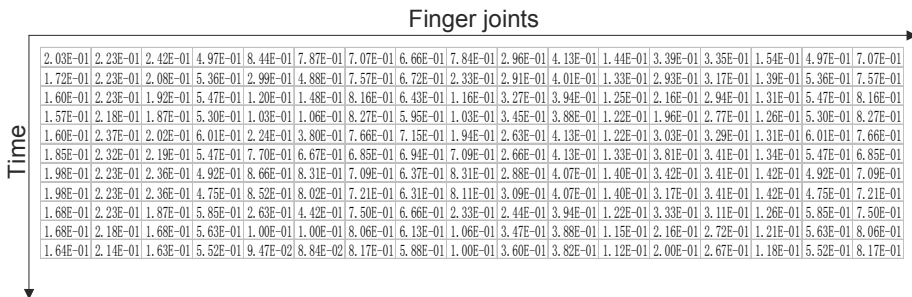


Fig.1. Dynamic data for the 'Grabbing' gesture.

2.Dynamic Data (cont'd)

- Example: (2) Raw data for the 'Quote' gesture:



2.Dynamic Data (cont'd)

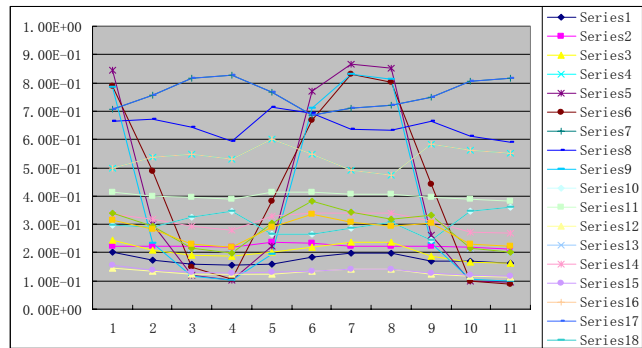


Fig.2. Dynamic data for the 'Quote' gesture.

7

2.Dynamic Data (cont'd)

- We collected another group of data:

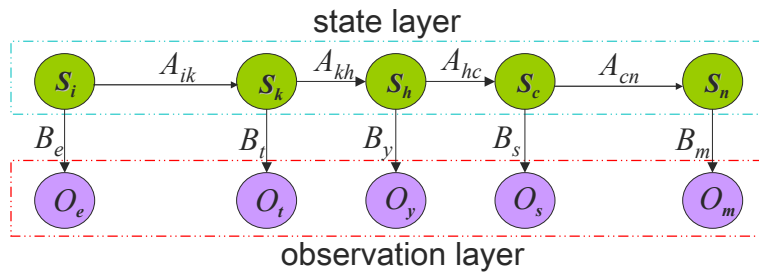
5.21E-01	3.68E-01	7.75E-01	6.42E-01	7.65E-01	6.60E-01	4.67E-01	7.55E-01	7.16E-01	3.47E-01	5.42E-01	7.76E-01	5.17E-01	5.44E-01	8.55E-01	6.42E-01	4.67E-01
5.21E-01	3.74E-01	7.75E-01	6.42E-01	7.65E-01	6.60E-01	4.54E-01	7.55E-01	7.16E-01	3.44E-01	5.42E-01	7.76E-01	5.31E-01	5.44E-01	8.55E-01	6.42E-01	4.54E-01
5.00E-01	3.44E-01	7.26E-01	5.90E-01	7.01E-01	5.94E-01	3.51E-01	7.15E-01	6.43E-01	3.65E-01	5.23E-01	7.22E-01	6.08E-01	4.97E-01	8.23E-01	5.90E-01	3.51E-01
4.86E-01	3.32E-01	6.63E-01	4.97E-01	6.55E-01	5.64E-01	2.94E-01	6.60E-01	5.63E-01	3.85E-01	5.10E-01	5.71E-01	6.48E-01	4.83E-01	7.53E-01	4.97E-01	2.94E-01
4.93E-01	3.27E-01	5.78E-01	3.78E-01	6.62E-01	5.68E-01	3.52E-01	5.82E-01	5.04E-01	3.85E-01	4.84E-01	5.16E-01	5.94E-01	4.50E-01	6.92E-01	3.78E-01	3.52E-01
4.79E-01	3.50E-01	5.29E-01	3.18E-01	6.42E-01	5.57E-01	3.77E-01	5.38E-01	4.46E-01	3.91E-01	4.64E-01	4.60E-01	5.67E-01	4.36E-01	6.29E-01	3.18E-01	3.77E-01
4.50E-01	3.81E-01	4.55E-01	2.64E-01	6.00E-01	5.41E-01	4.37E-01	4.74E-01	3.97E-01	3.80E-01	4.32E-01	3.98E-01	5.21E-01	3.97E-01	5.32E-01	2.64E-01	4.37E-01
4.29E-01	4.25E-01	3.67E-01	1.97E-01	5.56E-01	5.33E-01	5.39E-01	3.81E-01	3.35E-01	3.77E-01	3.52E-01	3.32E-01	4.34E-01	3.00E-01	4.85E-01	1.97E-01	5.39E-01
4.01E-01	4.44E-01	3.22E-01	1.68E-01	5.04E-01	5.34E-01	6.34E-01	2.80E-01	3.65E-01	3.78E-01	2.59E-01	3.04E-01	3.52E-01	1.83E-01	4.91E-01	1.68E-01	6.34E-01
3.68E-01	4.44E-01	2.94E-01	1.45E-01	4.15E-01	5.59E-01	7.09E-01	2.09E-01	2.84E-01	3.97E-01	1.87E-01	2.78E-01	2.76E-01	1.39E-01	4.16E-01	1.45E-01	7.09E-01
3.74E-01	4.57E-01	2.13E-01	1.31E-01	3.38E-01	5.26E-01	7.49E-01	1.67E-01	2.52E-01	4.19E-01	1.47E-01	2.41E-01	2.32E-01	1.21E-01	2.74E-01	1.31E-01	7.49E-01

- What kind of gesture is it?

8

3.HMM in a Nutshell

- A doubly embedded stochastic process;
- Two layers: state & observation



9

3.HMM in a Nutshell (cont'd)

- Only the observation layer is observable;
- The state sequence can only be exposed through the observation sequence;
- Three basic HMM problems:
 - (1) The **Evaluation** Problem: Given the observation sequence $O=O_1O_2O_3\dots O_T$, and a HMM $\lambda=(A,B, \pi)$, how to compute $P(O|\lambda)$?
 - (2) The **Decoding** Problem: Given the observation sequence $O=O_1O_2\dots O_T$, and the HMM λ , how to choose a corresponding optimal state sequence $Q=q_1q_2\dots q_T$?
 - (3) The **Learning** Problem: Given the observation sequence $O=O_1O_2\dots O_T$, how to adjust the model parameters $\lambda=(A,B, \pi)$ to maximize $P(O|\lambda)$?
- The HMM we will use is 'Discrete' HMM.

10

[4.Data Processing]

- Objective: transform multi-dimensional raw data to single-dimensional discrete data suitable for DHMM.
- Key problems:
 - (1) What does state correspond to?
 - (2) What does observation correspond to?
 - (3) How to preprocess the raw data from the gesture input device into a sequence of discrete symbols?

11

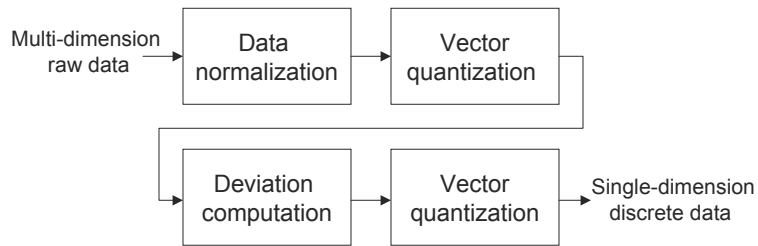
[4.Data Processing (cont'd)]

- Proposed method:
 - states: finger joints
 - observation: joint angles
 - one-dimensional DHMM
- Advantages:
 - state layer is exposed so that the probability calculation is eliminated;
 - classification accuracy can be improved;
 - more straightforward than Multi-dimensional DHMM.

12

4.Data Processing (cont'd)

- Multi-dimension \Rightarrow Single-dimension observation sequence transformation:

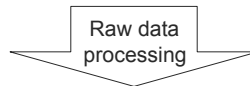


13

4.Data Processing (cont'd)

- Example:

2.03E-01 2.23E-01 2.42E-01 4.97E-01 8.44E-01 7.87E-01 7.07E-01 6.66E-01 7.84E-01 2.96E-01 4.13E-01 1.44E-01 3.39E-01 3.35E-01 1.54E-01 4.97E-01 7.07E-01
 1.72E-01 2.23E-01 2.09E-01 5.36E-01 2.99E-01 4.88E-01 7.57E-01 6.72E-01 2.33E-01 2.91E-01 4.01E-01 1.33E-01 2.93E-01 3.17E-01 1.39E-01 5.36E-01 7.57E-01
 1.60E-01 2.23E-01 1.92E-01 5.47E-01 1.20E-01 1.48E-01 8.16E-01 6.43E-01 1.16E-01 3.27E-01 3.94E-01 1.25E-01 2.16E-01 2.94E-01 1.31E-01 5.47E-01 8.16E-01
 1.57E-01 2.18E-01 1.87E-01 5.30E-01 1.03E-01 1.06E-01 8.27E-01 5.95E-01 1.03E-01 3.45E-01 3.88E-01 1.22E-01 1.96E-01 2.77E-01 1.26E-01 5.30E-01 8.27E-01
 1.60E-01 2.37E-01 2.02E-01 6.01E-01 2.24E-01 3.80E-01 7.66E-01 7.15E-01 1.94E-01 2.63E-01 4.13E-01 1.22E-01 3.03E-01 3.29E-01 1.31E-01 6.01E-01 7.66E-01
 1.85E-01 2.32E-01 2.19E-01 5.47E-01 7.70E-01 6.67E-01 6.85E-01 6.94E-01 7.09E-01 2.66E-01 4.13E-01 1.33E-01 3.81E-01 3.41E-01 1.34E-01 5.47E-01 6.85E-01
 1.98E-01 2.23E-01 2.36E-01 4.92E-01 8.66E-01 8.31E-01 7.09E-01 6.37E-01 8.31E-01 2.88E-01 4.07E-01 1.40E-01 3.42E-01 3.41E-01 1.42E-01 4.92E-01 7.09E-01
 1.98E-01 2.23E-01 2.36E-01 4.75E-01 8.52E-01 8.02E-01 7.21E-01 6.31E-01 8.11E-01 3.09E-01 4.07E-01 1.40E-01 3.17E-01 3.41E-01 1.42E-01 4.75E-01 7.21E-01
 1.68E-01 2.23E-01 1.87E-01 5.85E-01 2.63E-01 4.42E-01 7.50E-01 6.66E-01 2.33E-01 2.44E-01 3.94E-01 1.22E-01 3.33E-01 3.11E-01 1.26E-01 5.85E-01 7.50E-01
 1.68E-01 2.18E-01 1.68E-01 5.63E-01 1.00E-01 1.00E-01 8.06E-01 6.13E-01 1.06E-01 3.47E-01 3.88E-01 1.15E-01 2.16E-01 2.72E-01 1.21E-01 5.63E-01 8.06E-01
 1.64E-01 2.14E-01 1.63E-01 5.52E-01 9.47E-02 8.84E-02 8.17E-01 5.88E-01 1.00E-01 3.60E-01 3.82E-01 1.12E-01 2.00E-01 2.67E-01 1.18E-01 5.52E-01 8.17E-01

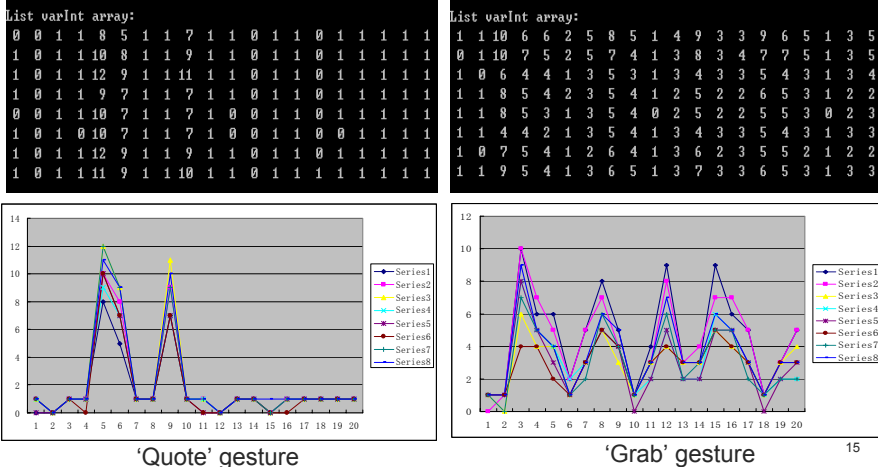


1 0 1 1 12 9 1 1 11 1 1 0 1 1 0 1 1 1 1

14

4. Data Processing (cont'd)

- 2 examples for 8 groups of raw data processing results:

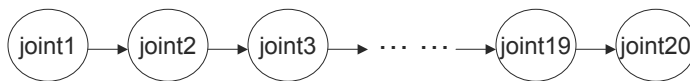


5. Model Training

- The **Learning** Problem: Given the observation sequence $O=O_1O_2\dots O_T$, how to adjust the model parameters $\lambda = (A, B, \pi)$ to maximize $P(O|\lambda)$?
- EM(Expectation-Modification), or equivalently Baum-Welch method, can locally maximize $P(O|\lambda)$;
- EM uses an iterative expectation/maximization procedure to find an HMM which is most likely to produce the training observation sequences locally;
- The accuracy of estimation improves with the number and length of the training sequences.

5. Model Training

- HMM training is a batch process;
- 8 groups of raw data for the same gesture are employed to train HMM;
- State transition matrix is decided by the data collection sequence:



- The HMM for each dynamic gesture is trained offline.

17

6. Classification

- The **Evaluation** Problem: Given the observation sequence $O=O_1O_2O\ldots O_T$, and a HMM $\lambda=(A,B, \pi)$, how to compute $P(O|\lambda)$?
- Forward-backward procedure efficiently resolve the problem!
- Based on the trellis structure which can reduce the computation cost from $2TN^T$ to N^2T , where N is the number of states, and T is the number of the observations.

18

6. Classification (cont'd)

- An HMM Classification example with 2 states, 2 observation symbols :

```
***** Model 1 *****
transition matrix:
0.50 0.50
0.50 0.50
observation symbol matrix:
0.10 0.90
0.20 0.80
Training data loaded...
SEQ = <
  0 = <
    0, 1, 0, 1, 0, 0, 1, 1, 0, 1;
  >;
>;
Here is the classification:
log-p of this sequence (forward algorithm): -10.298195

***** Model 2 *****
transition matrix:
0.50 0.50
0.50 0.50
observation symbol matrix:
0.80 0.20
0.70 0.30
Training data loaded...
SEQ = <
  0 = <
    0, 1, 0, 1, 0, 0, 1, 1, 0, 1;
  >;
>;
Here is the classification:
log-p of this sequence (forward algorithm): -8.269882

***** Model 3 *****
transition matrix:
0.50 0.50
0.50 0.50
observation symbol matrix:
0.60 0.40
0.50 0.50
Training data loaded...
SEQ = <
  0 = <
    0, 1, 0, 1, 0, 0, 1, 1, 0, 1;
  >;
>;
Here is the classification:
log-p of this sequence (forward algorithm): -6.981723
```

- Model 3 produced the biggest log-p value, which verified the effectiveness of forward-backward procedure.

19

7. Conclusions & Future Work

- HMM can effectively resolve the classification problem for dynamic gesture data;
- The flexibility of HMM make it a generic mathematic model for recognition problems;
- Proposed data processing method effectively transformed multi-dimensional data to single-dimensional data while reserving the dynamic property;
- For dynamic gesture data, segmentation still need to be effectively resolved in order to meet the HMM requirements.

20