HMM in Wearable Computing

Presented by Cong Wang

Wearable Computing

What's that?


@王可可是个碧池
weibo.com/u/5194257804

Motivation

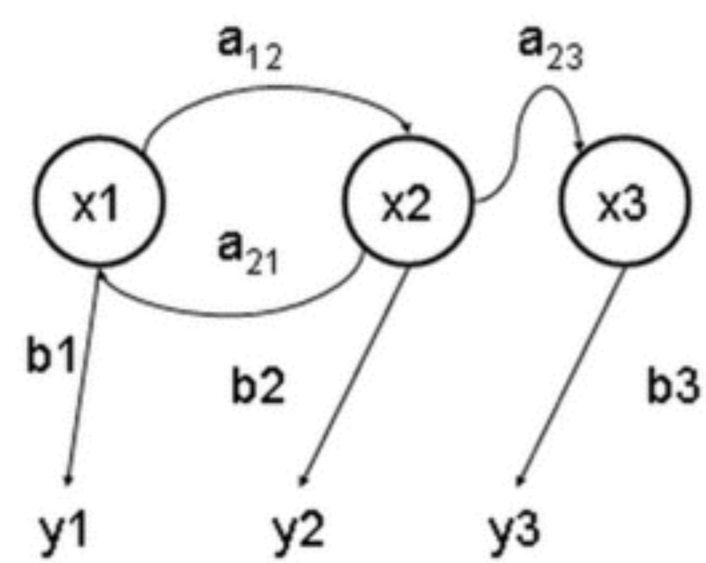
- Wearable devices become a hit
- A wearable computing system with multi-sensors(gyroscope,accelerometer…)
- Action recognition & Energy-saving

System

- Sensors(gyroscope,accelerometer)
- Arduino pro mini 320p
- Multiple data transmitted to Android

Hidden Markov Model(HMM)

- A statistic model
- **Invisible** hidden states
- **Visible** observed symbols
- Transition probabilities



Elements

- *N*—the number of hidden states
- *Q*—set of states $Q = \{1, 2, \ldots, N\}$
- *M*—the number of symbols
- *V*—set of symbols $V = \{1, 2, \ldots, M\}$

Elements

- A—the state-transition probability matrix

$$a_{ij} = P(q_t = j | q_{t-1} = i) \qquad 1 \leq i, j, \leq N$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2j} & \cdots & a_{2N} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} & \cdots & a_{iN} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{Nj} & \cdots & a_{NN} \end{bmatrix}$$

Elements

- B—Observation probability distribution

$$B_j(k) = P(o_t = k | q_t = j) \quad 1 \leq k \leq M$$

- π—Initial state distribution

$$\pi_i = P(q_1 = i) \quad 1 \leq i \leq N$$

Elements

- λ—the entire model

$$\lambda = (A, B, \pi)$$

Assumptions

- First order Markov assumption

$$P(q_t = j | q_{t-1} = i, q_{t-2} = k, \ldots) = P(q_t = j | q_{t-1} = i)$$

- Stationarity

$$P(q_t = j | q_{t-1} = i) = P(q_{t+l} = j | q_{t+l-1} = i)$$

- Output Independent

Example

S={stand,walk,run}

π={0.5,0.3,0.2}

a_{ij}	Stand	Walk	Run
Stand	0.9	0.7	0.5
Walk	0.6	0.8	0.5
Run	0.4	0.7	0.8

O={data1,data2,data3}

Q=SSWRWWS

b_{ij}	data1	data2	data3
Stand	0.9	0.2	0.1
Walk	0.2	0.7	0.6
Run	0.1	0.6	0.7

Three Basic Problems

- The Evaluation Problem—Forward Algorithm
- The Decoding Problem—Viterbi Algorithm
- The Learning Problem—Baum-Welch Algorithm

Forward Algorithm

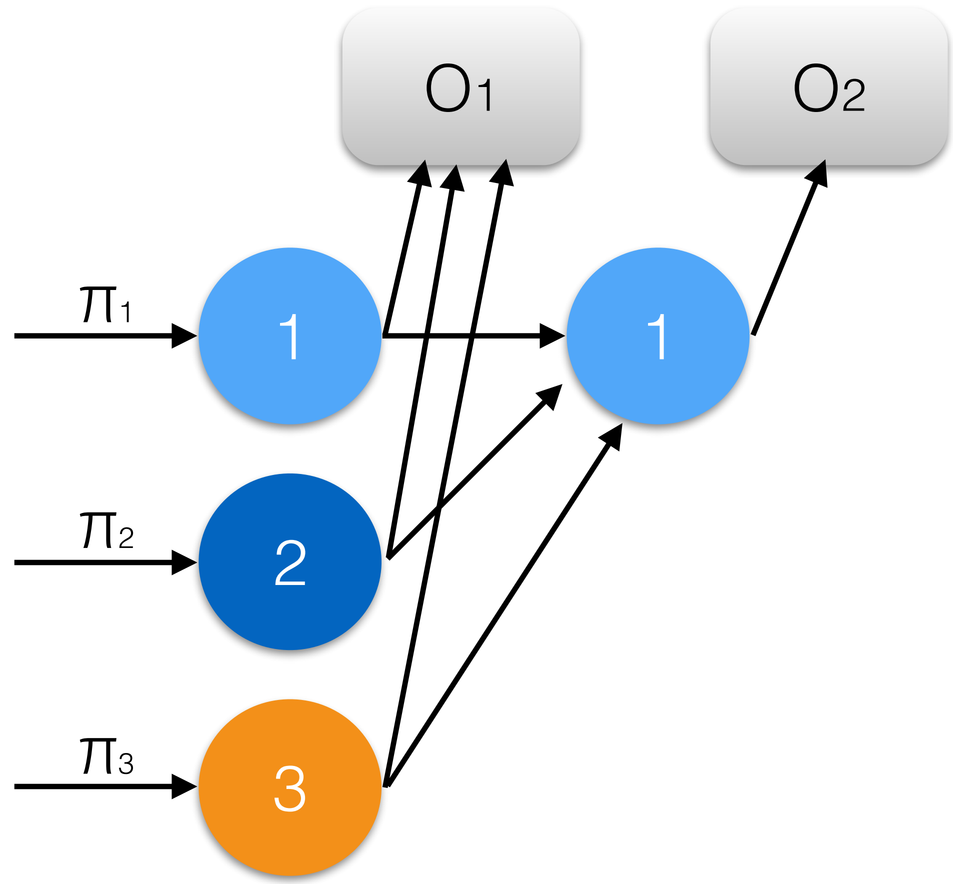
Forward variable $\alpha_t(i)$

$$P(O_1O_2, q_2=s_1|\lambda)=\alpha_1(1)\times a_{11}\times b_1(O_2)+\alpha_1(2)\times a_{21}\times b_1(O_2)+\alpha_1(3)\times a_{31}\times b_1(O_2)=\alpha_2(1)$$

$$\alpha_1(i)=\pi_1\times b_i(O_1)$$

$$\alpha_{t+1}=\left(\sum_{i=1}^{N}\alpha_t(i)a_{ij}\right)b_j(O_{t+1})$$

$$P(O|\lambda)=\sum_{i=1}^{N}\alpha_T(i)$$

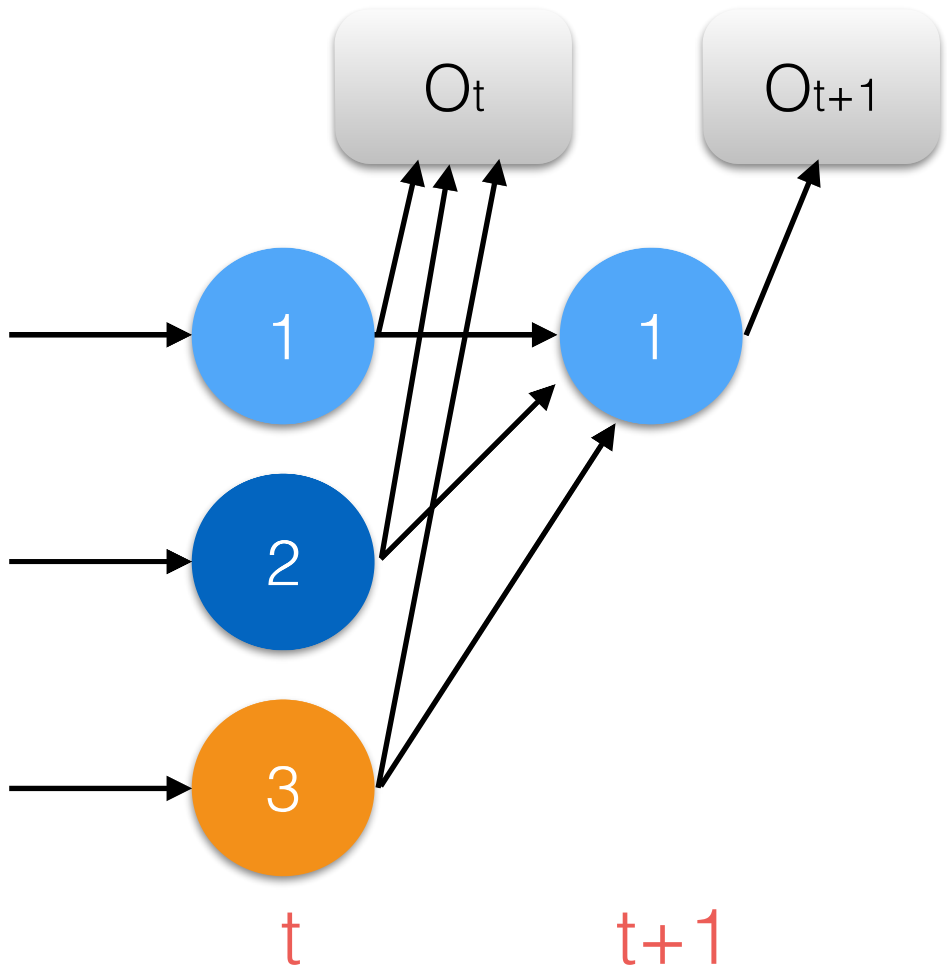


Viterbi Algorithm

Viterbi variable $\delta_t(i)$

$$\delta_t(i)=\max P(q_1 q_2 \ldots q_t = s_i, O_1 O_2 \ldots O_t | \lambda)$$

$$\delta_{t+1}(i)=\max_j \delta_t(j)\times a_{ji}\times b_i(O_{t+1})$$



Baum-Welch Algorithm

- Given O & S, calculate λ to maximize P(O|λ)
- E & M steps

$$\xi_t(i,j) = P(q_t = s_i, q_{t+1} = s_j | O, \lambda)$$
$$= \frac{P(q_t = s_i, q_{t+1} = s_j, O, \lambda)}{P(O|\lambda)}$$
$$= \frac{\alpha_t(i) \times a_{ij} \times b_j(O_{t+1}) \times \beta_{t+1}(j)}{P(O|\lambda)}$$
$$= \frac{\alpha_t(i) \times a_{ij} \times b_j(O_{t+1}) \times \beta_{t+1}(j)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t(i) \times a_{ij} \times b_j(O_{t+1}) \times \beta_{t+1}(j)}$$

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

$$\grave{\pi}_i = r_1(i)$$

$$\grave{a}_{ij} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} r_t(i)}$$

$$\grave{b}_j(k) = \frac{\sum_{t=1}^{T} r_t(j) \times \delta(O_t, v_k)}{\sum_{t=1}^{T} r_t(j)}$$

Baum-Welch Algorithm

- Step 1:Initialization **λ** randomly satisfying

$$\sum_{i=1}^{N} \pi_i = 1$$

$$\sum_{j=1}^{N} a_{ij} = 1, 1 \leqslant i \leqslant N$$

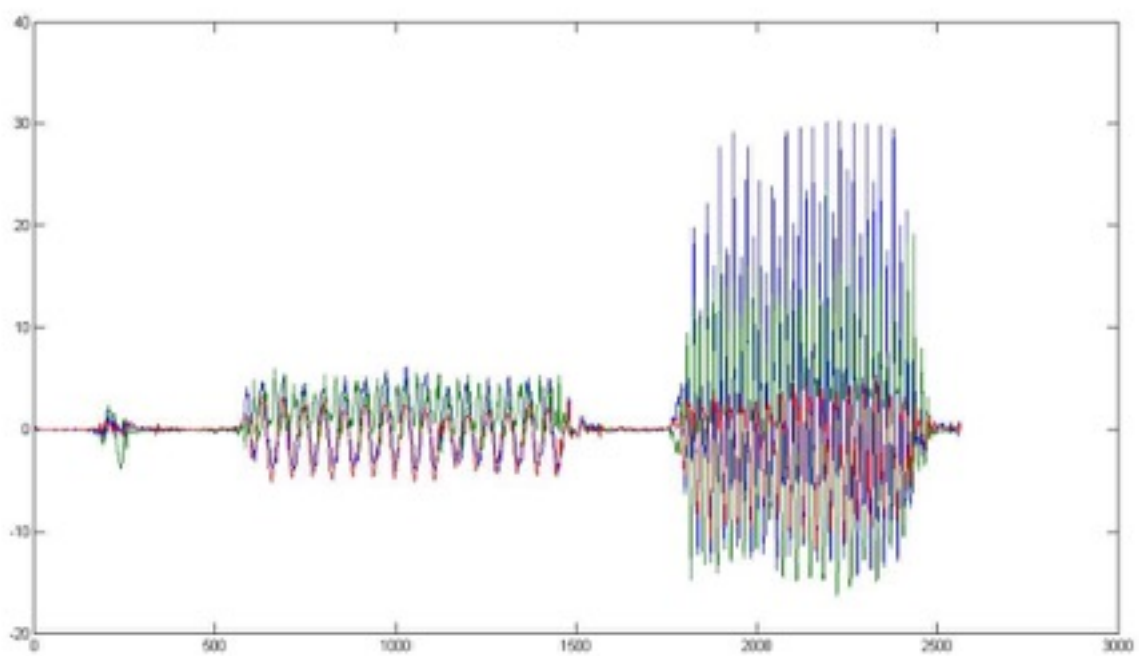
$$\sum_{k=1}^{M} b_j(k) = 1, 1 \leqslant j \leqslant N$$

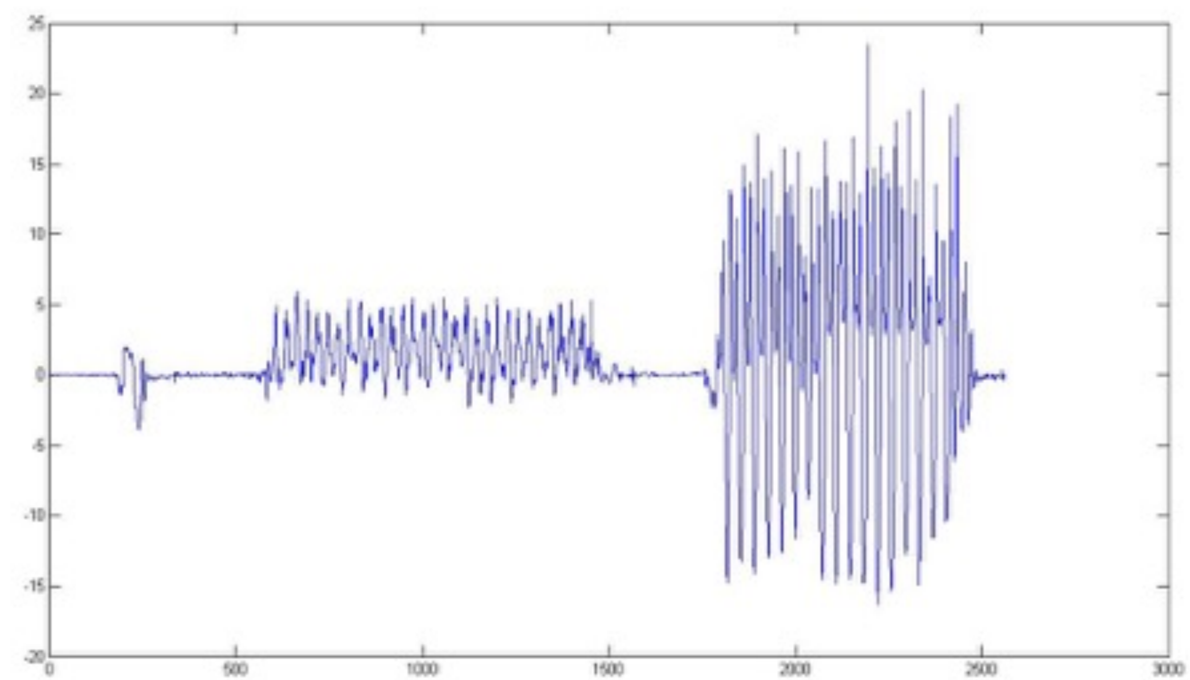
- Step 2:Calculate the parameters of E&M

- Step 3:Circulate calculation until convergent

Combination

- Get λ using Baum-Welch Algorithm for our system
- Classify the hidden state according to the data observed





Sit-Sit_Stand-Stand-Walk-Stand-Run

Future Work

- Validation of HMM in our system
- Research focusing on Energy-saving part with Zhuo Li

Thanks

- Prof.Wang, Prof.Tian
- Group Leader: Siyang Liu
- Vice Group Leader: Xiaoguang Zhu
- Co-workers: Zhuo Li, Shan He, Haixu Ying, Zhifeng Zhang

Thank you