Body Posture Identification using Hidden Markov Model with a Wearable Sensor Network

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Outline

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• Application of Hidden Markov Model (HMM)
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• Summary
Body Area Network and Applications

- **Human health applications:**
  - Patients’ health and vital information monitoring
  - Sleep monitoring
  - Physical activity monitoring

- **Battlefield applications:**
  - Soldiers monitoring
  - Identify the wounded soldier’s posture
  - Assess the soldier’s context
  - Delivering information to commanders about soldiers health
Accelarometer based Posture Identification

• Based on the acceleration levels of different body parts
  – Direct indication of physical activity
• It works very well for postures with high level of activity:
  – Walking
  – Jogging
  – Sprinting
• There are many applications require to identify very low physical activity postures:
  – Standing
  – Sitting
  – Lying down
• For these postures the accelerometer based solutions do not work well
Proximity based Identification

- Detecting non activity-intensive body postures
  - Measuring the proximity between body segments
  - The relative RF signal strength between the sensors are measured
  - The orientation of the body segments and the overall body postures can be determined
- Proximity sensing errors can be caused by:
  - Clothing
  - Body structure
  - Sensor mounting
- A HMM is developed to deal with these sensing errors
Wearable Sensor Network

- Multiple sensors are mounted
- Sensors movement reflect body segments displacement
- Mica2Dot, 570mAH button cell, a total weight of 5.9 grams
- Sensor card MTS510 from Crossbow
Sensor Modalities

- **Acceleration:**
  - It is proportional to the physical activities
- **Relative Proximity**
  - It is measured using Radio Signal Strength Indication (RSSI)
  - *Hello* messages are sent from all sensors to all neighbors
  - Each node creates a local neighbor table contains information about the local topology and relative proximity for all neighbors
Sensor Placements

- Two sensors on both front upper arms and two sensors on front thighs
- There is variability in the inter-node link quality, caused by:
  - Body movements
  - Antenna mis-orientation
  - Signal blockage
- The network topology becomes unpredictably dynamic
- The proximity information by the RSSI values can also vary
- We use a Hidden Markov Model to address these measurement errors and variability
Posture Identification using Accelerometry

- Postures we attempt to detect are SIT, STAND, WALK and RUN
- Both activity and non-activity intensive Postures
- Controlled experiments are developed, where sequence of postures the subjects need to follow

![Graph showing posture sequence over time with accelerometer readings.]
Posture Identification using Multi-Modality Sensing

- **Target Postures**
  - Low: SIT, STAND
  - Moderate: WALK
  - High: RUN

- **Activity Level**
  - Low: SIT, STAND
  - Moderate: WALK
  - High: RUN

- **Accelerometry**
  - SIT, STAND: Not applicable
  - WALK, RUN: Applicable for posture detection
Posture Modeling and Generation

- Sit-stand behavior is modeled as a Markov process
- Transition probabilities represent the subject’s behavior
- Generate a sequence of 50 states of SIT and STAND using the probability transition matrix of:

\[
A = \{a_{ij}\} = \begin{bmatrix} 0.7 & 0.3 \\ 0.5 & 0.5 \end{bmatrix}
\]

\[O: [v_1, v_2, \ldots, v_M] \]
\[O_1, O_2, O_3, \ldots, O_T \text{ Observed output symbol} \]

- S: SIT and T: STAND
- 10 sec are spent in each posture
- Total experiment time of 500 sec

Averages RSSI values are collected on a compute server

The overall average represent the mean relative distance between the subject’s body segments

Two mechanisms are proposed to identify the posture:
- Threshold based
- HMM based
Threshold Based Identification

- High RSSI dB value indicates low received radio signal strength
- Low RSSI value indicates high received radio signal strength
- High value indicates SIT posture and low value indicates STAND posture
- While generally maintaining this trend, lots of anomalies are observed
Threshold Based Identification (contd.)

- It is possible to identify the SIT and STAND postures by using a carefully chosen RSSI threshold value.
- Sensitive to the individual subjects’ physical structure, clothing and posture.
- The optimal threshold value for individual subject can change over time.

![Graph showing percentage match against RSSI threshold value for Subject-1, Subject-2, and Subject-3.](image)
Hidden Markov Model (HMM)

• A stochastic process represented by a discrete Markov Chain
• The states are hidden from the observer
• A number of observable parameters are visible
• Using HMM we can estimate the current state if transition and observation probability information are known a-priori
• It is also possible to compute the probability a specific state sequence
HMM Mapping for Posture Identification

• $N$ postures are modeled as $N$ hidden states $S = \{S_1, S_2, \ldots, S_N\}$
• In our case $N = 2$ for postures SIT and STAND
• At each state there are $M$ distinct observable parameters $O = \{v_1, v_2, \ldots, v_M\}$
• Each $v_m$ can take one of multiple possible values
• Observation made at time instant $t$ is represented as $O_t$
• $O_t$ vector is constructed from the average RSSI values
• Each $v_m$ is a binary variable which can be either ‘0’ or ‘1’
• The value of $M$ determines the granularity of observation
HMM Mapping (contd.)

• The HMM can be fully specified by the parameters $A$, $B$ and $\pi$ as:

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

(1)

• The posture transition probability matrix, $A = [a_{ij}]$

$$a_{ij} = p(q_t = S_j | q_{t-1} = S_i), \quad 1 \leq i, j \leq N$$

(2)

• $A$ is an $N \times N$ matrix, and $q_t$ denotes the actual posture at time $t$

• The observation probability matrix, $B = [b_{jm}]$

$$b_{jm} = p(O_t = [v_1 = 0, ..., v_m = 1, ..., v_M = 0] | q_t = S_j), \quad 1 \leq m \leq M$$

(3)

• $B$ is an $N \times M$ matrix, and $O_t$ is the observation vector at time $t$

• The initial state distribution, $\pi = [\pi_i]$ of length $N$

$$\pi_i = p(q_0 = S_i), \quad 1 \leq i \leq N$$

(4)
Experimental Results

• The $B$ matrix is constructed by computing the $b_{jm}$ probabilities
• As for the Initial State Distribution $\pi$, we have used $[1, 0]$.
• The observation sequence $\{O_1, O_2, O_3, \ldots, O_T\}$ is constructed from the RSSI values.
• We have experimented with different observation granularity vector, $M$ ranging from 2 to 10.
Posture Detection Performance using HMM

- For subject-2, HMM provides 92% to 94% match, but threshold provides 88% match
- Higher observation granularity for HMM provides better rate
- Large observation granularities, the system becomes subject-independent
Self Calibration of B Matrix

- In the previous results, the observation probability matrix $B$ has been manually constructed during an observation calibration phase.
- B matrix should be calibrated automatically, without having to manually calibrate for each individual subject.
- We implement a self-calibration process of the $B$ matrix, which is based on Baum-Welch iterative algorithm.
- Start with initial $B$ matrix, and then iteratively adjust it based on the HMM stochastic differences.
Baum-Welch Algorithm

1. Collect observations \( O = O_1O_2\ldots O_T \)
2. Initialize \( \lambda \) using a starting \( B \) matrix with constant \( A \) and \( \pi \)
3. Given observation sequence \( O = O_1O_2\ldots O_T \) and \( \lambda \), compute new \( B \) matrix using HMM parameters
4. Set new \( \lambda_{\text{new}} \) using the new \( B \) matrix
5. Compute a new quantity \( \text{MAXLIKELIHOOD} \) as:
   \[ \text{MAXLIKELIHOOD} = \max[P(O_1\ldots O_T \mid \lambda), P(O_1\ldots O_T \mid \lambda_{\text{new}})] \]
6. \( \lambda = \lambda_{\text{new}} \)
7. Go to step-3 and repeat till the quantity MAXLIKELIHOOD converges
Self Calibration Results

- The identification accuracy gradually increases over time
- Within 13 iterations the process starts delivering the best performance
Summary

• Posture detection using a wearable sensor network is presented
• A novel proximity sensing with HMM based detection techniques, has been used
• HMM method is able to deliver significantly better detection performance than the threshold based mechanism in a more individual-independent manner
• HMM based detection process is applied with observation self-calibration using the Baum-Welch algorithm

Video Demo