Feature extraction for human activity recognition on streaming data

Nawel Yala (PhD Student), Belkacem Fergani (Professor), LISIC Laboratory, USTHB, Faculty of Electronics and Computer Sciences Algiers

Anthony Fleury (Ass. Professor), Mines Douai, France
Outline

- **Introduction**
  - Human Activity Recognition using simple binary sensors

- **Methods**
  - Offline and Online Human Activity recognition
  - Data segmentation
  - Feature extraction

- **Results**

- **Conclusions**
Introduction

Objective: Using sensors placed on daily objects to identify high level human activities such as take medicine, sleeping, etc.

Applications
- Health/Elderly care
- Emergency
- Security
- Smart Environment
- Surveillance
- Context-aware-systems

Sensor types
- Contact switch sensors, pressure sensors, object identification sensors, etc.
- Camera

Binary sensors are simple, cheap, easy to install, and NOT as INTRUSIVE as camera.
Data Segmentation

Segmentation

- Divide the data into windows most suitable for activity recognition
- On each window a feature vector is computed to use it as an instance for learning or testing phase.

A difficult task:
- Human activities can be performed consecutively or concurrently → The exact boundaries of an activity are difficult to define.
Offline vs. Online methods (1)

☑️ Offline method

☑️ Segment data into time slices
☑️ Each time slice labeled with activity that dominates it.
☑️ Wait for future data to identify which activity is being executed (duration of the window)
☑️ Suitable for sequential activities, it is not effective in the case of interleaved or concurrent activities.

Activity sequence
Sensor Events sequence

(a) - Time windows

ΔT ΔT ΔT ΔT ΔT ΔT ΔT ΔT ΔT ΔT ΔT ΔT
Offline vs. online methods (2)

✓ Online method

✓ The method classify each event when recorded.
✓ Data is segmented into windows of K sensor events.
✓ Each window contains events that precede the last one and describe it.
✓ Each window is labeled with the one of the last event.
✓ Suitable for non sequential activities and multi-residents smart-home.
✓ Better for health-care or assistance in living applications that require prompt intervention/reaction.

Activity sequence

Sensor Events sequence

6 events in window
Feature extraction (1)

1. BaseLine feature extraction method (with 5 sensors in the smart-home)

Window of 9 events

\[
\begin{bmatrix}
S_1 \\
S_2 \\
S_5 \\
S_1 \\
S_2 \\
S_5 \\
S_5 \\
S_2 \\
S_1 \\
\end{bmatrix}
\]

Feature vector

\[
\begin{bmatrix}
T \text{ of } S_1 \\
T \text{ of } S_2 \\
T_{2-T1} \\
3 \\
3 \\
0 \\
0 \\
2 \\
\end{bmatrix}
\]

Vector is labeled with the activity of the last event (\(S_1\))

Drawback: window can contain sensor events far away from the last one (in time)

How often each sensor appear in the window

\(\rightarrow\) perhaps do not correctly describe the last event?
Feature Extraction (2)

2. Sensor-Dependency extraction

Computation of a mutual information matrix $\text{MI}$ between sensors on the whole stream. For N sensors, NxN matrix (example still with 5 sensors).

$$
\text{MI} = \\
\begin{bmatrix}
\text{MI}_{s1,s1} & \text{MI}_{s2,s1} & \text{MI}_{s3,s1} & \text{MI}_{s4,s1} & \text{MI}_{s5,s1} \\
\text{MI}_{s2,s1} & \text{MI}_{s2,s2} & \text{MI}_{s3,s2} & \text{MI}_{s4,s2} & \text{MI}_{s5,s2} \\
\text{MI}_{s3,s1} & \text{MI}_{s2,s3} & \text{MI}_{s3,s3} & \text{MI}_{s4,s3} & \text{MI}_{s5,s3} \\
\text{MI}_{s4,s1} & \text{MI}_{s2,s4} & \text{MI}_{s3,s4} & \text{MI}_{s4,s4} & \text{MI}_{s5,s4} \\
\text{MI}_{s5,s1} & \text{MI}_{s2,s5} & \text{MI}_{s3,s5} & \text{MI}_{s4,s5} & \text{MI}_{s5,s5}
\end{bmatrix}
$$

$\text{MI}_{si,sj}$ represents the probability of appearance of $s_i$ just before $s_j$.

Higher $\text{MI}_{s1,s2}$ is, stronger is the relationship between $s_1$ and $s_2$ ⇒ a strong influence between them for an activity.
3. Sensor Dependency feature extraction EXTENDED method

- In the previous method, Mutual information is computed on the consecutive apparition of two sensor events.
- In this extension, computation is done in a window of K sensors instead

→ with this modification allow more than one path of execution for each activity.
Feature extraction (4)

4. Last State Sensor feature extraction method

<table>
<thead>
<tr>
<th>Window of sensor events</th>
<th>Event value</th>
<th>Feature vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1 S2 S5 S1 S2 S5 S2 S5 S1 S2 S5</td>
<td>ON ON OFF OFF OFF ON ON OFF</td>
<td>T of S1 T of S2 T 2- T1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0 0 0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>

- It is efficient for instance with IR sensors of different kind (large and small cone).
- The last value of the sensor in the windows became more descriptive for the last event.
Experiments

- **Datasets from WSU CASAS smart-home project**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Gender &amp; age</th>
<th>Number of Sensors</th>
<th>Time Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aruba</td>
<td>Elderly / female</td>
<td>34</td>
<td>7 months</td>
</tr>
<tr>
<td>Tulum</td>
<td>2 married residents</td>
<td>16</td>
<td>4 months</td>
</tr>
</tbody>
</table>

- **Classification stage**

  One vs. one SVM (LibSVM library)

- **Experiment**:

  Two series of experiments:
  
  - Learning on data excluding the “other” activity
  - Learning on data containing “other” activity

(« Other » activity: data with missing labels, transitions, etc.)
## Results

### Learning excluding ‘other events’

<table>
<thead>
<tr>
<th>Feature extraction Method</th>
<th>Aruba dataset</th>
<th>Tulum dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc</td>
<td>F-score</td>
</tr>
<tr>
<td>Baseline</td>
<td>87.23</td>
<td>63.29</td>
</tr>
<tr>
<td>Sensor Dependency</td>
<td>87.71</td>
<td>65.56</td>
</tr>
<tr>
<td>Sensor Dependency extension</td>
<td>87.71</td>
<td>68.68</td>
</tr>
<tr>
<td>Last Stat Sensor</td>
<td>87.55</td>
<td>69.24</td>
</tr>
</tbody>
</table>

### Learning data containing ‘other events’

<table>
<thead>
<tr>
<th>Feature extraction Method</th>
<th>Aruba dataset</th>
<th>Tulum dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc</td>
<td>F-score</td>
</tr>
<tr>
<td>Baseline</td>
<td>67.82</td>
<td>49.52</td>
</tr>
<tr>
<td>Sensor Dependency</td>
<td>64.18</td>
<td>47.54</td>
</tr>
<tr>
<td>Sensor Dependency extension</td>
<td>67.38</td>
<td>50.39</td>
</tr>
<tr>
<td>Last Stat Sensor</td>
<td>69.09</td>
<td>47.38</td>
</tr>
</tbody>
</table>
Conclusions & future works

✓ We achieved a classification rate of over 69% on data containing “Other” activity.

✓ Last Stat Sensor feature extraction method gives the best performance in that case.

✓ Performance of recognition system is sensitive to the problem of missing labels data.

✓ Improving the performance of the system using data containing “other” activity.

✓ Finding a way to improve the computational complexity.
Feature extraction for human activity recognition on streaming data

Nawel Yala (PhD Student), Belkacem Fergani (Professor), LISIC Laboratory, USTHB, Faculty of Electronics and Computer Sciences Algiers

Anthony Fleury (Ass. Professor), Mines Douai, France