Performing Activity Recognition Using an Android Smartphone

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Introduction
Environmental sensors have shown to be effective in collecting data for activity recognition purposes. However, they have limited usefulness due to their inherent immobility. Dedicated body sensors, although mobile, are a bulky and unnatural accessory. Smartphones resolve the issues of mobility, bulkiness, and acceptance as an accessory. The built-in sensors in smartphones allow for performing autonomous activity recognition.

Overview

Participants were instructed to wear a phone naturally. Accelerometer and orientation readings were then collected as participants performed both simple (single action) and complex (multi-action) activities. The accelerometer in Android phones detects acceleration along three axes dependent upon the orientation of the phone. These axes were normalized so that the x, y, and z axes always run north/south, east/west, and up/down respectively. Features were then extracted from time windows of varying lengths and used to train learning algorithms in WEKA (open-source machine learning software).

Activities

Simple
- Biking
- Climbing
- Driving
- Lying
- Not on Person
- Running
- Sitting
- Standing
- Walking

Complex
- Cleaning
- Cooking
- Medication
- Sweeping
- Washing Hands
- Watering Plants

Feature List

- Mean
- Min
- Max
- Standard Deviation
- Correlation
- Zero-Crosses

Mean, min, max, and standard deviation were calculated for each direction of acceleration and angle of orientation (6 total values per window). Correlation was calculated between each pair of axes for both acceleration and orientation (6 total values). Zero-cross was calculated for each axis of acceleration (3 total values). A total of 33 different features are extracted from each sample window.

Results

Accuracy of Activities over Various Window Lengths

<table>
<thead>
<tr>
<th>Window Length (Seconds)</th>
<th>Simple Activities</th>
<th>All Activities</th>
<th>Complex Activities</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9</td>
<td>0.88</td>
<td>0.78</td>
</tr>
<tr>
<td>2</td>
<td>0.95</td>
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</tr>
<tr>
<td>4</td>
<td>0.98</td>
<td>0.95</td>
<td>0.9</td>
</tr>
<tr>
<td>8</td>
<td>0.99</td>
<td>0.97</td>
<td>0.93</td>
</tr>
<tr>
<td>12</td>
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<tr>
<td>16</td>
<td>0.96</td>
<td>0.93</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Conclusion

In general, activity recognition performed very well for simple activities with a peak performance of over 93% using a multi-layer perceptron network and a 2 second time window.

Complex activities did not perform as well. Peak performance was just over 90% when exclusively looking at complex activities given a defined time window. However, an accuracy of over 77% can be achieved if starting and stopping times are defined for each activity.

Future Work

Work remains to determine the effectiveness of recognizing complex activities when the phone is used in conjunction with environmental sensors.

The data collection application.

Accuracy of Simple Tasks over Various Learning Algorithms

All Activities
- Simple Activities
- Complex Activities

The motion sensors in one of WSU's smart apartments.

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