On-body Localization of Wearable Devices: An Investigation of Position-Aware Activity Recognition

Timo Sztyler, Heiner Stuckenschmidt
Introduction

I. Motivation

II. Data Set

III. Methods / Results

IV. Conclusion
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IV. Conclusion
Motivation

Wearable devices feature a variety of sensors that are carried all day long

- Opportunity: Continuous monitoring of human activities
- Many existing studies were conducted in a (highly) controlled environment
- Focus shifts to real world application

We aim to develop robust activity recognition methods
Motivation

*Real World*: Activity Recognition quality depends on the on-body device position.

Previous studies ....

... identified the relevant on-body positions
... focused on the acceleration sensor
... investigated position-independent activity recognition
... provided different results regarding the usefulness

Only a couple of researchers addressed the localization problem.

Nobody considered all relevant positions and activities.
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Data Collection

To address the mentioned problem it was necessary to create a new data set

• 15 subjects (8 males / 7 females)
• seven wearable devices / body positions
  • chest, forearm, head, shin, thigh, upper arm, waist
• acceleration, GPS, gyroscope, light, magnetic field, and sound level
• climbing stairs up/down, jumping, lying, standing, sitting, running, walking
• each subject performed each activity ≈10 minutes
Data Collection

We focused on realistic conditions

• common objects and clothes to attach the devices
• subjects walked through downtown or jogged in a forest.
• each movement was recorded by a video camera
• We recorded for each position and axes 1065 minutes

complete, realistic, and transparent data set
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   • Position Detection
   • Activity Recognition

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Methods – Feature Extraction

So far, there is no agreed set of features ...

- time and frequency-based features
- gravity-based features (low-pass filter)
  - derive device orientation (roll, pitch)

... but splitting the recorded data into small overlapping segments has been shown to be the best setting.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time</strong></td>
<td>Correlation coefficient (Pearson), entropy (Shannon), gravity (roll, pitch), mean, mean absolute deviation, interquartile range (type R-5), kurtosis, median, standard deviation, variance</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Frequency</strong></td>
<td>Energy (Fourier, Parseval), entropy (Fourier, Shannon), DC mean (Fourier)</td>
</tr>
</tbody>
</table>
Methods – Random Forest Classifier

A previous work suggested that this classifier is very suitable for this scenario.

• A forest of Decision trees can prevent overfitting
• A Random Tree is build by choosing features at random
• For each branching decision only a randomly selected subset is considered.

Result: Set of uncorrelated decision trees

The unseen feature vector is labeled by the principle of bagging
Methods – Position Detection

- We focused on all data of a subject but not across subjects
- position data of lying, standing, and sitting lead to misclassification
  - We distinguish between static and dynamic activities
  - we detected that the gravity provided useful information but ...
    - ... it is no indicator of the device position
- We used stratified sampling combined with 10-fold cross validation
- To compare the results we also considered further classifiers
Results – Position Detection

We evaluated two approaches ...

- activity-independent position detection (left)
- activity-level specific position detection (right)

**Two Steps**: static/dynamic split (97%), then training the classifier on an activity-level depended feature set.

In most of the cases the position is correct recognized.

<table>
<thead>
<tr>
<th>Class</th>
<th>Precision</th>
<th>Recall</th>
<th>F-Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>chest</td>
<td>0.79</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>forearm</td>
<td>0.79</td>
<td>0.78</td>
<td>0.79</td>
</tr>
<tr>
<td>head</td>
<td>0.79</td>
<td>0.82</td>
<td>0.80</td>
</tr>
<tr>
<td>shin</td>
<td>0.90</td>
<td>0.86</td>
<td>0.88</td>
</tr>
<tr>
<td>thigh</td>
<td>0.83</td>
<td>0.80</td>
<td>0.82</td>
</tr>
<tr>
<td>upper arm</td>
<td>0.79</td>
<td>0.78</td>
<td>0.78</td>
</tr>
<tr>
<td>waist</td>
<td>0.79</td>
<td>0.81</td>
<td>0.80</td>
</tr>
<tr>
<td><strong>avg.</strong></td>
<td><strong>0.81</strong></td>
<td><strong>0.81</strong></td>
<td><strong>0.81</strong></td>
</tr>
</tbody>
</table>

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<th>Recall</th>
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</thead>
<tbody>
<tr>
<td>chest</td>
<td>0.87</td>
<td>0.89</td>
<td>0.88</td>
</tr>
<tr>
<td>forearm</td>
<td>0.87</td>
<td>0.85</td>
<td>0.86</td>
</tr>
<tr>
<td>head</td>
<td>0.86</td>
<td>0.89</td>
<td>0.87</td>
</tr>
<tr>
<td>shin</td>
<td>0.95</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>thigh</td>
<td>0.91</td>
<td>0.90</td>
<td>0.91</td>
</tr>
<tr>
<td>upper arm</td>
<td>0.86</td>
<td>0.84</td>
<td>0.85</td>
</tr>
<tr>
<td>waist</td>
<td>0.91</td>
<td>0.92</td>
<td>0.92</td>
</tr>
<tr>
<td><strong>avg.</strong></td>
<td><strong>0.89</strong></td>
<td><strong>0.89</strong></td>
<td><strong>0.89</strong></td>
</tr>
</tbody>
</table>
Results – Position Detection

To compare the results we also evaluated further classifiers

• RF outperforms the other classifier (89%)
• The training phase of RF was one of the fastest
• k-NN (75%), ANN (77%), and SVM (78%) achieved reasonable results
  (parameter optimization was performed)
Methods – Activity Recognition

*Feasibility*: Used the results of the previous experiment (including all mistakes)

Again, we evaluated two approaches ...

- position-independent activity recognition
- position-aware activity recognition

Set of individual classifiers for each position and subject

1) First decide if static or dynamic
2) Apply activity-level depended classifier (different feature sets)
3) Apply position-depended classifier
Result – Activity Recognition

The position-independent approach recognized the correct activity with an F-Measure of 80%.

The position information improves the F-Measure by 4%

- In general, there are groups of activities that are confused
- Problematic: Activities that are characterized by low acceleration

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<th>Class</th>
<th>Precision</th>
<th>Recall</th>
<th>F-Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>stairs down</td>
<td>0.84</td>
<td>0.77</td>
<td>0.81</td>
</tr>
<tr>
<td>stairs up</td>
<td>0.78</td>
<td>0.81</td>
<td>0.79</td>
</tr>
<tr>
<td>jumping</td>
<td>0.99</td>
<td>0.95</td>
<td>0.97</td>
</tr>
<tr>
<td>lying</td>
<td>0.90</td>
<td>0.88</td>
<td>0.89</td>
</tr>
<tr>
<td>standing</td>
<td>0.74</td>
<td>0.981</td>
<td>0.77</td>
</tr>
<tr>
<td>sitting</td>
<td>0.78</td>
<td>0.87</td>
<td>0.76</td>
</tr>
<tr>
<td>running</td>
<td>0.94</td>
<td>0.91</td>
<td>0.92</td>
</tr>
<tr>
<td>walking</td>
<td>0.85</td>
<td>0.88</td>
<td>0.86</td>
</tr>
<tr>
<td>avg.</td>
<td>0.84</td>
<td>0.83</td>
<td>0.84</td>
</tr>
</tbody>
</table>
Result – Activity Recognition

In contrast to the position as target class ...

... some activities are more often misclassified

- walking, stairs up/down
- lying, standing, sitting

<table>
<thead>
<tr>
<th>Predicted</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
<th>A6</th>
<th>A7</th>
<th>A8</th>
</tr>
</thead>
<tbody>
<tr>
<td>stairs down</td>
<td>5080</td>
<td>849</td>
<td>2</td>
<td>4</td>
<td>42</td>
<td>24</td>
<td>40</td>
<td>548</td>
</tr>
<tr>
<td>stairs up</td>
<td>526</td>
<td>6820</td>
<td>1</td>
<td>26</td>
<td>134</td>
<td>87</td>
<td>31</td>
<td>768</td>
</tr>
<tr>
<td>jumping</td>
<td>7</td>
<td>5</td>
<td>1130</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
<td>1</td>
</tr>
<tr>
<td>lying</td>
<td>18</td>
<td>94</td>
<td>0</td>
<td>7660</td>
<td>324</td>
<td>579</td>
<td>57</td>
<td>8</td>
</tr>
<tr>
<td>standing</td>
<td>19</td>
<td>99</td>
<td>0</td>
<td>217</td>
<td>7000</td>
<td>1020</td>
<td>244</td>
<td>15</td>
</tr>
<tr>
<td>sitting</td>
<td>19</td>
<td>112</td>
<td>0</td>
<td>582</td>
<td>1380</td>
<td>6470</td>
<td>141</td>
<td>18</td>
</tr>
<tr>
<td>running</td>
<td>70</td>
<td>96</td>
<td>11</td>
<td>38</td>
<td>535</td>
<td>142</td>
<td>8830</td>
<td>24</td>
</tr>
<tr>
<td>walking</td>
<td>287</td>
<td>709</td>
<td>1</td>
<td>3</td>
<td>50</td>
<td>24</td>
<td>14</td>
<td>7720</td>
</tr>
</tbody>
</table>
Result – Activity Recognition

To compare the results we also evaluated further classifiers.

- RF achieved the highest recognition rate (84%).
- k-NN (70%) and SVM (71%) performed almost equal but worse than ANN (75%) and DT (76%).
- All classifier performed worse in a position-independent scenario.
  - RF performed the best in all settings.
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Conclusion

• on-body device position is recognizable with 89%
• there is no best on-body device position
  e.g., climbing stairs up is best handled by the chest
• static activities are hard to recognize even with the position
  Additional information is required in context of activities that are characterized by low acceleration
• activities that are characterized by high acceleration are easier to recognize (e.g., running, jumping)
• device position that are located on the arm are a special case and need special attention
• device position information improves activity recognition
Future Work

First, we want to focus...
... on improving the position/activity recognition rate
... reduce the effort concerning the training-phase (groups?)
... combing sensor data of several device (cross-position features)

Second, we want to focus...
... on deriving more precise activities
Which kind of task is performed during sitting?
This also necessitate to address the problem regarding
The flexibility of the arm.
Thank you