Online Personalization of Cross-Subjects based Activity Recognition Models on Wearable Devices

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1. Motivation
Motivation

Most of the existing works target subject-specific activity recognition

- requires training data for each subject
- is not available immediately
- behavior changes are often not considered

→ evolving cross-subjects based activity recognition
Idea

1. Build a cross-subjects activity recognition model
   ■ reduces data collection and training effort
   ■ is available at hand
   ■ focus on specific groups of people (child vs. elder)

2. Personalize the base model
   ■ use online learning to avoid retraining or storing all data
   ■ use active learning to query the user (uncertainty)
2. Data & Features
Data Set

- 15 subjects (8 males / 7 females)
- seven wearable devices / 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
Feature Extraction

Previous experiments have shown ...

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

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

<table>
<thead>
<tr>
<th>Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time</strong></td>
</tr>
<tr>
<td><strong>Frequency</strong></td>
</tr>
</tbody>
</table>
3.1. Online Random Forest
Online Random Forest

Considering online mode, the main differences are ...

- **Bagging (generation of subsamples)**
  - replace *sample with replacement* with Poisson(1)

- growing of the individual trees
  - Select thresholds and features randomly
    *(Extreme Randomized Forest)*

**Diagram:**

- **Training Sample**
  - k=Poisson (1)
  - ...,
  - k=Poisson (1)

- **Prediction**
  - k-times
  - Tree #1
  - Tree #n

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IEEE International Conference on Pervasive Computing and Communications 2017
3.2. Cross-Subjects Activity Recognition
Cross-Subjects Activity Recognition (1/2)

Recognition model relies on labeled data of several people expect target person

most common approach: leave-one-out

Problem: Children and elders walk differently

Model only covers most dominant behavior across all people
Cross-Subjects Activity Recognition (2/2)

We aim to build a model that considers physical characteristics

Rely only on specific people ...
... same/similar gender and physique (walking)
... similar fitness level (running)

We follow a group-based approach ...
3.3. Personalization: Online and Active Learning
Personalization: Online and Active Learning

Active Learning

- New labeled data set
- Ask User
  - aggregate uncertain recognitions

Online Learning

- Update
- Classification result
  - update

Labeled data set for base model

Body Sensor Network

New labeled data set

Updatable Model

Smoothing

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**Personalization: Online and Active Learning**

*Smoothing* adjusts the classification result of a single window if it is surrounded by another activity.

1. **Online Learning**
   - The adjusted window is used to update the model.

2. **Focuses on minor classification errors**

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**Diagram:**

- **Online Learning**
  - Classification result
  - Update
  - *Smoothing*
User-Feedback queries the user regarding uncertain classification results

- infeasible to ask for a specific window (1 sec)
- specified a duration of uncertainty
- query result is a new data set

focuses on major classification errors
4. Results
Cross-Subject Activity Recognition

Inspecting the individual activities ...

- static and dynamic perform comparable (~78%)
- walking and climbing stairs have the lowest rates

<table>
<thead>
<tr>
<th>Class</th>
<th>Randomly</th>
<th>Leave-one-out</th>
<th>Our approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>stairs up</td>
<td>0.62</td>
<td>0.66</td>
<td>0.69</td>
</tr>
<tr>
<td>stairs down</td>
<td>0.63</td>
<td>0.67</td>
<td>0.69</td>
</tr>
<tr>
<td>jumping</td>
<td>0.79</td>
<td>0.88</td>
<td>0.87</td>
</tr>
<tr>
<td>lying</td>
<td>0.81</td>
<td>0.83</td>
<td>0.86</td>
</tr>
<tr>
<td>standing</td>
<td>0.71</td>
<td>0.73</td>
<td>0.79</td>
</tr>
<tr>
<td>sitting</td>
<td>0.59</td>
<td>0.63</td>
<td>0.68</td>
</tr>
<tr>
<td>running</td>
<td>0.88</td>
<td>0.90</td>
<td>0.96</td>
</tr>
<tr>
<td>walking</td>
<td>0.60</td>
<td>0.67</td>
<td>0.70</td>
</tr>
<tr>
<td>avg.</td>
<td>0.69</td>
<td>0.74</td>
<td>0.78</td>
</tr>
</tbody>
</table>
Personalization (1/3)

Using online and active learning ...

- online vs. offline learning → lower recognition rate
- user-feedback → walking, stairs are mostly resolved
- smoothing → minor errors decrease rapidly

<table>
<thead>
<tr>
<th></th>
<th>Base</th>
<th>+ Smoothing</th>
<th>+ User-Feedback</th>
<th>+ Both</th>
</tr>
</thead>
<tbody>
<tr>
<td>static</td>
<td>0.76</td>
<td>0.76</td>
<td>0.79</td>
<td>0.79</td>
</tr>
<tr>
<td>dynamic</td>
<td>0.76</td>
<td>0.80</td>
<td>0.86</td>
<td>0.87</td>
</tr>
<tr>
<td>w. avg.</td>
<td>0.76</td>
<td>0.78</td>
<td>0.83</td>
<td>0.84</td>
</tr>
</tbody>
</table>
Personalization (2/3)

Focusing on interesting combinations ...

- offline mode: phone and (watch 69% or glasses 72%)

improved significantly, especially walking

<table>
<thead>
<tr>
<th>Class</th>
<th>Watch &amp; Phone</th>
<th></th>
<th></th>
<th>Glasses &amp; Phone</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Precision</td>
<td>Recall</td>
<td>$F_1$</td>
<td>Precision</td>
<td>Recall</td>
<td>$F_1$</td>
</tr>
<tr>
<td>static</td>
<td>0.75</td>
<td>0.73</td>
<td>0.73</td>
<td>0.80</td>
<td>0.80</td>
<td>0.80</td>
</tr>
<tr>
<td>dynamic</td>
<td>0.87</td>
<td>0.85</td>
<td>0.86</td>
<td>0.88</td>
<td>0.87</td>
<td>0.87</td>
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<td>w. avg.</td>
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<td>0.80</td>
<td>0.84</td>
<td>0.84</td>
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</tr>
</tbody>
</table>
Personalization (3/3)

*Personalization is a continuous process* ...

- especially dynamic activities improve significantly
- most improvement in the first two time intervals

- first iteration +4%, five iterations +8%
- number of windows with a low confidence value decrease with each iteration

![Graphs](image)
Parameter

Considering different confidence thresholds ...

- **turning point** $\rightarrow t=0.5$
- **10 questions** $\rightarrow +8$

Considering a different number of trees...

- **10 trees vs. 100 trees**
- **a smaller forest is more feasible concerning wearable devices**
5. Conclusion and Future Work
Conclusion

*Our results show that* ...

- ... physical characteristics allow to build promising cross-subjects models (78%)
- ... personalized model achieves a recognition rate of 84%, for dynamic activities even 87%
- ... personalization is significantly less effort than creating a labeled data set (10 questions)

personalized cross-subjects based models are feasible (online and active learning)
Future Work

• **Data Set**
  
  We got access to a large data set (~150 people), including vital parameter.

• **User Acceptance (Scenario)**
  
  error rate, emotional condition, environment

• **HAR vs. ADL**
  
  physical activities are often insufficient
Thank you for your attention :)

Timo Sztyler
Cross-Subject Activity Recognition

*We trained a single classifier for each subject...*

- our group-based approach performs better
- at least a four-sensor setup is necessary

→ not feasible in a real world scenario

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Randomly</td>
<td>0.61</td>
<td>0.69</td>
<td>0.75</td>
<td>0.77</td>
<td>0.79</td>
<td>0.80</td>
</tr>
<tr>
<td>Leave-one-out</td>
<td>0.65</td>
<td>0.74</td>
<td>0.79</td>
<td>0.82</td>
<td>0.83</td>
<td>0.85</td>
</tr>
<tr>
<td>Our Method</td>
<td>0.68</td>
<td>0.78</td>
<td>0.82</td>
<td>0.85</td>
<td>0.87</td>
<td>0.88</td>
</tr>
</tbody>
</table>
Offline Random Forest

Considering offline mode, typically ...

- ... for each tree *sample with replacement* is applied
- ... at each node features are selected at random
- ... a quality measure is used to determine best split
- ... after a split samples are propagated to child nodes
- ... majority vote over the individual results is applied
Personalization: Online and Active Learning

Online learning enables ...

- ... to delete already seen/processed data/records
- ... to adapt a model to new behavior
- ... to weight new information higher (unlearn)

Active learning enables ...

- ... to gather the most informative unlabeled data