Introduction

• Human Activity Recognition (HAR): methods and techniques to automatically identify Activities of Daily Living (ADLs) from inertial sensors of smartphones and smartwatches

• Recent statistics show that more than 5.19 billion people (67% of the world’s population) use smartphones, with user numbers up by 124 million (2.4%) over the past year.

• HAR can be extensively used in several domains. For example, in healthcare to keep track of elderly people or the rehabilitation process after accidents and injuries, or in the guide to safe travel

Methods

• The incremental learning procedure consists in three phases: (1) data preparation, (2) model generation, and (3) personalization:

  • Data preparation: the subjects, except subject x, are used to train the base model in the model generation phase. The subject x is used in the personalization phase to adapt the model trained in the previous phase.

  • The model generation phase consists of obtaining an initial model from all the samples of the dataset except those from the user x. This model is called user-independent model.

  • For the personalization phase we experimented three different approaches: non-supervised approach, semi-supervised, and supervised

  • Proposed CNNs: Residual Network (ResNet), Simplified CNN

  • We compared deep learning with a previous method based on Learn++ with hand-crafted features

Personalization in HAR

• Deep learning techniques have proven to be more efficient than traditional ones in classifying ADLs

• A very interesting approach is that of Siirtola et al. that exploits incremental learning to generate a personalized model without requiring data from the target user.

• The aim of this work is to experiment the effectiveness of an approach that combines incremental learning and deep learning techniques.

Materials

• Auginta: includes 3-axis linear acceleration, 3-axis angular velocity, and gyroscope sensor data of 11 ADLs recorded with Samsung Galaxy S II (30 subjects)

• Shoabib: includes 3-axis acceleration, gyroscope, magnetometer, and linear acceleration sensor data of 7 ADLs recorded with Samsung Galaxy S II (10 subjects)

• Siirtola: includes 3-axis acceleration sensor data of 5 ADLs recorded with Nokia N8 smartphones. The activities have been performed by 8 volunteers.

Results

Performance is measured in terms of macro average accuracy

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Segment size</th>
<th># segments</th>
<th># per user</th>
<th># classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auginta</td>
<td>1980</td>
<td>9.72</td>
<td>~ 120</td>
<td>11</td>
</tr>
<tr>
<td>Shoabib</td>
<td>1980</td>
<td>61.890</td>
<td>4.353</td>
<td>3</td>
</tr>
<tr>
<td>Siirtola</td>
<td>1200</td>
<td>6.851</td>
<td>~ 85</td>
<td>5</td>
</tr>
</tbody>
</table>

Conclusions

• In this paper we evaluated how deep learning can be employed in an incremental learning procedure and we compared deep learning with a previous method based on Learn++.

• Experiments carried out on 3 different datasets showed that, overall, deep learning outperforms Learn++. In particular, we evaluated two different networks: a ResNet and a simplified CNN. Both CNNs demonstrated to be faster than Learn++ to adapt to a new user thus demonstrating to require less user interaction than Learn++.

• We are now working on the design of a software component that implements the S-CNN and the transfer learning techniques. The component will be deployed on an Android mobile device. Once implemented, we will analyze the performance from the point of view of both power consumption and performance on real scenarios.