Determination of Mobility Context using Low-Level Data

Daniel Braun
German Research Center for Artificial Intelligence
Saarbruecken, Germany
daniel.braun@dfki.de

Christoph Endres
German Research Center for Artificial Intelligence
Saarbruecken, Germany
christoph.endres@dfki.de

Christian Müller
German Research Center for Artificial Intelligence
Saarbruecken, Germany
christian.mueller@dfki.de

ABSTRACT

Mobility can include a variety of transportation modes, spanning from walking over public transportation (bus, train, etc.) to driving. All these different modes have different contexts, which have unique features and different requirements to the user and his need for information. In this paper we present and evaluate some heuristics for determining the mobility context of a user based on low-level data collected using a smartphone and discuss possible applications. We identify the challenging aspects of the approach and discuss the next steps.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search Heuristic methods; I.3.6 [**Artificial Intelligence**]: Methodology and Techniques Ergonomics [user context]

1. INTRODUCTION

The users mobility context strongly affects which information is relevant for him and also how much information he can perceive without getting overwhelmed or distracted. Automatic context information could for instance help to adapt the way information is presented in a car with consideration for the cognitive load of the user. Furthermore, functionalities could be changed to suit the users need, e.g., from a schedule in a bus to a navigation system in the car. In addition, the same information could be used to give the user additional information about his mobility profile, e.g., calculating his carbon footprint or make suggestions for a more economic or ecologic use of the different transportation means.

Mobility can include a variety of transportation modes, spanning from walking over public transportation (bus, train, etc.) to driving. All these different modes have different contexts, which have unique features and different requirements to the user and his need for information.

AutomotiveUI'11, November 29-December 2, 2011, Salzburg, Austria
Adjunct Proceedings

Figure 1: Visualization of a trace using google earth. Correct determination of transportation means is depicted in green, incorrect results depicted in red. The recognition of railway line in parallel to the highway is confused with driving by car.

Most of the related work is published under the broad term of human activity recognition. Thereby, the particular set of activities and target applications differ. [3], for example, address the problem from a very general point of view, proposing an ontology-based approach, which is intended to cover a broad range of activities from writing on a blackboard to riding a motorbike. In contrast to that, [4] restrict there approach to indoor moving patterns based on wireless LAN, while [1] cover outdoor activities like jogging, walking, or riding a bicycle. [2] address the recognition of transportation modes, which comes very close to what our work is targeted at. However, all mentioned studies have in common that the downstream application is adaptation of the mobile application itself, mostly formulated rather vague as "optimization of the mobile device behavior". We intend to learn human activity in order to predict future activity (transportation needs).

2. OUR APPROACH

In order to make our context recognition as flexible and universally usable as possible, we decided to only use low-level GPS data which are provided by every smartphone or navigation system. During our series of tests, we used Android powered smartphones with a simple logging app, which writes every GPS-data change in a plain text file. Bases on these information, we attempt recognize the users mobility context.

We recorded 25 traces with up to 45,000 individual mea-

Figure 2: Visualization of a trace with afoot parts. Incorrect (red) results are caused by inaccuracy of the GPS signal.

Figure 3: Visualization of a trip on the highway. Red parts are caused by traffic jams which are confused with walking.

suring points each. 10 data sets were used to develop the heuristics, 15 for cross validation. The traces were recorded in everyday situations, using car, train or walking. The raw data was converted into an XML format for further processing. The measured positions were clustered in sections of approx. 30 meters length.

We use some heuristics (see Algorithm 1) based on speed and acceleration values obtained from GPS positions in order to determine the current mobility context based on the sensor data.

3. EVALUATION

To evaluate the heuristics, we applied them to our cross validation data sets.

We identified some areas with suboptimal recognition rates, especially confusing train rides with riding a car (Figure 1). The routing and the speed of a train is too similar to a car to be distinguished using the low level GPS data on which our heuristics are based.

Furthermore, the recognition of walking is challenged by the inherent inaccuracy of the GPS signal (Figure 2). In our annotated data we have found walking speed up to 30 km/h. Another problem was encountered in connection with loss of the GPS signal, e.g., when entering a building.

Algorithm 1 Heuristic for determining mobility context

```
for allSection do
  {speed infos}
  if thisSection.speed > 120 then
    thisSection.carProb(+0.8)
    thisSection.trainProb(+0.2)
    thisSection.afootProb(-1.0)
  else if thisSection.speed > 50 then
    thisSection.carProb(+0.5)
    thisSection.trainProb(+0.5)
    thisSection.afootProb(-1.0)
  else if thisSection.speed > 10 then
    thisSection.carProb(+0.5)
    thisSection.trainProb(+0.5)
    thisSection.afootProb(-1.0)
  else
    thisSection.carProb(0.0)
    thisSection.trainProb(0.0)
    thisSection.afootProb(+0.5)
  end if
  {future context}
  for next20Sections do
    if (accelerateToMoreThan120) then
      thisSection.carProb(+0.8)
      thisSection.trainProb(+0.2)
      thisSection.afootProb(-1.0)
      break
    end if
  end for
  if (accelerateToMoreThan10) then
    thisSection.carProb(+0.5)
    thisSection.trainProb(+0.5)
    thisSection.afootProb(-0.2)
    break
  end if
end for
```

Another challenge we discovered is the recognition of traffic jams (Figure 3). Under some special constellations of speeds, length and other parameters a traffic jam could be detected as a walk.

4. CONCLUSION AND OUTLOOK

The use of low level GPS data as only source is not sufficient for recognizing the mobility context of a user. As an additional challenge, the current heuristics are looking ahead in the data stream which is not feasible for immediate context determination.
It is necessary to connect the low level data with other information, such as street maps, schedules or additional sensor data (e.g., accelerometer) to obtain more reliable results.

5. REFERENCES

[1] J. R. Kwapisz, G. M. Weiss, and S. A. Moore. Activity recognition using cell phone accelerometers. *SIGKDD Explor. Newsl.*, 12:74–82, March 2011.

[2] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava. Using mobile phones to determine transportation modes. *ACM Trans. Sen. Netw.*, 6:13:1–13:27, March 2010.

[3] D. Riboni and C. Bettini. COSAR: hybrid reasoning for context-aware activity recognition. *Personal Ubiquitous Comput.*, 15:271–289, March 2011.

[4] J. Yin, Q. Yang, D. Shen, and Z.-N. Li. Activity recognition via user-trace segmentation. *ACM Trans. Sen. Netw.*, 4:19:1–19:34, September 2008.