Spatial Big Data for Human-Computer Interaction

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Abstract

The importance of spatial data for the area of human-computer interaction is discussed in this vision paper as well as how machine learning and spatial big data can be utilized for optimizing and adapting the interaction modalities in outdoor spaces. This paper briefly introduces and tries to connect previous work in order to highlight the vision towards a space adaptive personalized system and list important research questions.

2012 ACM Subject Classification Human-centered computing

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1 Introduction

We often use several types of digital devices in outdoor spaces, e.g., smartphones, tablets, smartwatches, in order to interact with the surrounding environment [4] and other people which are not necessarily co-located. Depending on several characteristics of our surroundings, e.g., environmental complexity [5], type of space (e.g., dense urban area, open green field) as well as our activity, e.g., interaction with a map [7], the interface of such a device could adapt accordingly when we ask for it [6] in order to ease the interaction for the current situation.

Our vision is a personalized interactive system that is able to recognize the activity of its user, the user's cognitive load [1], the user's familiarity with the surrounding environment as well as the type of the environment and adapt accordingly.

2 Relevant Big Spatial Data

In order to come closer to the presented vision, several data sources are necessary for the prediction of the relevant classes. In our current approach we utilize environmental data, human behavior data as well as geo-spatial semantics[1] [9]. The environmental data we utilize are based on street networks, e.g., types of intersections [2] in the surroundings of the user, the geo-spatial semantics of this area, or even the probability for certain routes from the user's current location [3]. Furthermore, we use eye tracking technology in order to track the visual attention of the user [8], e.g., what is the user looking at, as well as location tracking in order to record the user's mobility patterns, aiming at understanding the underlying human behavior.

All this data is tracked with different frequencies and the amount of data that has to be analyzed at each relevant time instance varies according to the source. For instance, although typical mobile eye tracking devices run with a frequency of 120 Hz, the size of data is very lightweight compared with the tracked environmental data [2]. For instance, the types and number of intersections in the spatial proximity of the user can be extracted and compared

[1] http://linkedgeodata.org/About

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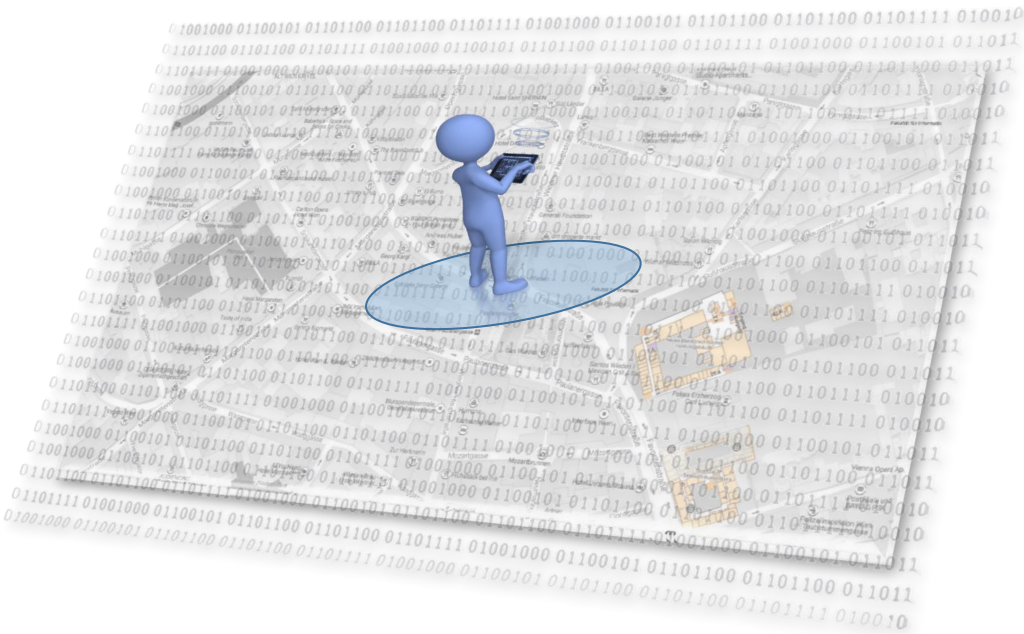

Figure 1 A hypothetical scenario of a user interacting with a digital system at a specific location. The system adapts based on the users activity and the spatial characteristics in the local proximity of the user, e.g., based on the spatial semantics and the surrounding urban structure.

with the same type of data of a larger relevant region in order to extract features for machine learning. Figure 1 illustrates such an example.

Although the size and variety of the mentioned data sources is cumbersome to deal with, the big challenge is to find existing and novel programming paradigms to deal with all these different sources and decide for an efficient data fusion that would allow to come closer to the presented vision.

3 Research Questions

- Which types of urban classes (e.g., historic and touristic places) can we predict and what type of data do we need?
- Which land-cover classes can be of potential interest for adaptive interfaces?
- What type of human behavior and spatial data are necessary in order to detect familiarity with the surrounding environment?
- Which classes of human spatial behavior should we be able to predict?

The above research questions are not complete by any means. These questions demonstrate important aspects of the presented vision and highlight parts of the research we are currently conducting in order to come closer to the presented vision.

4 Current and Future Challenges

Of course there are several challenges when presenting research which is based on predictions. How good can these predictions be? How good do we need them to be? How much from these big data do we actually need for good predictions? Can we be fast enough for real time applications? What is the elasticity between good predictions and real time application? These are only a few of the important challenges that demonstrate the decision making process that we have to go through when we have to cope with real time applications, the size and variety of data.

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