Prediction of passenger density in underground Systems

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ABSTRACT

This paper provides a provides a comparison between several prediction accounts in the area of the underground stations.

1. INTRODUCTION

Underground transportation systems are big energy consumers and have significant impacts on energy consumptions at a regional scale [2]. Approximately 30% of the required energy is needed for operating the metro stations and surroundings, such as ventilation, vertical transportation and lighting [1].

To realize energy saving in this area already an intelligent control system for metro stations was developed. The control system is adaptive on the basis of environmental factor forecasts and occupancy flow patterns [5].

Changing the parameter doesn't have an immediate effect. Therefore it would the number of passenger needs to be predicted.

This paper focuses the prediction of number of passenger in the station.

2. STATE OF THE ART

Context prediction breaks the border from reaction on past and present stimuli to proactive anticipation of actions. Initiated by the pioneering work ofMayrhofer et al. [9], researchers have for about one decade now considered the prediction of context to enablepro-active context computing. Research directions spread from applications for context prediction [7] over event prediction [18], architectures for context prediction [8, 11, 14], data formats [3] and algorithms [6]. Recent work focuses on three main challenges:

1. Prediction mostly limited to location

2. No benchmarks and common data sets

3. No common development framework

While there have been contributions targeting some of these challenges, we still see them as unsolved and in the following

will further elaborate on these challenges. First, several authors have studied aspects of future context with the aim of enabling proactive behaviour in applications. Applications considered are diverse and range across basically all aspects of daily life. Still, the survey of Voigtmann and David shows that a great share of context prediction research so far concentrates on location prediction [17]. Recently the research on location prediction tends to focus on new approaches for indoor location, e.g. [12, 10] and the use of social networks as data source [19]. We see a great potential for the use of context prediction in applications to enable sustainability, e.g. applications for energy efficiency. An important building block for this is the prediction of user preferences. Since preference settings in many applications tend to be complicated and have important implications, for example on the user's privacy, predicting the user's preferences was shown to solve the problem of too lax preference settings [4]. Also, important to enable applications for sustainability and energy efficiency, is the prediction of user routine, e.g. [13].

Secondly, regarding missing benchmarks and data sets, although utilized by numerous algorithms, a comprehensive comparison of their strengths and weaknesses on benchmark data sets is yet missing. To raise context prediction to a professional level at which it might be integrated in commercial applications, we need to establish common, widely accepted data sets, develop and disseminate accepted benchmarks and provide more general description of algorithmic performance not only restricted to specific applications but to a whole class of applications utilising input data with similar properties. One promising approach is to utilize data that users share over social networks [19].

And last, although several authors have considered architectures for context prediction [8, 14], a common methodology or platform has not yet crystallised. Application developers are forced to start from scratch. One reason for this is that previous authors seldom provided usable sources of their applications that could be extended. In order to foster the integration of context prediction into applications, support for application developers has to be greatly improved. [16, 15]

3. DATA ACQUISITION

The prediction is based on occupancy data gathered in a metro station. First some facts regarding the metro station will be given. Subsequently the data acquisition will be explained.

3.1 Line Station

In this section the "station" is described. First the word "station" in the area of metro networks needs to be defined.

A metro network is composed by one or more metro lines. Each line has a fixed railway with a given number of stops to allow people to get on or off the trains by means of a platform: each of these stops is called "line station". A "metro station" is the concept that represents the point in space through which a passenger gets underground and into a line station. Metro station and line station can be the same physical entity, but it is possible that there are some "metro stations" that receive two or more "metro lines" in different platforms, and have therefore, two or more "line stations" within.

The data, used in this work, are gathered in line station in Passeig de Gràcia - Line 3 (PdG-L3) in Barcelona. Passeig de Gràcia (PdG) is a station in the metro network of "Transports Metropolitans de Barcelona" (TMB) and lies in a very iconic and touristic part of Barcelona. Some of the most popular buildings designed by Antoni Gaudi are in the proximity (Casa Batllò, Casa Milà), as well as the city's most renown and exclusive boutiques. The metro station is a historic icon of the Barcelona metro network. First opened in December of 1924, as a (line) station for Line 3, nowadays PdG holds three different line stations: L2, L3, and L4. The stations were built in three different periods and using different construction technologies in each of the premises (contemporary to the building periods). All line stations station has been refurbished a few times since 1924 and new equipment has been added recently.

Passeig de Gràcia - Line 3 (PdG-L3) turns out to be representative for many station within TMBs metro network. Table ?? depicts the statistical reasons behind this [1]. Furthermore PdG-L3 is a crowded station which have low-rate usage hours as well. This provides a wide range of data which allows to test with very busy peak hours as well as with off-peaks. Figure 1 depicts the platforms of PdG-L3.

Figure 1: PdG-L3 Plattforms. [1]

The line station PdG-L3 consists of several public spaces: halls, transit areas, accesses to the platforms, and platforms. Furthermore there are private spaces such as technical rooms or staff dependencies. The private spaces are not part of the investigation in this work. Figure 2 depicts the line station schematic where the accesses to platforms are highlighted in red.
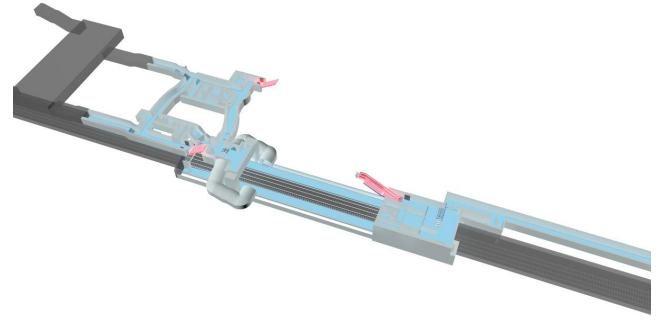

Figure 2: Schematic representation of PdG-L3. The accesses to platforms are highlighted in red. [1]

The public spaces are equipped with a Closed Circuit Television (CCTV) for security reasons. The cameras of the CCTV-system provide images which contains the information how many people are on a dedicated time on a dedicated place. To gather these information the images needs to be processed. In the following the processing of the camera images is described in short.

3.2 Data collecting

The Data are gathered via CCTV. The CCTV images are stored on a video recorder. A crowd density estimator processes the images and returns the number of passengers on this image. The number of passenger are saved in a database together with a timestamp and the location. For privacy reasons the images are not saved over a longer time period. Figure 3 depict the processing chain.
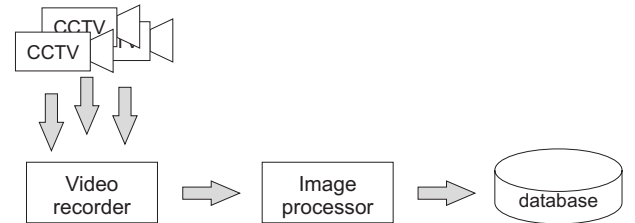
Figure 3: Gathering number of people out of the camera images

4. RESULTS

Results

5. CONCLUSION

Conclusion

6. ACKNOWLEDGEMENTS

7. REFERENCES

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