Prediction of passenger density in underground Systems

Andreas Jahn and Klaus David
Kassel University
Wilhelmhöher Allee 73
Kassel, Germany
{andreas.jahn,david}@uni-kassel.de

Stephan Sigg and Xiaoming Fu
Goettingen University
Goldschmidtstr. 7
Göttingen, Germany
{stephan.sigg,
fu}@informatik.uni-goettingen.de

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].

An approach to realize energy saving is to make the station "smart". That means the stations adapts settings "intelligent" on changes in the environment. In the area of underground station this could be e.g. the shutting down of escalators, when the last passengers of the day left the station.

For this aim an intelligent control system for metro stations was developed. The control system is adaptive on the basis of environmental factor forecasts and passenger occupancy [5].

While shutting down or turning on the escalators have an immediate effect, this in not the case for slow reacting systems, e.g. the ventilation. In order to satisfy the restrictions, i.e. guarantee the required air quality on every point in time, the ventilation needs to be operated in a foreseen manner, e.g. dependent on the expected number of passenger in the station.

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

The remainder of this paper is organized as follows. In Section 2 an overview of the related literature is given. Section 3 focuses on the data acquisition and the experiments, followed by Section 4, the evaluation and results. Last, Section 5, summarizes the results.

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 methodol-

ogy 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 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.

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.

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

Figure 1: PdG-L3 Plattforms. [1]

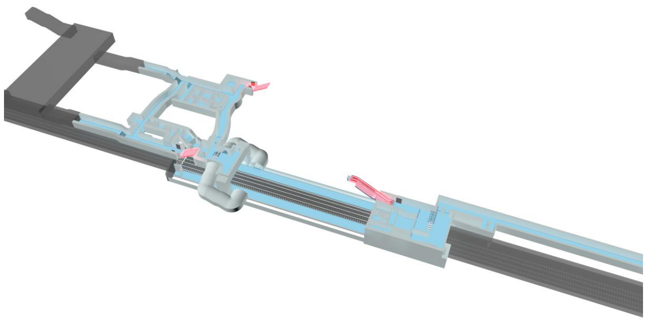

Figure 2: Schematic representation of PdG-L3. The accesses to platforms are highlighted in red. [1]

processed. In the following the processing of the camera images is described in short.

3.2 Passenger density Data

Throughout the station a CCTV surveillance system already exists. 22 CCTV cameras are in place where each camera provides in a circuit design subsequently the images. The images provided by each CCTV-camera 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 as well as date, time and the camera-ID are saved in a database. For privacy reasons the images are not saved. Figure 3 depict the processing chain.

The system runs 24 hours, 7 days a week. Each day 31680 datasets are saved.

Overall a database of 90 days was available. These database of passenger density information are the base for the investigations in this paper.

3.3 Data Analysis

Simply depicting the data shows periodicities during a day. Where Monday till Thursday have the same outlook, Friday, Saturday and Sunday have it own frequency. Within the working days (Mo-Thu) a high ... Picture 4 depicts a periodicity on a Wednesday.

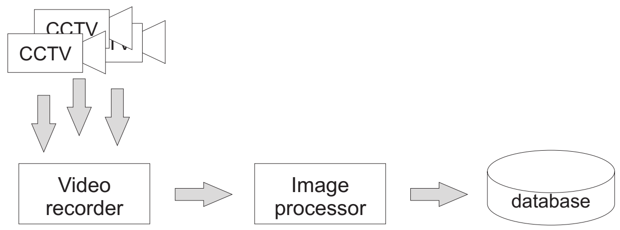

Figure 3: Gathering number of people out of the camera images

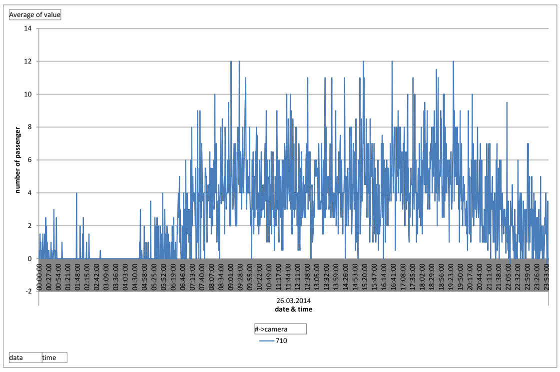

Figure 4: Occupancy distribution of one camera during one day. [1]

4. RESULTS

This section focuses on the evaluation and the results. First the evaluation of the recorded sensor data is shown. Subsequently the results are presented and discussed.

4.1 Evaluation

The evaluation analyses the prediction occupancy and provides a measurement in order to depict the prediction performance. The evaluation in detail is depicted in the following.

4.1.1 Performance measurement

In order to understand how good the predicted value and the actual value match, a performance measurement is needed. A standard measurement is the accuracy. The accuracy describes the performance of the system in a percent value. An accuracy value of 100 % represents a perfect prediction, while 0 % represents a poor prediction. In case of the Usermodel an easy way of calculation could be, a division of the lower number of passenger by the higher number of passenger value as depicted in equation 1.

$$accuracy = \frac{lower\ value}{heigher\ value} \tag{1}$$

Following this equation the accuracy for a predicted value of two and an actual value of one is calculated to 50 % (equation 2).

$$accuracy = \frac{1}{2} = 0.5 = 50\ \% \tag{2}$$

In this example the accuracy is 50 % even though the predicted value is close to the actual value. Predicted and actual value differs only by one. A difference of one person does not have big impact on the controller in order to satisfy the restrictions. Therefore the accuracy does not fulfil the needs as a performance measure.

Instead the absolute difference between the predicted number of passenger as well as the actual number of passenger seems to provide a meaningful measurement. A measurement-value of zero (0) represents a perfect prediction, while the higher the worse the prediction. In this deliverable absolute difference between predicted number of passenger and the actual number of passenger is used as the performance measure for the detection accuracy of the number of passenger prediction. Staying in the mentioned example the accuracy is calculated to one (Equation 3).

$$accuracy = |1 - 2| = 1 \tag{3}$$

One is already close to zero and allows therefore the conclusion of a good prediction.

4.2 Results

This section depicts the prediction results and is aimed to figure out:

1. the overall prediction accuracy,
2. the best performing penalty setup,
3. the best performing history and observation length, and
4. the average prediction duration.

5. CONCLUSION

Conclusion

6. ACKNOWLEDGEMENTS

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