The Foretelling Subway: Anticipative Sensing for the 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

In this work we introduce the concept of Anticipative Sensing, a paradigm in which current stimuli, general trends and history are analysed in order to anticipate likely future evolution of observed stimuli. In particular, we provide a comprehensive discussion of the toolchain for anticipatory sensing, discuss latest developments and trends that lead to this sensing paradigm and present a case-study in which the approach is utilised.

In this case-study, CCTV sensors in a Metro station in Barcelona, Spain are exploited in order to predict crowd. The video data is first piped through an image processing chain in order to extract relevant features which are then utilised for the anticipatory sensing toolchain. We are able to show good prediction accuracy of our approach.

1. INTRODUCTION

Underground transportation systems are big energy consumers and have significant impacts on energy consumptions at a regional scale [2].

So far the optimization of the energy efficiency of transportation equipments, e.g. trains have been considered. Optimization of the energy efficiency of the metro stations operations, however, is only minimally exploited.

But realizing savings in energy consumption are meaningful for two reasons: (i) Despite the relatively small percentage that can be gained with optimal management of one metro station compared to optimizing trains, the high numbers of metro stations in the underground transportation will yield large energy savings in overall terms. In other words, in the management of metro stations is a high multiplication factor that boosts each relative small saving at a station level to a high saving at a metro network level. Moreover (ii) the optimization of the energy efficiency of the metro stations involves much less investments than the ones that are usually applied to transportation means and equipments. Consequently is it possible to distributed the technology easily across the whole metro network, as well as other transportation systems and realize savings in short term.

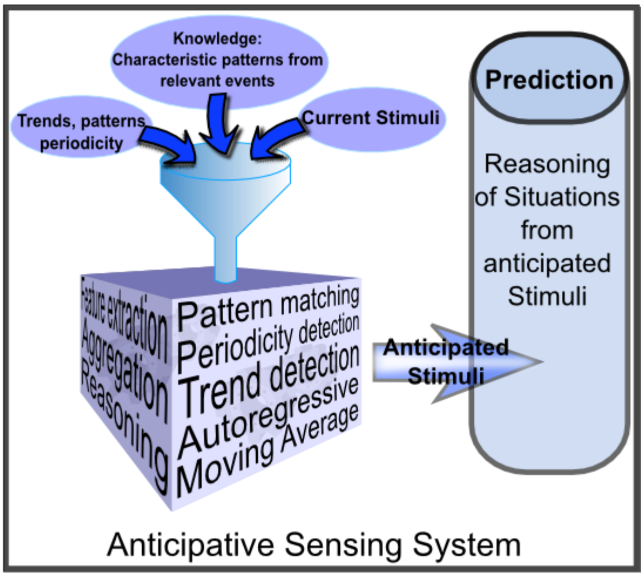


Figure 1: TODO: Improve figure; Schematic illustration of an anticipative sensing system

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

For example all Barcelona (Spain) metro stations consumes 63,1 millions of kWh annually [1]. A relative small saving of, e.g. 5% in the electricity consumption of one metro station, is equivalent to the electricity consumed in more than 700 households during one year.

The optimized management of stations and surroundings, such as ventilation, vertical transportation and lighting does have an impact.

An approach to optimize the energy efficiency and to realize energy savings is to enable the station to control the surroundings, such as ventilation, vertical transportation and lighting "intelligent" according the current situation. A simple example of "intelligent" control could be the slowing down the frequency of the ventilation-fans of the station, when the count of passenger doesn't make full speed necessary.

To achieve the context aware behaviour of a metro station basically two parts are necessary. (i) A controller which calculate the appropriate actions. A controller which is adaptive on the basis of various environmental factors, forecasts and passenger occupancy was developed [5]. (ii) The environmental factors, and prediction must be available for the controller.

Staying in the given example the controller needs be aware about the current count of passengers in order to decrease the fan frequency if possible. However, increasing the fan frequency is more complex. Since the decreasing of the fan frequency doesn't have an immediate effect for the air quality the fan frequency needs to be decreased in a appropriate time before the stations is abruptly crowed again. To guarantee the required air quality on every point in time, the ventilation needs to be controlled in a foreseen manner, i.e. controlled on the prospectively number of passenger in the station.

This paper presents an approach for predicting 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 of Mayrhofer et al. [9], researchers have for about one decade now considered the prediction of context to enable pro-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 that

1. prediction is mostly limited to location
2. no benchmarks and common data sets exist
3. no common development framework exists

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. 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, 11], 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 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.

Depending on the weekday PdG is open 19 hours, 21 hours or 24 hours. Between Monday and Thursday PdG service starts at 5:00 and ends at 24:00 (19 hours). Friday service starts at 5:00 and ends at 2:00 (21 hours). On Saturday service starts at 5:00 to but remain the entire night until midnight on Sunday.

Passeig de Gràcia - Line 3 (PdG-L3) turns out to be representative for many station within TMBs metro network [1]. Moreover 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 2: 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.

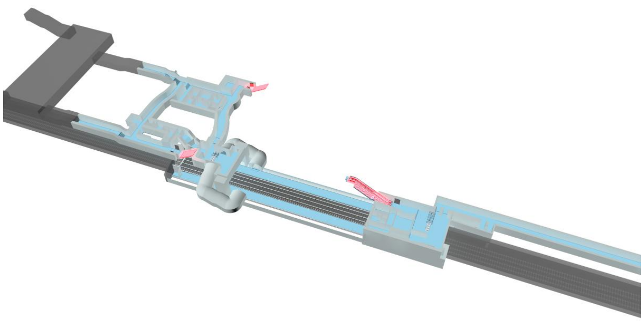


Figure 3: Schematic representation of PdG-L3. The accesses to platforms are highlighted in red. [1]

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 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 different reasons, e.g. bad camera picture or network errors it is possible that the image processing fails. In this case the error value "-1" is saved in the database.

The process images are not saved for privacy reasons. Figure 3 depict the processing chain.

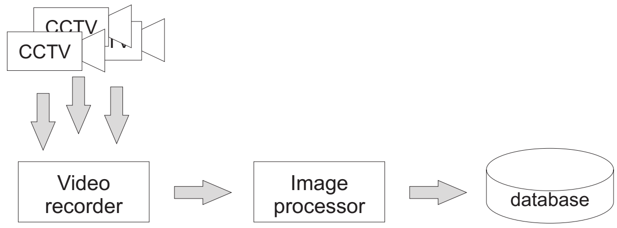


Figure 4: Gathering number of people out of the camera images.

The CCTV and image processing runs 24 hours, 7 days a week. Each day 31680 datasets are saved to the database. Overall the database contains 90 days of data. Figure 4(a) illustrates exemplary the available values of a week. At a more detailed view of a day the service times are visible (Figure 4(b)).

This database of passenger density information are the base for the investigations in this paper.

4. RESULTS

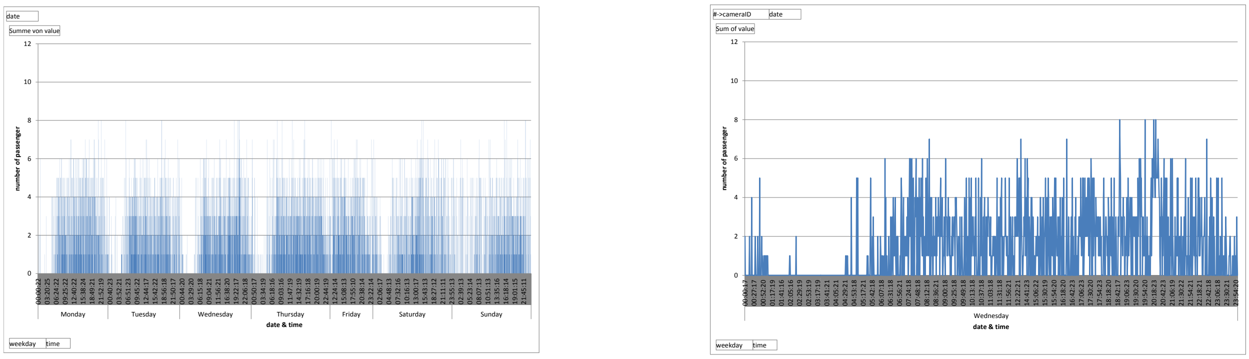
This section focuses on the evaluation and the results. First the evaluation of the recorded sensor data is shown. Subsequently the results are presented and discussed.

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 prediction approach

Alignment is a context time series prediction algorithm that is inspired by algorithms with a focus on computational biology and based on local alignment techniques like the Smith and Waterman algorithm (T.F. Smith and M.S. Waterman 1981). Basically Alignment compares two context sequences and therefore belongs to the branch of the pattern matching algorithms. For the use of number of passenger prediction, the first sequence represents the current sensed occupancy of the same location, called observation. The second sequence represents the history of passenger occupancy. During the matching process that pattern in the history will be identified whose similarity to the given current observation pattern is the highest and therefore obtained the lowest penalty costs for a given cost matrix. Subsequently, the con-



(a) Passenger density distribution of one camera during one week.

(b) Passenger density distribution of one camera during one day.

Figure 5: Passenger density distribution of one camera. [1].

text that follows next to the identified pattern will be predicted. Figure 5 illustrates the approach. In this example the values of five, nine and 17 are in the observation pattern as well as in the history pattern. Consequently both patterns match. The next value in the history pattern, the seven, is the prediction.

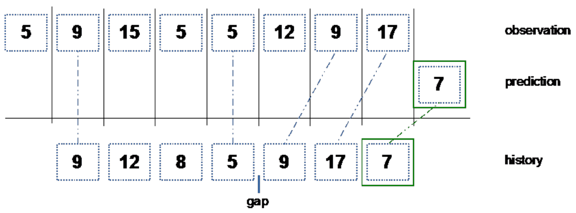


Figure 6: Alignment approach

If and how two pattern "match" is calculated during the matching process and noted in the cost matrix. Whenever to strings are not matching, e.g. because of a gap, a penalty is added. The goal is to stay with zero costs, the optimal value.

	penalty
match	0
mismatch	1
gap in first sequence	1
gap in second pattern	1

Table 1: example of alignment penalties

Penalty costs are a way to influence the alignment results. If gabs need to be avoided during the matching process, penalties can be increased. A different rating of gaps in the first and second sequence is possible. If gaps in the first sequence are not acceptable but gaps in the seconds sequence are tolerable penalty for gaps in the first sequence can be set higher than penalty for gaps in the second sequence. In general penalty cost can be freely selected. The highest similarity between history pattern and the current observation is given on the lowest penalty costs. Figure 3 depicts the filled cost matrix.

4.1.2 *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 User-model 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).

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

A difference between predicted and actual number of passenger of one allows 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

Acknowledgements

This work was partially funded by the EU-FP7 project "Sustainable Energy mAnageMent 4(for) Underground Systems" (SEAM4US, FP7-ICT, EEB-ICT-2011.6.4). The authors would like to acknowledge the contributions of their colleagues.

6. REFERENCES

[1]

[2] Richard Anderson, Rory Maxwell, and Nigel G. Harris. Maximizing the potential for metros to reduce energy consumption and deliver low-carbon transportation in cities. *MetroRail Asia, Delhi*, pages 1–13, 2009.

[3] D. Bannach, K. Kunze, J. Weppner, and P. Lukowicz. Integrated tool chain for recording and handling large, multimodal context recognition data sets. In *Proceedings of the 12th inernational conference on Ubiquitous Computing*, pages 357–358, 2010.

[4] G. Bigwood, F. B. Abdesslem, and T. Henderson. Predicting location-sharing privacy preferences in social network applications. In *First Workshop on recent advances in behavior prediction and pro-active pervasive computing*, 2012.

[5] Hongliang Guo and Alfons H. Salden. Intelligent control for sustainable energy management in underground stations. In Jean-Louis Ferrier, Oleg Yu Gusikhin, Kurosh Madani, and Jurek Z. Sasiadek, editors, *ICINCO 2*, pages 566–571. SciTePress, 2013.

[6] S. Intille, K. Larson, E. Tapia, J. Beaudin, P. Kaushik, J. Nawyn, and R. Rockinson. Using a live-in laboratory for ubiquitous computing research. In *Lecture Notes in Computer Science*, volume 3968/2006, pages 349–365, 2006.

[7] Rene Mayrhofer. Context prediction based on context histories: Expected benefits, issues and current state-of-the-art. In T. Pronte, B. Beyers, G. Fitzpatrick, and L.D. Harvel, editors, *Proceedings of the 1st international Workshop on exploiting context histories in smart environments (ECHISE) at the 3rd Int. Conference on Pervasive Computing*, 2005.

[8] Rene Michael Mayrhofer. *An Architecture for Context Prediction*. PhD thesis, Johannes Kepeler University of Linz, Altenbergstrasse 69, 4040 Linz, Austria, Oktober 2004.

[9] Rene Michael Mayrhofer, Harald Radi, and Alois Ferscha. Recognising and predicting context by learning from user behaviour. In *The International Conference On Advances in Mobile Multimedia (MoMM2003)*, volume 171, pages 25–35, September 2003.

[10] K. Murao, T. Terada, A. Yano, and R. Matsukura. Detecting room-to-room movement by passive infrared sensors in home environments. In *First Workshop on recent advances in behavior prediction and pro-active pervasive computing*, 2012.

[11] P. Nurmi, M. Martin, and J. A. Flanagan. Enabling proactiveness through context prediction. In *CAPS 2005, Workshop on Context Awareness for Proactive Systems*, June 2005.

[12] G. Ruscher. Simultaneous counting and location of persons based on a heterogeneous sensor setup. In *First Workshop on recent advances in behavior prediction and pro-active pervasive computing*, 2012.

[13] J. Seiter, O. Amft, and G. Troester. Assessing topic models: How to obtain robustness? In *First Workshop on recent advances in behavior prediction and pro-active pervasive computing*, 2012.

[14] Stephan Sigg, Dawud Gordon, Georg von Zengen, Michael Beigl, Sandra Haseloff, and Klaus David. Investigation of context prediction accuracy for different context abstraction levels. *IEEE Transactions on Mobile Computing*, 11(6):1047 –1059, june 2012.

[15] M. Tenorth, J. Bandouch, and M. Beetz. The tum kitchen data set of everyday manipulation activities for motion tracking and action recognition. In *IEEE International Workshop on Tracking Humans for the Evaluation of their Motion in Image Sequences in conjunction with ICCV2009*, 2009.

[16] T. van Kasteren, A. Noulas, G. Englebienne, and B. KrÃűse. Accurate activity recognition in a home setting. In *Proceedings of the 10th international conference on Ubiquitous computing*, pages 1–9, 2008.

[17] C. Voigtmann and K. David. A survey to location-based context prediction. In *First Workshop on recent advances in behavior prediction and pro-active pervasive computing*, 2012.

[18] Gary M. Weiss and Haym Hirsh. Learning to predict rare events in categorical time-series data. In *Predicting the future: ai approaches to time-series problems; Workshop in conjunction with the fifteenth national conference on artificial intelligence*, pages 83–90, 1998.

[19] R. Zhang, M. Chu B. Price, and A. Walendowski. Location-based predictions for personalized contextual services using social network data. In *First Workshop on recent advances in behavior prediction and pro-active pervasive computing*, 2012.