The Foretelling Subway: Anticipatory Sensing for the Prediction of Passenger Density in Underground Systems

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ABSTRACT

In this work we introduce the concept of Anticipatory 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 discuss the toolchain for Anticipatory Sensing, 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 [3]. So far, the optimization of the energy efficiency of transportation equipment, the trains, have been considered. However, although a single train is the largest individual consumer of energy from the overall energy load necessary to run a complete underground system, the investments required for this kind of optimisation are also tremendous. Considering the cost and amount of energy that can potentially be saved in different components of an overall underground metro system, it is suggestive to instead intensify the effort towards other directions. In particular, 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. Although only a relatively small percentage can be gained with optimal management of a single metro station compared to optimizing trains, the high number of stations in the underground transportation system in total will yield large energy savings in overall terms. For example, all Barcelona (Spain) metro stations consume 63,1 million kWh annually [1]. A relatively small saving of, for instance, only 5% in the electricity consumption of a single metro station is equivalent to the electricity consumed in more than 700 households during one year. In other words, the management of energy consumption in individual metro stations is a high multiplication factor that boosts each relative small saving at a station level to tremendous savings at a metro network level.

Yet, optimization of the energy efficiency of the metro stations operations, is only minimally exploited. Possible directions are the optimized management of stations and surroundings, such as ventilation, vertical transportation and lighting which would have a significant impact on the overall energy consumption. Currently, the controller for these systems follow simple time and experience-based coarse schedules. In particular, these systems are optimised for peak times and are therefore operating in an inefficient mode over most part of a day.

A seminal opportunity 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 adaptively according to the current situation. For instance, the ventilation-fans of a station could be slowing down when the count of passengers does not necessitate full speed.

In order to achieve such context-aware pro-active behaviour in a metro station, basically three parts are required.

A: Sensors that are suited to capture the situation over time accurately

B: A controller which is able to calculate the appropriate actions.

C: Prediction mechanisms that can anticipate the future evolution of the situation in a metro station

An underground metro system features a high number of sensors (A) that can be employed to realise pro-active operation. These cover even the tracking of people movement and count which is easily possible via the prominently installed CCTV surveillance systems. Recently, also a controller (B) which is adaptive on the basis of various environmental factors, forecasts and passenger occupancy has been developed [15]. The predictive component (C) is necessary since changes applied to the system do not immediately take effect. Staying in the above example with the ventilation-fans, it is sufficient for the controller to be aware of the current count of passengers in order to decrease the fan frequency. However, increasing the fan frequency is more

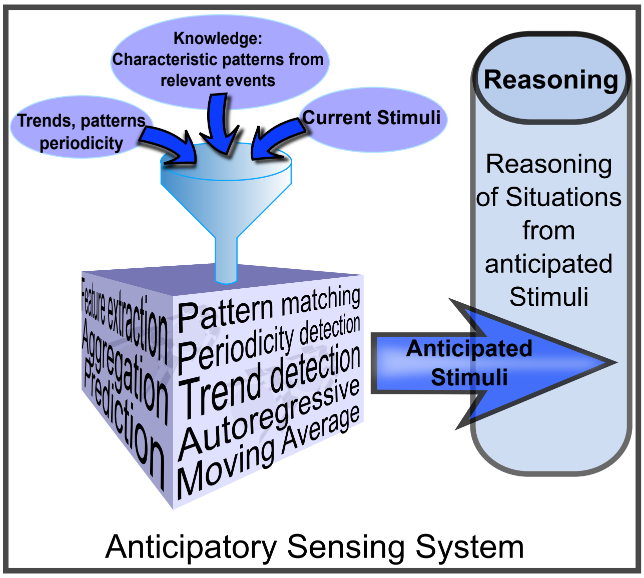


Figure 1: TODO: Improve figure; Schematic illustration of an anticipative sensing system

complex. Since the increasing of the fan frequency does not have an immediate effect for the air quality, the fan frequency needs to be increased an appropriate time before the station fills again. It is important to note, that such events can typically occur abruptly in an underground metro system. Examples are, for instance, periodic events such as rush hours or the arrival of connecting trains but also rather spontaneous events like sudden strong rain downfall or simply one of the frequent excursion trips from schools where groups of several hundred people float a station in a short time.

To guarantee the required air quality on every point in time, the ventilation needs to be controlled in a foreseen manner, that means based on the prospective number of passengers in a station.

This paper presents the approach of Anticipatory Sensing for the prediction of the number of passengers in a station.

Anticipatory Sensing relies on current stimuli from the sensing system, recent historical stimuli that represent trends, typical patterns or periodicity over time and explicit knowledge about relevant events and their corresponding characteristic patterns as depicted in figure 1.

From this information, the series of the current and recent stimuli are analysed for decisive patterns that allow the computation of likely continuation of the observed series of stimuli. In particular, in this Anticipatory Sensing step, first, features are extracted from the recent historical time series of stimuli, aggregated and then this series of aggregated features is analysed following multiple approaches from context prediction, pattern matching and time-series forecasting in order to enable a reasoning on possible continuation of this series of stimuli together with their probability.

These anticipated stimuli, which are expected to be observed via the sensing system in the near future are then forwarded to a reasoning component where the anticipated low-level stimuli are classified for situations. Note that this order of prediction and reasoning also follows a recent recommendation from [31] where the impact of the order of computations on the prediction accuracy was analysed.

Based on these reasoned situations, the controller of the underground metro system is then in the position to take informed actions, such as, for instance, to increase the fan frequency an appropriate time prior to the actual arrival of the crowd 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, draws our conclusion.

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. [21], 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 [19] over event prediction [37], architectures for context prediction [20, 24, 31], data formats [4], algorithms [16] and datasets and benchmarks [35]. 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 [36]. Recently the research on location prediction tends to focus on new approaches for indoor location, e.g. [26, 23, 2, 11] and the use of social networks as data source [38]. Although critisized prominently, for instance in [27], this trend only slowly changes to more general prediction cases in recent years. Notable exceptions are considering, for instance, prediction to reduce energy consumption in sensor nodes by powering only those components that are likely needed in the near future [14], prediction for the comptation of trust in other pervasive devices [6] or also the prediction of tasks a user likely engage in next in order to adapt the user interface over several devices properly [17]. Further exmamples are the prediction of user intention in order to proactively plan tasks of a robot the human is interacting with [28] and the popular smart home use-case in which mobility patterns and device usage of inhabitants are predicted [8, 34]. Recently, we observe that a small trend has been started towards non-location prediction applications by the 2013 AwareCast workshop [9]. For instance, Zhang et al. consider the prediction of waiting times in cues of humans [39]. The authors compare several machine learning and prediction methods for their prediction error. Also, Caruso et al. utilise a simulation environment of a gaming engine in order to learn user behaviour in this scenario and to synthesize it for later application in realistic scenarios [7].

A more general result on the stability of Context Prediction was presented by Koenig et al. [18]. The authors present means to correct or detect prediction errors in order to improve the overall prediction accuracy.

Regarding algorithms for context prediction, diverse approaches from various fields spanning, for instance, time-series forecasting or pattern matching have been applied. Prominent examples for context prediction techniques are Markov predictors [13], SOM prediction methods [33, 20], the state predictor method [25, 20], neural network approaches [25, 22], Bayesian networks [25], prediction based on the principal component analysis [10], ARMA predictors [20] as well as Kalman filter methods [6], Fuzzy-State Q-Learning [12] or alignment-based prediction [32].

These approaches are applied and implemented for a given use-case mostly from scratch, however, few architectures for context prediction have been proposed that would allow a generic implementation of context prediction while utilising arbitrary of these prediction algorithms [30, 20, 24]. However, 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.

We see a good potential for the use of Context Prediction in applications to enable sustainability, for instance 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 [5]. Also, important to enable applications for sustainability and energy efficiency, is the anticipation of user routine, e.g. [29].

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 [38].

But Context Prediction is just a mere building block in the implementation and instrumentation of a holistic application case. It consideres the important but yet isolated task of inferring probable continuations for a given time series. Anticipatory sensing goes beyond this and covers also the capturing, analysis, feature extraction and aggregation of a context time series as well as the reasoning based on the predicted stimuli.

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 2 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 3 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

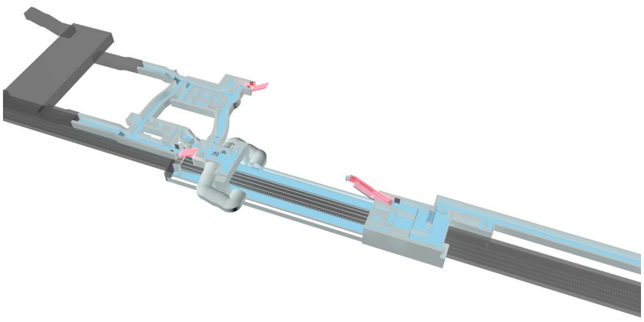


Figure 3: Schematic representation of PdG-L3. The accesses to platforms are highlighted in red. [1]

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 image processing system returns the error value "-1".

The process images are not saved for privacy reasons. Figure 4 depict the processing chain.

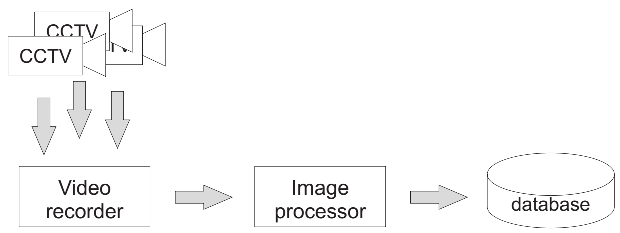


Figure 4: Gathering number of people out of the camera images.

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 5(a) illustrates exemplary the available values of a week. At a more detailed view of a day the service times are visible (Figure 5(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 context that follows next to the identified pattern will be predicted. Figure 6 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.

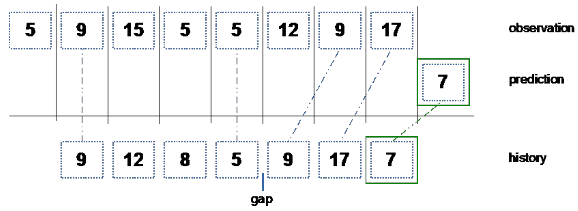


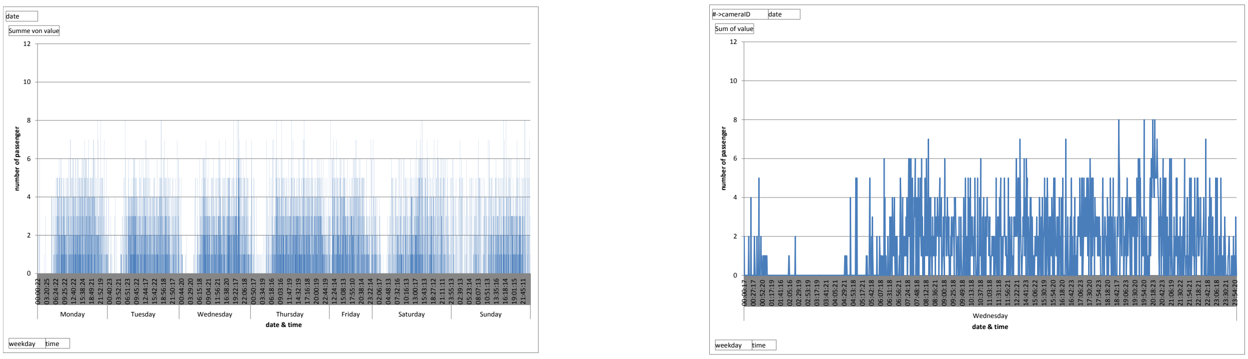
Figure 6: Alignment approach

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



(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].

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

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6. REFERENCES

[1]

[2] Jorge Alvarez-Lozano, J Antonio García-Macías, and Edgar Chávez. Learning and user adaptation in location forecasting. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 461–470. ACM, 2013.

[3] 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.

[4] 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.

[5] 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.

[6] Licia Capra and Mirco Musolesi. Autonomic trust prediction for pervasive systems. In *AINA '06: Proceedings of the 20th International Conference on Advanced Information Networking and Applications (AINA'06)*, pages 481–488, Washington, DC, USA, 2006. IEEE Computer Society.

[7] Mario Caruso, Çağri Ilban, Francesco Leotta, Massimo Mecella, and Stavros Vassos. Synthesizing daily life logs through gaming and simulation. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 451–460. ACM, 2013.

[8] Sajal K. Das, Diane J. Cook, Amiya Bhattacharya, Edwin O. Heierman, and Tze-Yun Lin. The role of prediction algorithms in the mavhome smart home architecture. *IEEE Wireless Commmunications*, December 2002.

[9] Klaus David, Bernd Niklas Klein, Sian Lun Lau, Stephan Sigg, and Brian Ziebart. 2nd workshop on recent advances in behavior prediction and pro-active pervasive computing. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 435–440. ACM, 2013.

[10] Nathan Eagle and Alex Sandy Pentland. Eigenbehaviors: Identifying structure in routine. *Behavioral Ecology and Sociobiology*, 63(7):1057–1066, Mai 2009.

[11] Muawya Habib Sarnoub Eldaw, Mark Levene, and George Roussos. Collective suffix tree-based models for location prediction. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 441–450. ACM, 2013.

[12] Mohamed Ali Feki, Sang Wan Lee, Zeungnam Bien, and Mounir Mokhtari. Context aware life pattern prediction using fuzzy-state q-learning. In Takeshi Okadome, Tatsuya Yamazaki, and Mounir Makhtari, editors, *Pervasive Computing for Quality of Life Enhancement*, volume 4541 of *Lecture Notes in Computer Science*, pages 188–195. Springer Berlin / Heidelberg, 2007.

[13] Karthik Gopalratnam and Diane J. Cook. Active lezi: An incremental parsing algorithm for sequential prediction. *International Journal of Artificial Intelligence Tools*, 14:917–930, 2004.

[14] Dawud Gordon, Stephan Sigg, Yong Ding, and Michael Beigl. Using prediction to conserve energy in recognition on mobile devices. In *Proceedings of the 9th IEEE International Conference on Pervasive Computing and Communications (PerCom2011)*, 2011.

[15] 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.

[16] 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.

[17] C. L. Isbell, Jr, O. Omojokun, and J. S. Pierce. From devices to tasks: automatic task prediction for personalised appliance control. In *Personal and Ubiquitous Computing*, number 8, pages 146–153, 2004.

[18] Immanuel König, Bernd Niklas Klein, and Klaus David. On the stability of context prediction. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 471–480. ACM, 2013.

[19] 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.

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

[21] 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.

[22] M. C. Mozer. Neural net architectures for temporal sequence processing. In A. S. Weigend and N. A. Gershenfeld, editors, *Predicting the Future Understanding the Past*. Addison Wesley, 1994.

[23] 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.

[24] 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.

[25] J. Petzold, A. Pietzowski, F. Bagci, W. Trumler, and Theo Ungerer. Prediction of indoor movements using bayesian networks. In *First International Workshop on Location- and Context-Awareness (LoCA 2005)*, May 2005.

[26] 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.

[27] A. Schmidt and M. Beigl. There is more to context than location: Environment sensing technologies for adaptive mobile user interfaces. In *Workshop on Interactive Applications of Mobile Computing (IMC'98)*, 1998.

[28] Oliver C. Schrempf, Uwe D. Hanebeck, Andreas J. Schmid., and Heinz Wörn. A novel approach to

proactive human-robot cooperation. In *Proceedings of the 2005 IEEE International Workshop on Robot and Human Interactive Communication (ROMAN 2005)*, pages 555–560, Nashville, Tennessee, 2005.

[29] 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.

[30] Stephan Sigg. *Development of a novel context prediction algorithm and analysis of context prediction schemes.* PhD thesis, University of Kassel, Chair for Communication Technology, ComTec, May 2008.

[31] 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.

[32] Stephan Sigg, Sandra Haseloff, and Klaus David. An alignment approach for context prediction tasks in ubicomp environments. *IEEE Pervasive Computing*, Oct-Dec 2010, 2010.

[33] G. Simon, A. Lendasse, M. Cottrell, J.-C. Fort, and M. Verleysen. Time series forecasting: Obtaining long term trends with self-organising maps. *Pattern Recognition Letters*, 26(12):1795–1808, September 2005.

[34] 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.

[35] 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.

[36] 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.

[37] 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.

[38] 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.

[39] Ye Zhang, Le T Nguyen, and Joy Zhang. Wait time prediction: how to avoid waiting in lines? In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication*, pages 481–490. ACM, 2013.