Passenger prediction in metro stations: Analysis of passenger data from security cameras

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Abstract
CCTV camera systems for monitoring and surveillance are widely utilized in enterprises or public systems. They can provide a holistic view on a system and allow security and maintenance personnel to quickly react on changes in the system in an informed manner. However, mostly, the analysis of the data is done manually which is a tedious task and prone to errors or the missing out of information. Automatic analysis of such video-recorded data can help to improve this task in efficiency and accuracy and also enables novel applications build on top of it.

In this paper, we present the work done in the SEAM4US consortium that focuses on the automatic analysis of image data captured from CCTV cameras in a Barcelona metro system and to react on the extracted stimuli. We present the sensing environment and detail specifics of the system, introduce the steps for feature extraction from the video data, discuss peculiarities of the recorded data and demonstrate its predictability with an Artificial Neural Fuzzy Inference System (ANFIS).

Author Keywords
subway, passenger density, CCTV cameras, prediction, Adaptive Network-based Fuzzy Inference System

Introduction

Context prediction describes the task of forecasting future evolution of a recorded time-series of contextual stimuli from knowledge on historical data, such as trends, periodicity or typical patterns [7, 5]. A number of architectures and algorithms have been proposed for context prediction recently [8, 2, 3] which could achieve respectable performance on various application domains [9, 11]. However, in order to make an educated choice from the range of available methods for a particular prediction problem at hand, more and widely adopted datasets are required [6]. In this paper, we contribute towards this aim by reporting on the SEAM4US dataset which is recorded in a Barcelona Metro station. [1]

Possible use cases for prediction include passenger density prediction, passenger navigation prediction or the prediction for energy efficient operation. To investigate on energy efficient subsystems (ventilation, escalator, lightning), the EU funded in the Seventh Framework Programme the project "Sustainable Energy mAnageMent for Underground Stations" (SEAM4US). The SEAM4US project develops a predictive control architecture, which controls proactively the metro station subsystems, taking current and predicted count of persons within the station into account. The count of persons is provided by an enhanced CCTV system. On the same time the count of persons is the basis for the prediction.

Figure 1: Passeig de Gràcia Entrance/Exit Gran Via. [10]

The remainder of this paper is organized as follows. First an overview on the SEAM4US project is given. This is followed by a description of the pilot station. Subsequently the count of persons extraction is described, followed by a detailed view on the passenger density data. Last, our conclusions are drawn.

[1] If you are interested in the dataset, please contact the first author

SEAM4US project

The aim of SEAM4US "is to develop advanced technologies for optimal and scalable control of metro stations" [1].

The SEAM4US consortium consists of nine partners from six different EU countries, namely Cofely Italia Spa (Italy, Energy-efficient system management), Universita Politecnica Delle Marche (Italy, Building and environmental physics construction, Universitat Politecnica De Catalunya (Spain, Building and environmental physics and construction), Fraunhofer-Gesellschaft zur Foerderung der Angewandten Forschung E.V (Germany, middleware), Teknologian Tutkimuskeskus VTT (Finland, middleware), University of Kassel (Germany, User and agent-based scheduling modeling), Almende B.V. (Netherlands, User and agent-based scheduling modeling), CNet Svenska AB (Sweden, System integrator) and Transports Metropolitans De Barcelona Sa (Spain, Metro network operator).

The control architecture, the prediction models as well as hardware components compose the SEAM4US system, which is installed in a pilot station in Barcelona (Spain). The following section gives more details about the pilot station.

Pilot Station "Passeig de Gràcia - Line 3"

The SEAM4US system is implemented in the pilot station Passeig de Gràcia - Line 3 (PdG-L3), which is a station within TMBs metro network in Barcelona (Figure 1). This section describes the station in more detail.

In general, a metro network consists of one or more metro lines. Each line has a defined railway with a given number of stops to allow passengers to get on or off the trains.

Figure 2: PdG-L3 Plattforms. [10]

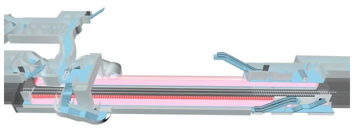

Figure 3: PdG-L3 schematic representation. [10]

Figure 4: CCTV camera in PdG-L3 platform. [10]

Figure 5: CCTV camera in a PdG transit area. [10]

Each of these stops is called "line station". In contrast, a "metro station" represents the architecture through which passengers get underground and into a line station. Metro station and line station can be the same physical entity, but it is possible that a metro stations holds more than one line stations.

The metro station Passeig de Gràcia (PdG) was chosen as a representative station for the SEAM4US project. It is located in the iconic and touristic part of Barcelona. Some popular buildings designed by Antoni Gaudí (Casa Batllò, Casa Milà) as well as the city's most renown and exclusive boutiques are in the proximity. The metro station is one of the oldest of the Barcelona metro network. First opened in December 1924, as station for Line 3 (L3), nowadays PdG holds three different line stations: Line 2, Line 3, and Line 4. The line stations were built in three different periods, using different construction technologies. All line stations have 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 too but remain the entire night and day until Sunday midnight.

PdG-L3 was as pilot station selected since it turned out to be representative for many stations within TMBs metro network [10]. The count of fans, escalators, and the platform schema is comparable to other stations. Moreover, PdG-L3 is a crowded station which have low-rate usage hours as well. Therefore, a wide range of data is available, that allows to test with very busy peak hours as well as with off-peaks.

The line station PdG-L3 consists of private (staff only) and public spaces. Private spaces such as technical rooms or staff dependencies are not part of the investigation of the SEAM4US project, whereas public spaces, such as halls, transit areas, accesses to the platforms, and platforms are, in the focus for the energy efficient control. The platforms are an essential part of (every) line station, since it allows passengers to leave and enter the trains. For the passenger model it is essential because every passenger who uses the line station is visible here. Figure 2 depicts the platform.

A schematic representation of PdG-L3 is drawn in Figure 3, where the platforms are highlighted in red. At the beginning and end of the platforms, the accesses to the platforms are visible.

Throughout the station a Closed Circuit Television (CCTV) surveillance system is installed. 20 CCTV cameras on different locations provide images for security reasons. Figure 4 and Figure 5 show exemplary CCTV cameras on the platform as well as in the transit area.

The CCTV system provides the basis for the predictive passenger model. In the following, the data extraction is explained.

Count of persons extraction

The SEAM4US system utilizes a prediction model for proactively controlling the subsystems. Besides others, the passenger model is a part of the predictive controlling architecture. To predict count of persons for a point in the future, the model utilizes the output of the CCTV monitoring system. The count of persons is extracted by enhancing the CCTV system with image processing.

Whenever camera pictures are processed privacy issues are

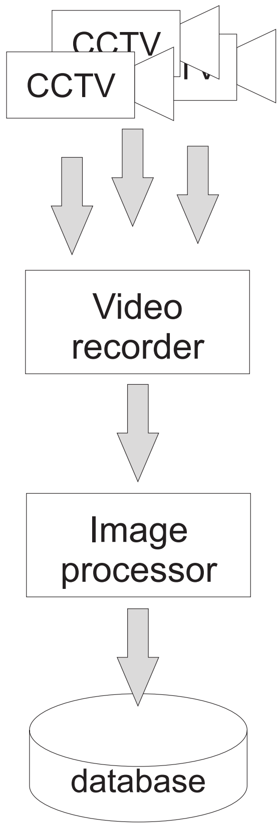

Figure 6: Gathering count of persons out of the camera images.

tackled. In order to ensure the passengers privacy several design constraints were defined:

1. All CCTV images are processed within the station.
2. All CCTV images are processed "on the fly". For the purpose of count of persons extraction, no CCTV image is saved.
3. The image processing is performed on a separate computer, which is not connected to other TMB Systems and is only accessible via a dedicated VPN connection.
4. The image processing works without human interaction.
5. The image data is filtered to avoid recognisability of individuals.
6. The image processing results are transmitting only in terms of integer numbers to the database.

With respect to these design constraints, the count of persons extraction was implemented. The workflow is described briefly in the following.

First, the video streams extracted from all cameras are combined into one single video stream by a video recorder. The video recorder creates a carousel video composed of intervals for the individual camera, appearing in a predefined order. The duration of the camera intervals is set to 3 seconds. With 20 cameras and 3 seconds hold on each, one turn of the carousel is completed in one minute.

The video recorder is connected to a local computer and transfers the images subsequently. On the local computer, an extraction algorithm processes the transferred images and extracts the count of persons. The extraction algorithm uses a combination of edge detection and background subtraction. First the algorithm separates background and foreground. Followed by creating the foreground mask. Through filtering the edges of the foreground only, is extracted. The foreground edges are combined with the foreground mask. Finally, the result is refined by dilating (and then eroding) the segmented blobs. For various reasons, for instance, occluded or damaged camera, the extraction algorithm can fail. In these cases, the algorithm returns the error value "-1".

The extracted count of passenger as well as date, time and the camera-ID of the image are transmitted to the database. The general approach is sketched in Figure 6.

The CCTV system as well as the image processing are running 24 hours, 7 days a week. Each day 28800 datasets are transmitted to the database. Overall the database currently contains 90 days of data.

Count of persons data

This section discusses the properties of the recorded data as well as its suitability for context prediction.

Properties of the data

In order to model the passenger density an understanding of the available data is necessary. In this section the data, visible pattern and other features are discussed.

Figure 7 illustrates exemplary the available values of a camera and week. The PdG service times are visible due to the low passenger density level between 01:00 and 05:00 on weekdays.

The figure details the passenger density data observed by one particular out of the 20 installed CCTV cameras (indexed with ID 700). Due to the acquisition process in which density information is extracted from circular

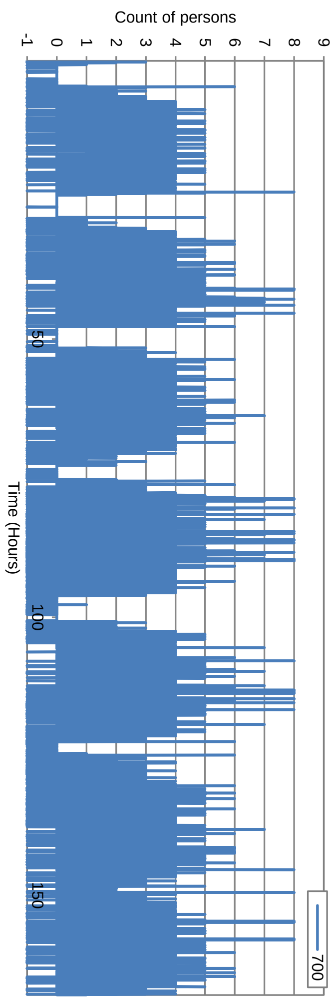

Figure 7: Passenger density distribution of one camera during one week.

snippets of the various cameras (see description of the recording process above), for each camera one estimate on passenger density is computed every one minute, leading to a total of 1440 samples per camera and per day. Again, due to the data processing operation, samples taken are not simultaneous for different cameras but taken sequentially so that pairwise samples are misaligned by at most 30 seconds.

The passenger density is highly correlated for the distinct cameras installed in the metro system which reflects that a specific share of the passengers is always observed by any of the cameras. This is depicted in Figure 8.

The figure displays the mean aggregated passenger density over the course of several days and observed by four different CCTV cameras (with IDs 711, 716, 7004 and 7112).

A single point in this figure reflects the mean aggregated passenger density over a window of 30 minutes with an overlap of 15 minutes.

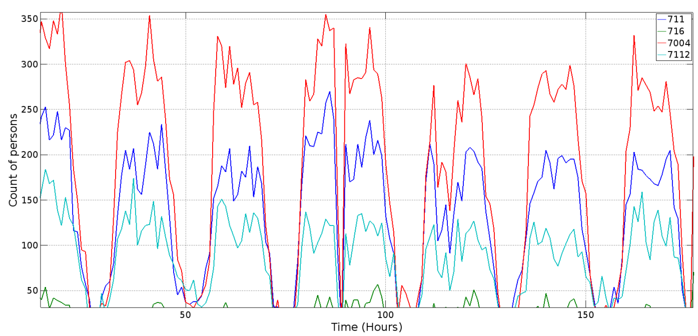

Figure 8: Passenger density evolution over the course of several days.

We observe that passenger density peaks for the respective cameras are correlated but of different magnitude. The overall mean passenger density and standard deviation observed over the same recording time per minute are depicted in Table 1.

Table 1: Mean and standard deviation of passenger density data observed at CCTV cameras.

CCTV ID	mean	standard deviation
700	1.4816	1.5189
701	2.1761	1.8969
704	2.8168	2.1960
705	1.8074	1.8482
710	2.8167	3.0868
711	2.306	2.1693
712	2.9604	2.4585
714	0.5541	1.0938
716	0.3369	0.8016
720	2.6819	3.046
721	1.8885	2.2247
722	1.2977	1.7984
731	1.7365	1.8192
732	1.3021	1.5656
733	1.024	1.3219
7100	0.1803	1.756
7104	0.9570	2.0948
7110	3.4162	10.2810
7111	0.8012	1.9145
7112	0.9918	1.0988

Prediction by Adaptive Network-based Fuzzy Inference System

Given the passenger density data provided from the CCTV camera system, we have attempted to predict passenger density with an Adaptive Network-based Fuzzy Inference System (ANFIS) [4]. The ANFIS algorithm was configured to conduct 10 training epochs with a training error goal of 0, an initial step size of 0.01 and step size decrease and increase rates of 0.09 and 1.1 respectively.

For the training of the system, we utilized data from three consecutive weekdays and attempted to predict the following two days. Exemplary prediction results are depicted in Figure 9 for four distinct CCTV cameras. The figures show the actual and the predicted evolution of passenger density data.

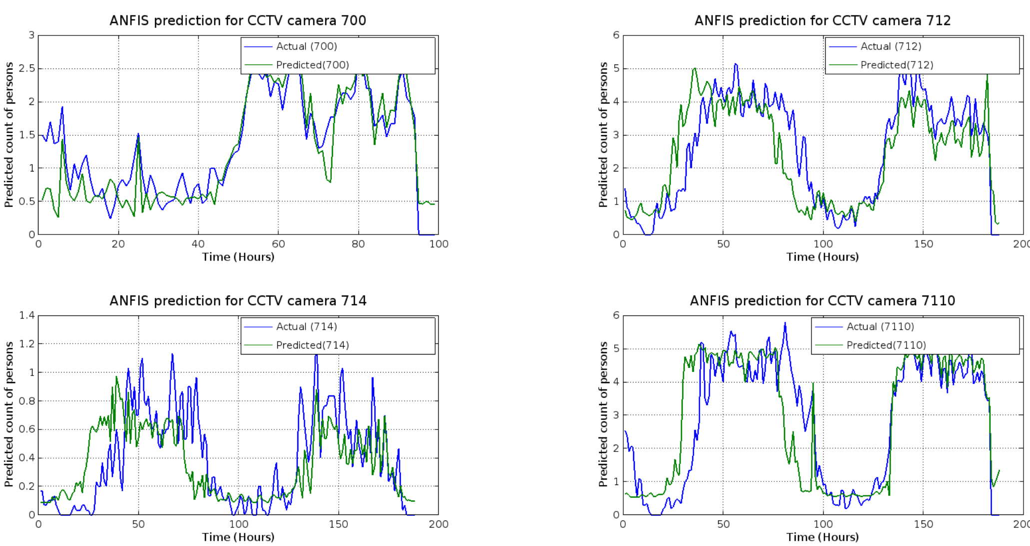

Figure 9: ANFIS prediction of passenger density.

We observe that a reasonable prediction accuracy was achieved while the evolution of the predicted sequence often briefly preceded the actual evolution of passenger density.

The prediction error over time is depicted in Figure 10. We observe that the prediction error is low in all cases and near zero.

Conclusion

In this paper we have discussed ongoing work in the SEAM4US project. In particular, we have discussed peculiarities of the Barcelona underground system under observation. This has in particular shown that there are plenty of CCTV cameras installed in underground metro systems which are capable to generate enormous amounts of feature data which can be utilized, for instance, for the analysis and prediction of passenger density over time. In particular, we could observe that, although the magnitude of passenger density fluctuation differs depending on where in the system the corresponding cameras are installed, this fluctuation is highly correlated among the CCTV cameras. Furthermore, the data shows clear patterns that allow prediction of passenger density over time. We have therefore investigated the predictability with an Adaptive Network-based Fuzzy Inference System, which has shown good potential for the prediction in various applications. In future work we will investigate the predictability of this data to exploit potential energy savings by controlling electricity and fan-speed more accurately and based on actual load. In particular, for energy efficient control of this subway subsystem the SEAM4US project develops a predictive control architecture. The control architecture proactively performs energy management tasks based on situations taking place in the future.

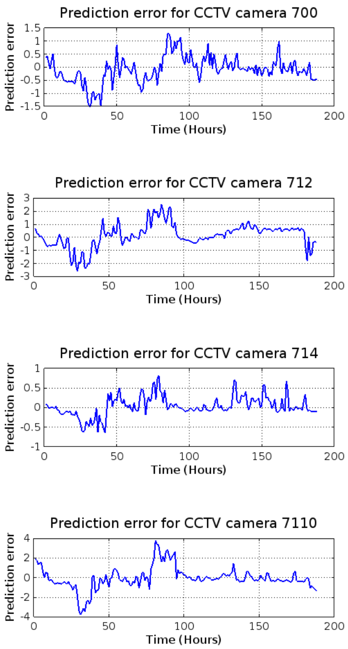

Figure 10: Passenger density prediction error utilising an Adaptive Network-based Fuzzy Inference System

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