
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 utilised 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, predictive controlling

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 [6, 5]. A number of architectures and algorithms have been proposed for context prediction recently [7, 3, 4] which could achieve respectable performance on various application domains [8, 10].

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 develop 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 bases for the prediction.

The remainder of this paper is organized as follows. First an overview of SEAM4US project is given. 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.

SEAM4US project

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

For optimal control, a predictive control architecture was developed. The control architecture proactively perform energy management tasks and controls the metro station subsystems, taking different passenger densities into

account [2]. Also situations taking place in the future are considered by utilizing, beside others, the passengers prediction model. The passenger prediction model predicts the count of persons in a certain section, on a certain time in the future.

The SEAM4US consortium consists of nine partners from six different EU countries, namely Cofely, UniVPM, UPC, Fraunhofer FIT, VTT, Almende, UniKassel, CNET, and TMB. Each partner supports the consortium with its expertise:

Cofely Cofely Italia Spa (Italy):

Energy-efficient system management.

UniVPM Universita Politecnica Delle Marche (Italy):

Building and environmental physics and construction.

UPC Universitat Politecnica De Catalunya (Spain):

Building and environmental physics and construction.

Fraunhofer FIT Fraunhofer-Gesellschaft zur Foerderung der Angewandten Forschung E.V (Germany):
R+D experts in middleware.

VTT Teknologian Tutkimuskeskus VTT (Finland):

R+D experts in middleware.

UniKassel University of Kassel (Germany):

User and agent-based scheduling modeling.

Almende Almende B.V. (Netherlands):

User and agent-based scheduling modeling.

CNet CNet Svenska AB (Sweden):

System integrator.

TMB 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. This section describes the station more in detail. Before the difference between "line stations" and "metro stations" is pointed out.

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. Each of these stops is called "line station". In contrast, a "metro station" represents the point in space 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.

As mentioned (line) station PdG-L3 serves as pilot station. In the following, details about the metro station Passeig de Gràcia (PdG) are given, followed by details about the pilot (line) station PdG-L3.

The metro station PdG lies 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



Figure 1: Passeig de Gràcia Entrance/Exit Gran Via. [9]

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. Figure 1 depicts an entrance/exit of metro station PdG.

PdG-L3 was as pilot station selected since it turned out to be representative for many station within TMBs metro network [9]. 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 are available, that allows to test with very busy peak hours as well as with off-peaks.

Spaces

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 a 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. PdG-L3 laid out on a PRRP schema - Platform-Rail-Rail-Platform. The PdG-L3 platforms are depicted on Figure 2.



Figure 2: PdG-L3 Platform

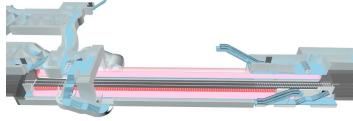


Figure 3: PdG-L3 Schematic [9]



(a) Camera in a PdG transit area. [9]



(b) Camera in PdG-L3 platform. [9]

Figure 4: Installed cameras

the platforms are visible.

CCTV System

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 show exemplary CCTV cameras on the platform (Figure 4(a)) as well as in the transit area (Figure 4(a)).

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 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 future, the model utilizes the output from the CCTV monitoring. The count of persons is extracted by enhancing the CCTV-system with image processing.

Whenever camera pictures are processed privacy issues are tackled. In order to ensure the passengers privacy several design constraints where 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 are 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 coming 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 transfer the images subsequently. On the local computer, a extraction algorithm processes the transferred images and extracts the count of persons. The extraction algorithm uses a combination of edge detection and background subtraction. In the following, the algorithm is described briefly. First the algorithm separates background and foreground. Followed by creating the foreground mask. Through filtering the edges of the foreground only are extracted. The foreground edges are combined with the foreground mask. Finally, the result is refined by dilating (and then eroding) the segmented the blobs. For different reasons, e.g. occluded or damaged camera, the extraction algorithm can fail. In these cases, the algorithm returns the error value "-1".

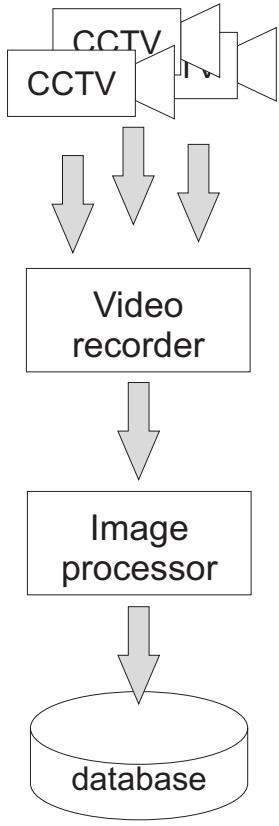
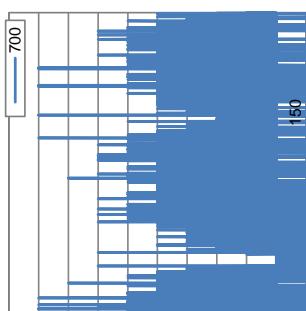


Figure 5: Gathering count of persons out of the camera images.



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 depicted in Figure 5.

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

Count of persons data

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 6 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.

Prediction by Artificial Neural Fuzzy Inference System

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 sensors installed in underground metro systems which are capable to generate enormous amounts of feature data which can be utilised, 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 sensors. Furthermore, the data shows clear patterns

that allow prediction of passenger density over time. We have therefore investigated the predictability with an Artificial Neural Fuzzy Inference System which as 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 optimal 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.

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 partners and colleagues.

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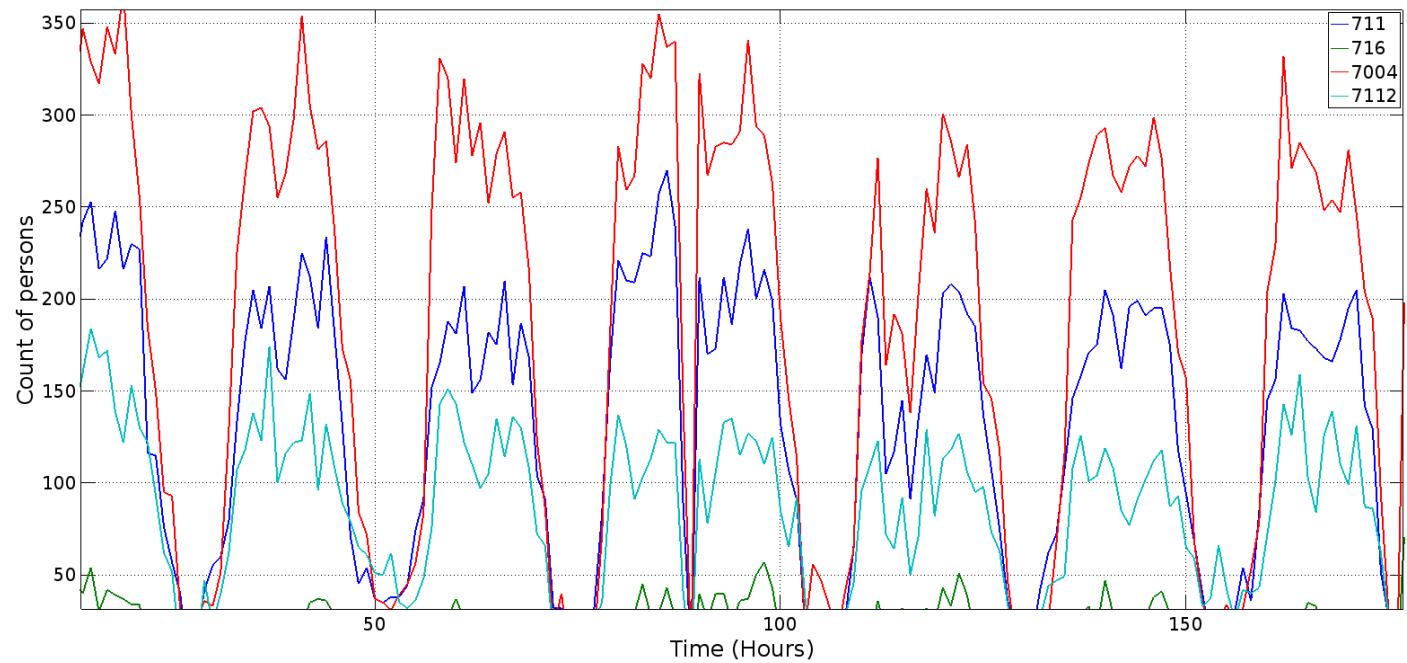


Figure 7: todo

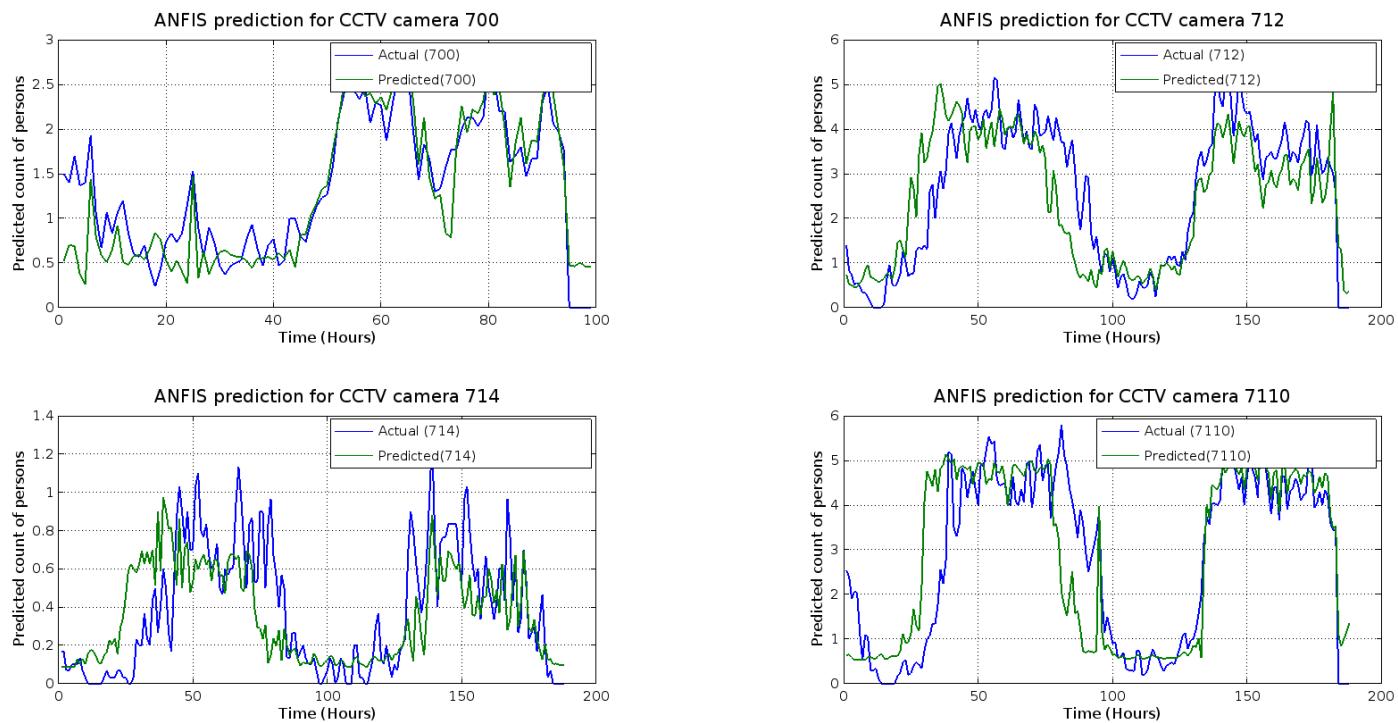


Figure 8: todo

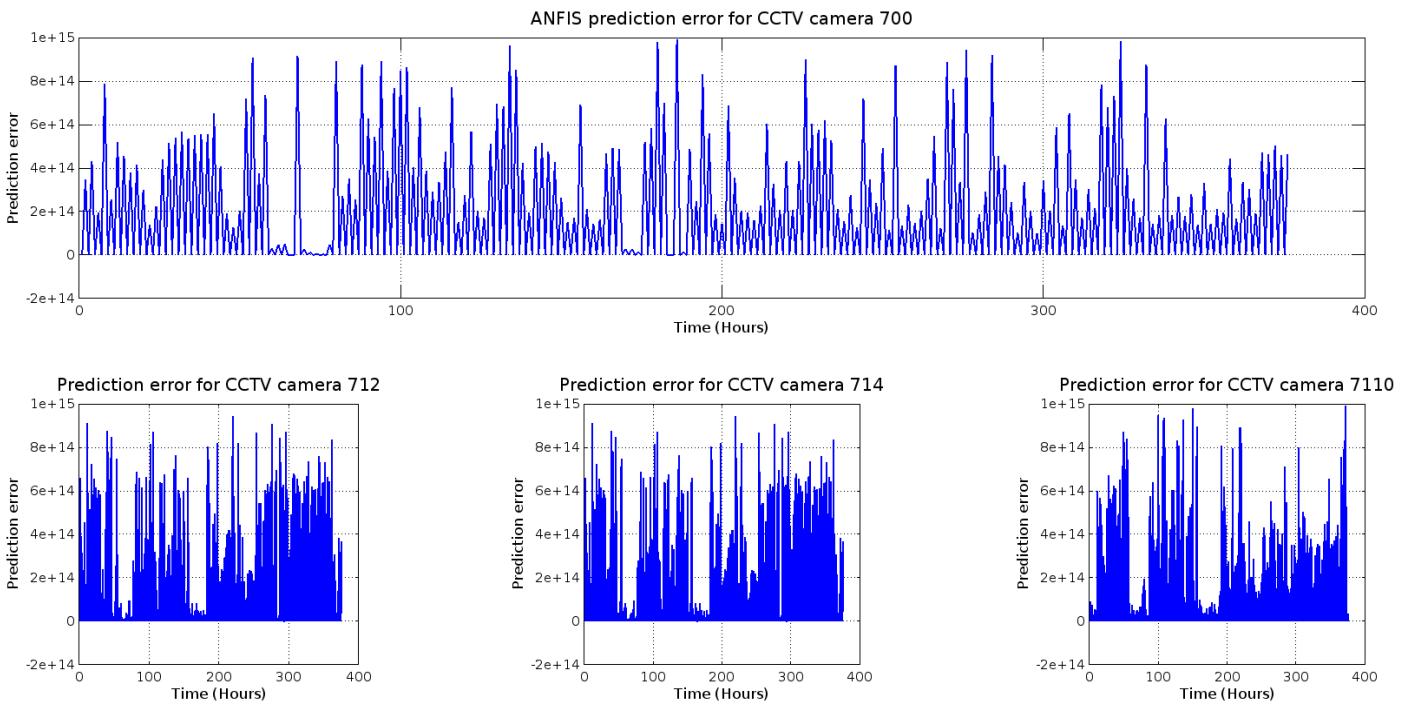


Figure 9: todo

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