Deep Learning-based Prediction Method for People Flows and Their Anomalies

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Abstract: This paper proposes prediction methods for people flows and anomalies in people flows on a university campus. The proposed methods are based on deep learning frameworks. By predicting the statistics of people flow conditions on a university campus, it becomes possible to create applications that predict future crowded places and the time when congestion will disappear. Our prediction methods will be useful for developing applications for solving problems in cities.

1 INTRODUCTION

Smooth transportation of people, materials and vehicles enhances the vitality of city life. To service a diversified society for future generations, transfer needs should be supported by providing not only conventional public traffic services but also new transportation services that can be adapted to city requirements, such as car- and bicycle-sharing services and autonomous car services. As these new transportation services are developed, it is essential to construct a personal mobility support system by combining services appropriately to provide smooth and efficient transportation adjusted to personal characteristics and needs.

To understand the characteristics and needs of movement within a city, it is necessary to first observe peoples activities using various sensing devices. To realize a sustainable society, various smart city frameworks have been proposed (Vilajosana et al., 2013), (Cheng et al., 2015), (Al Nuaimi et al., 2015), and demonstration experiments are being conducted all over the world. To achieve a co-evolutional society, the Center for Co-Evolutional Social Systems at Kyushu University aims to develop a new urban operating system (Fig. 1) that supports efficient, speedy, and seamless movement of people and materials, including energy and information . As part of this project, we have developed pole-type sensor nodes that can measure people's activity, and we are conducting demonstration experiments on our university campus using these sensor nodes. It is reasonable to predict that the activity state for a local person living in a city is the same as usual. However, it is difficult to optimally predict the actions of visitors. Furthermore, events such as conferences, festivals, and accidents will be associated with some unusual and difficult to predict the behaviors of both visitors and locals. Our goal is to sense and predict people's behavior in real time.

This paper proposes prediction methods for people flows and anomalies in people flows on our campus. The proposed methods are based on deep learning (LeCun et al., 2015). In our people flow prediction method, we convert people flow data measured by our sensor nodes to statistics for movement directions per unit time, and learn models that predict future statistical data from past data. Moreover, we develop a *k*-nearest neighbor (*k*-NN) based anomaly detection method (Goldstein and Uchida, 2016) for people flows in real time, where the anomaly data are accumulated over the long-term. By using the stored people flow and anomaly data, our anomaly prediction method learns a model for predicting an anomaly value for the next short time period. Predicting the statistics for people flow conditions on campus makes it possible to create applications that predict the next crowded place and the time when congestion

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will disappear. Therefore, our prediction methods are useful for developing a personal mobility support system for a smart city.

The rest of the paper is organized as follows. We introduce the pole-type sensor nodes and explain the people flow and anomaly detection methods in Section 2. Section 3 describes the methods of people flow and anomaly prediction. Section 4 presents an experimental environment and some experimental results. Section 5 concludes the paper.

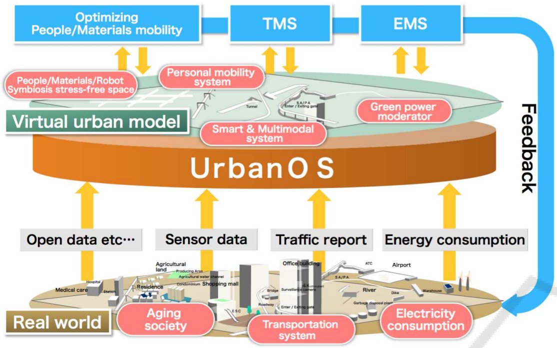

Figure 1: Overview of an urban operating system.

2 PEOPLE FLOW DETECTION AND ANOMALY DETECTION

2.1 Petit Sensor Box

A petit sensor box (P-Sen) is a pole-type sensor node equipped with multiple sensors for measuring peoples activity. The height of a P-Sen is approximately 3750mm, the width is 450mm and the depth is 500mm. An overview of a P-Sen is shown in Fig. 2. The sensors in a P-Sen are a network camera, a wireless LAN access point (WLAN-AP), an integrated circuit (IC) card reader, a temperature and humidity sensor and a laser range finder (LRF). To integrate the sensor data and to transport them to our cloud server, each P-Sen contains a desktop PC and a network hub. Because of the amount of raw data captured by the network camera and the LRF, the feature-extracted data are transmitted to the cloud server through the WLAN-AP.

In the following sub-sections, we explain in detail the sensor data obtained by each of the sensors in a P-Sen.

2.1.1 Network Camera

A network camera is put on the top of each P-Sen at a height of 3.75 m from the ground. The angles of view are 85° and 68° in the horizontal and vertical directions, respectively. The viewing angle can be extended by the pan-tilt functions. The image is captured at 30 frames per second, and the resolution can be selected from several standard formats (1280×960, 640×480 and 320×240 pixels).

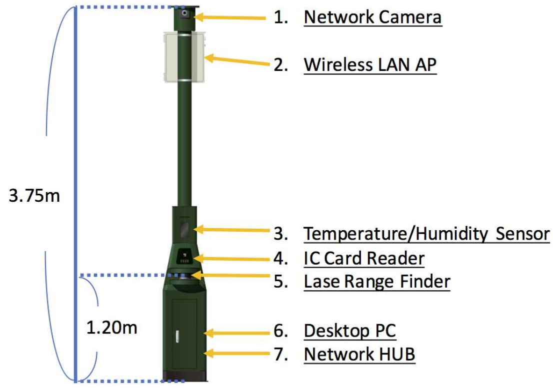

Figure 2: Overview of a P-Sen.

2.1.2 Wireless LAN Access Point

We construct a wireless sensor network (WSN) using the WLAN-APs in each of the P-Sens. This WSN can be used to send the sensor data collected by the P-Sens to the cloud server. Moreover, we can collect Wi-Fi probe requests that are broadcast by nearby mobile devices. Because the collected probe requests include the media access control (MAC) address of the mobile device, we can count the number of devices around the P-Sens.

2.1.3 IC Card Reader

The IC card reader in each P-Sen collects log data whenever a user touches the reader with their IC card, which in our case is the identification card for our university. Using the log data from the IC card reader, we know when the user is on campus.

2.1.4 Temperature and Humidity Sensor

Our sensor can measure the temperature and humidity around the P-Sen. The measured data are sent to the cloud server every minute.

2.1.5 Laser Range Finder

The LRF is set at a height of 1.0 m from the ground and the range of the scan angle is from $-95°$ to $+95°$. The LRF can measure the distance between a P-Sen and people or materials that are over a height of 1.0 m. The step angle is 0.125°, and the number of steps is 1520.

2.2 People Flow

Each P-Sen is equipped with multiple sensors that can measure people flow. Using the network camera in a P-Sen, we can implement people detection by applying image processing such as background subtraction to the captured images. However, there are privacy issues concerning facial image processing in public spaces.

By analyzing the request signal collected by the wireless LAN, it is possible to count the number of surrounding wireless terminals. Because the timing of the request signal depends on the settings of various terminals, it is possible to estimate the number of people around the P-Sen. We may also need to consider the encryption of MAC addresses from the viewpoint of privacy.

Using the LRF, we can measure the distance between a P-Sen and a human or materials accurately. Moreover, as shown Fig. 3, it is possible to measure the direction in which people are moving with high accuracy, and we do not need to consider privacy issues.

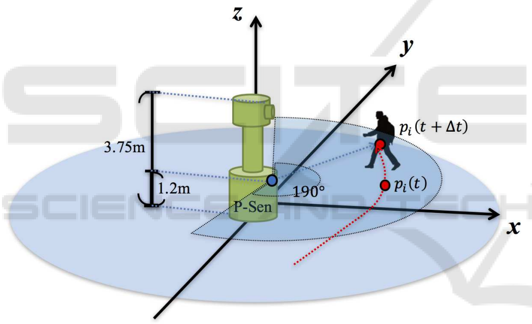

Figure 3: People flow measurement area using the LRF in a P-Sen.

Therefore, we use the LRF in each P-Sen to analyze people flow on campus. In this paper, we obtain location information for people and objects in front of each P-Sen at 0.1 second intervals by applying a people and object detection method (Kurazume et al., 2008) to the raw data sensed by the LRF.

Figure 4 shows an example of people flow measured by a P-Sen on our campus. In Fig. 4, the locations of the 14 P-Sens and the detected people are indicated by the red and green points, respectively.

Figure 4: An example of people flow on our campus.

2.3 Anomaly Detection

We develop an online anomaly detection algorithm based on the k-NN algorithm (Goldstein and Uchida, 2016) and calculate anomalies in people flows on our campus in real time. In this paper, we divide the measurement area in front of each P-Sen into 18 ($= 3 \times 6$) blocks and learn the anomaly detection model using 72-dimensional vectors generated from the pass frequency in four directions every 10 minutes as shown in Fig. 5. First, for recent 200days records in the dataset, the k-nearest-neighbors at each block have to be found. Then, an anomaly score is computed using the distance to the k-th-nearest-neighbor in each of 18 blocks.

This method can be used to learn an anomaly detection model without training data. An example of anomaly detection related to people flows on our campus is shown in Fig. 6, where the red regions indicate an anomaly and the density of the red color represents the anomaly score.

3 METHOD

We propose a method for predicting future people flow that uses campus people flow data collected over a long period and deep learning. In addition, we propose a convolutional neural network (CNN) based learning model for directly predicting future anomalies using images generated by past people flow data.

3.1 Imaging of People Flow

In this sub-section, we consider a method for imaging people flow in a short time period. Our imaging process is based on the detected point passing frequency in four directions for the time period T. The resolution of the image is $W \times H$ pixels.

We define a detected person's location at time t to be $P_i(t) = (x_i(t), y_i(t))$, where i is a local ID given

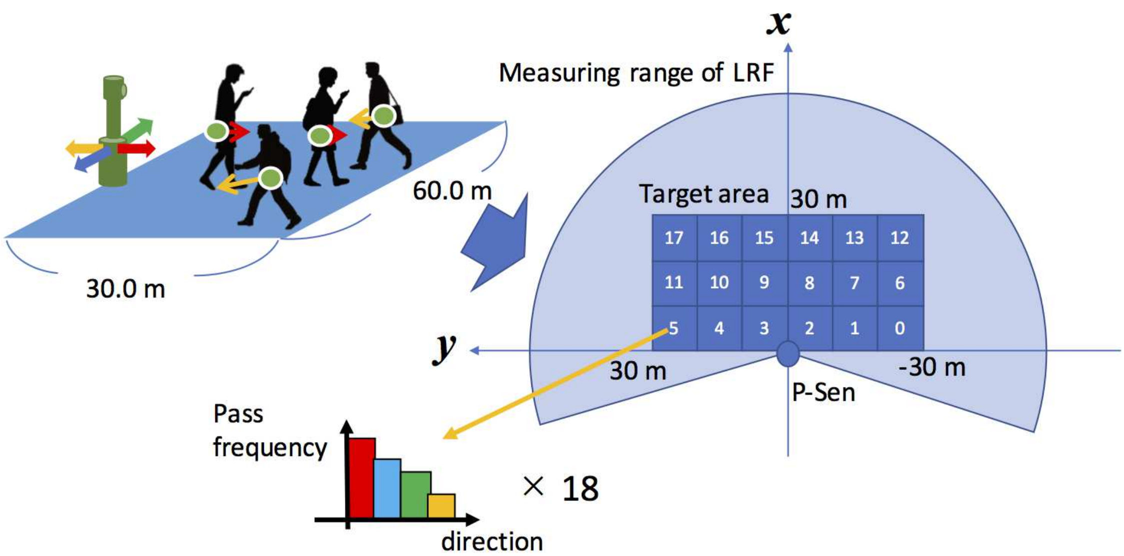

Figure 5: Quantization of people flow data.

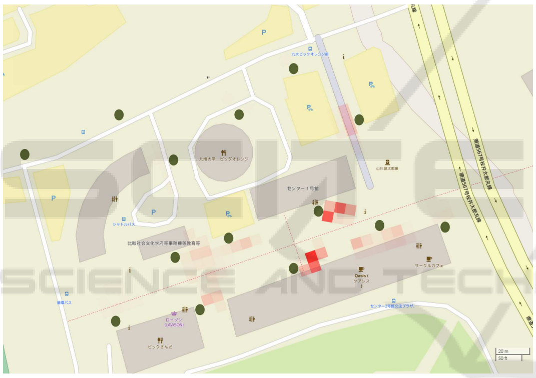

Figure 6: An example of anomaly detection.

by the P-Sen to each detected person or object. The coordinates $x_i(t)$ and $y_i(t)$ are quantized as integers so that $0 \leq x_i(t) \leq H$ and $0 \leq y_i(t) \leq W$.

The measured trajectory $P_i(t), t \in T$, is divided into sub-trajectories with a moving distance of 1.0 m. The travel time for each sub-trajectory is Δt, and the distance $L_i(t)$ and the direction $\theta_i(t)$ from $P_i(t)$ to $P_i(t+\Delta t)$ are written as

$$\begin{aligned} L_i(t) &= \sqrt{\Delta x_i^2 + \Delta y_i^2}, \\ \theta_i(t) &= \arctan\frac{\Delta x_i}{\Delta y_i}, \end{aligned}$$

where

$$\begin{aligned} \Delta y_i &= y_i(t+\Delta t) - y_i(t), \\ \Delta x_i &= x_i(t+\Delta t) - x_i(t). \end{aligned}$$

In each of the four quantized directions for the time period T, the four-channel image data $I_d^T, d = 1,2,3,4$, are generated by calculating the passing frequency for the midpoint of the sub-trajectory. The quantized direction d is determined using $\theta_i(t)$ as follows:

$$d = \begin{cases} 1, & -\pi/4 \leq \theta_i(t) < \pi/4, \\ 2, & \pi/4 \leq \theta_i(t) < 3\pi/4, \\ 3, & 3\pi/4 \leq \theta_i(t) < 5\pi/4, \\ 4, & 5\pi/4 \leq \theta_i(t) < 7\pi/4. \end{cases} \quad (1)$$

The proposed algorithm for imaging people flow data is shown in Fig. 7.

3.2 People Flow Prediction

To predict people flow, we propose a learning model based on a discrete neural network (DNN) as shown in Fig. 8. First, we generate images with $72 = 4 \times 6 \times 3$ ($4 \times W \times H$) pixels for each ten-minute (T) period by applying the proposed imaging algorithm to the people flow data as described in sub-section 3.1. Using the past people flow data at times $t-1$ and $t-2$, we learn an hourglass-type DNN that can predict future people flow data at time t. The pair of 72-dimensional vectors at times $t-1$ and $t-2$ is used as an input to the DNN, and the future people flow at time t is predicted by the DNN.

3.3 Anomaly Prediction

We propose a CNN based anomaly prediction method for people flow data. The proposed method uses four-channel images, each of which is 60×30 ($W \times H$) pixels and covers a ten-minute period as described in

INPUT: $\mathbf{P} = \{P_i(t) |$ All trajectories at the time period $T\}$
OUTPUT: $I_d^T, d = 1,2,3,4$
for $d = 1$ to $d = 4$ **do**
  for all $(x,y) \in W \times H$ **do**
    $I_d^T(x,y) = 0$
  end for
end for
for all $t \in T$ **do**
  $N_t \leftarrow$ Number of Local ID at Time t
  for all $i \in N_t$ **do**
    for all $p_i(t) \in P_i(t)$ **do**
      Compute $\theta_i(t)$ of $p_i(t)$
      if $-\pi/4 \leq \theta_i(t) < \pi/4$ **then**
        $d = 1$
      else if $\pi/4 \leq \theta_i(t) < 3\pi/4$ **then**
        $d = 2$
      else if $3\pi/4 \leq \theta_i(t) < 5\pi/4$ **then**
        $d = 3$
      else if $5\pi/4 \leq \theta_i(t) < 7\pi/4$ **then**
        $d = 4$
      end if
    end for
    $(x,y) \leftarrow (p_i(t) + p_i(t+\Delta t))/2$
    $I_d^T(x,y) += 1$
  end for
end for

Figure 7: Algorithm for imaging of people flow.

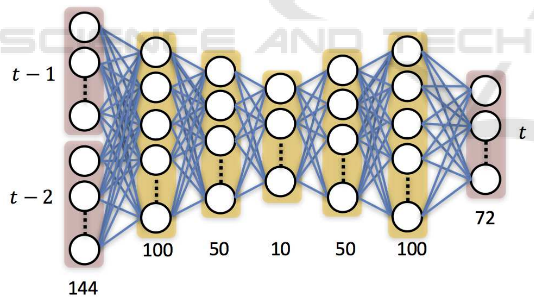

Figure 8: Hourglass-type DNN.

sub-section 3.1. Figure 9 shows an example of four-channel people flow images.

In the proposed method, a set of people flow images is generated using the campus people flow data collected over a long period. We learn a CNN based anomaly prediction model as shown in Fig. 10.

We use eight-channel image data, each of which is 60×30pixels, generated by combining people flow images at times $t-1$ and $t-2$ as the inputs to the CNN, and obtain an 18-dimensional anomaly prediction vector for people flow at time t.

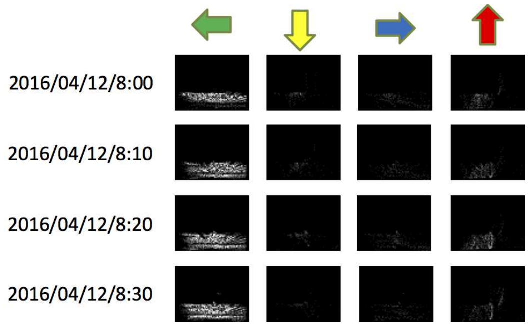

Figure 9: An example of people flow images.

4 EXPERIMENTS

4.1 Environment

We install 14 P-Sens in the central zone of the Ito Campus of Kyushu University, and conduct experiments using the measurements of activity on campus. The population of this central area in the daytime is over 5000. Therefore, there are some places where congestion occurs during rush hours and at lunch time, such as around the restaurants, stores and bus stops. Our first task is to develop an application for congestion prediction at certain places on campus using the sensor data obtained by the P-Sens.

Figure 11 shows the locations of the P-Sens in the central area of the campus. We place a P-Sen on each of the 14 red points shown in Fig. 11 facing in the direction of the arrow. We construct a WSN by connecting the P-Sens. To collect and send the sensor data to our analysis server, the fourth and tenth P-Sens are connected to the core nodes, which are linked to the Internet. Because of this WSN and the core nodes, we can obtain sensing data from our analysis server in real time.

4.2 Results

We first conduct experiments to predict future people flow using statistics from the accumulated people flow data. In this experiment, the training data was accumulated from April 2016 to July 2016 (4 months) by P-Sen #10. Because this four month period is the first semester for our university, the activities of many students were measured by the P-Sens. The test data was accumulated during the month of October 2016, which is the start of the second semester after summer vacation. Applying the proposed method described in sub-section 3.2, we obtain the people flow prediction model. The mean squared error (MSE) for the training and validation sets by epoch are shown in

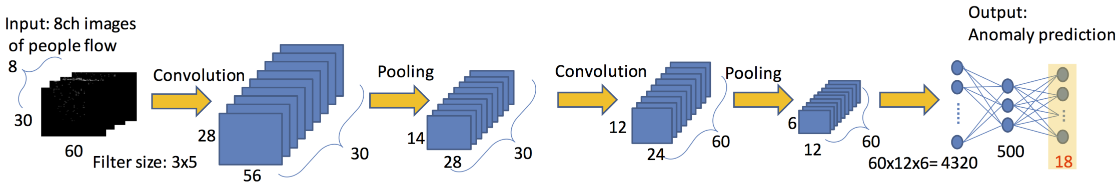

Figure 10: CNN for anomaly prediction.

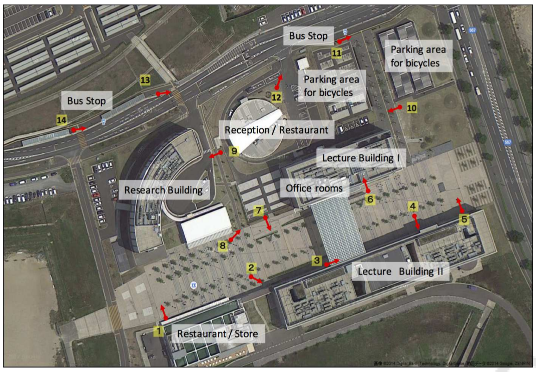

Figure 11: The locations of the P-Sens.

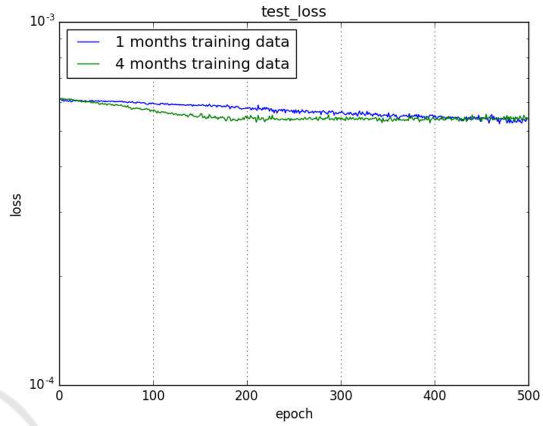

Figure 13: MSE for the validation set by epoch for people flow prediction.

Fig. 12 and Fig. 13. To estimate the accuracy of the prediction, the mean correlation coefficient for each epoch was also computed and is shown in Fig. 14.

Figure 12: MSE for the training set by epoch for people flow prediction.

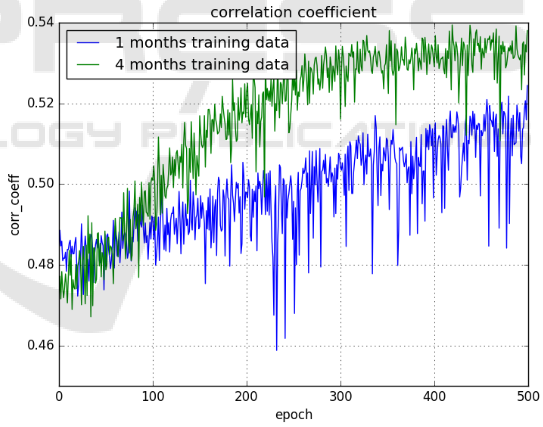

Figure 14: Mean correlation coefficient by epoch for people flow prediction.

A second experiment was performed along using data from the same place and period to learn and evaluate the proposed anomaly prediction model described in sub-section 3.3, The MSE for the training and validation sets by epoch are shown in Fig. 15 and Fig. 16. To estimate the accuracy of the prediction, the mean correlation coefficient for each epoch was also computed and is shown in Fig. 17.

4.3 Discussion

The proposed prediction model is a data-driven system realized by an unsupervised learning technique. Our method can learn a model without the preparation of training data in advance. In particular, our experiments suggest that prediction accuracy is improved by using long-term training data as shown in Fig. 17. However, further verification of this is necessary.

In our feasibility study, each prediction model was learned and verified using training data collected over

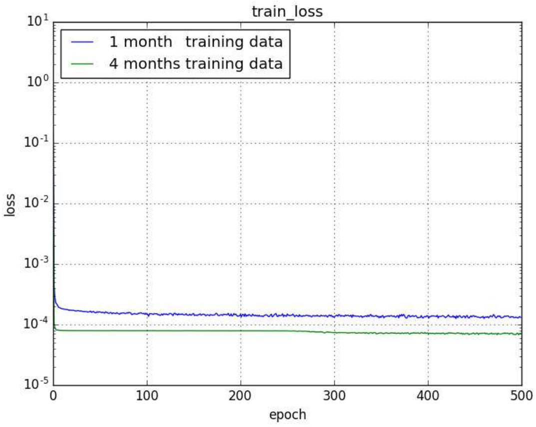

Figure 15: MSE for the training set by epoch for anomaly prediction.

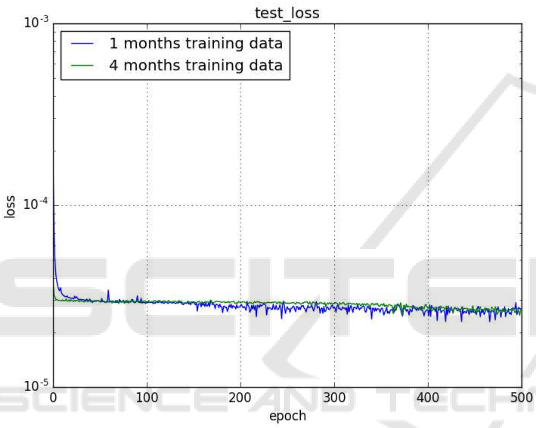

Figure 16: MSE for the validation set by epoch for anomaly prediction.

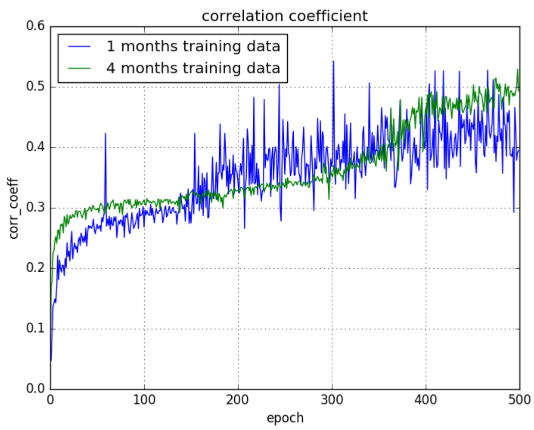

Figure 17: Mean correlation coefficient by epoch for anomaly prediction.

a short period (one month) or over a long period (eight months). We succeeded in predicting an anomaly value that is close to the true value by using the long-term prediction model as shown in Fig. 18.

(a) True anomaly

(b) Predicted anomaly

Figure 18: An example of anomaly prediction.

5 CONCLUSIONS

In this paper, we have proposed learning methods based on deep learning for predicting people flow and anomalies in people flow from data collected on our campus. Our experiments show that we can learn models for predicting people flow by using long-term data accumulated at our university. In the future, we plan to perform more analysis experiments and develop mobile applications for giving feedback on prediction results to our students.

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