URSI GASS 2020, Rome, Italy, 29 August - 5 September 2020

Study of the Crowd Behavior in Campus Based on WIFI Probe and Time Series Analysis

Liang Wei Chen(1), Zhi Gang Chen(2), Chong Xing Huang(3), Yong Qiu Lu(1), Jing Jing Yang*(1), and Ming Huang*(1)
(1)School of Information Science and Engineering, Wireless Innovation Lab. of Yunnan University, Kunming 650091, China
(2) School of Management, Tianjin University of Commerce, TianJin, 300134, China
(3) Radio Monitoring Center of Yunnan Province, Kunming 650228, China
*yangjingjing@ynu.edu.cn; huangming@ynu.edu.cn

Abstract

Recognizing and understanding the behavior of the campus crowd is of great significance for improving the management capabilities of the campus. The increasingly abundant of mobile terminal WiFi signals provide a unique data source for studying the crowd behavior. A WiFi-based personnel activity monitoring system is developed in this paper. Through monitoring and analyzing the MAC address (Media Access Control Address), RSSI(Received Signal Strength Indication) and Wireless AP (Access Point) in and around the Science Museum, Huaizhou building of Yunnan University, the association between WIFI signal and the crowd behavior is studied. Time series analysis is used to make predictions, and some valuable information about the gathering and activity status of crowd in campus is obtained. It provides an experimental platform for studying the dynamic behavior of people in campus and other crowd areas.
Keywords: WiFi; Crowd behavior; Time series analysis

1 Introduction

The mobile Internet has changed people's lifestyle. At present, people can't live without mobile terminals. Marta et al. [1] proved that human trajectories show a high degree of temporal and spatial regularity. Since human behavior affects the WiFi signal, which can be captured through the channel state information (CSI), human activity recognition based on the WiFi CSI has gained more attention [2]. Wang et al. [3] researched more than 100 latest CSI-based behavior recognition applications in the past 6 years and conducted a comprehensive survey of all aspects of human behavior recognition. Cao et al. [4] proposed a method of contactless human body motion recognition through WiFi signals. Therefore, how to perceive human behavior patterns through radio waves has become a hotspot of current research [5]. Unlike video-based mobile crowd surveillance, WIFI signal-based surveillance systems do not involve personal privacy and are not affected by factors such as heavy rain, heavy fog, and insufficient light at night. Recently, Fuxjaeger et al. [6] conducted a road traffic analysis study based on WIFI signals. The experimental results show that by properly processing the measured traffic data, meaningful travel time information can be obtained for each highway segment. Traunmuellera et al. [7] showed the huge potential of using WiFi probes to request data to understand the urban mobility model, while emphasizing data privacy issues due to the increased availability of public WiFi networks.

In summary, there are many reports on the identification of surrounding environment and human behavior characteristics based on measurements of WIFI CSI. However, the prediction of crowd behavior in campus based on WIFI probe using time series analysis has rarely been reported. In this paper, a Wifi-based system architecture for personnel activity monitoring is proposed. Application software for the monitoring node and the server is developed. Time series analysis is adopted to predict the crowd behavior in campus.

2 Architecture of the system

The architecture of the system is shown in Figure. 1. The Wifi monitoring node is comprised of a Wifi probe, computer, storage, processing and prediction module and the wireless bridge. The WIFI probe acquires the information of the WIFI user's MAC address, RSSI, and wireless AP by capturing Probe frames [8]; the data is stored in MongoDB a non-relational database; python scientific computing module is adopted for data processing; the data prediction uses LSTM (Long Short-Term Memory) algorithm and the data visualization module is developed using the web framework Django. The Wifi monitoring node and the back-end which can be a server or cloud is connected using wireless bridge.
The Wifi monitoring node has the edge computing capabilities. The storage, processing, prediction and Web publishing of monitoring data are performed simultaneously.

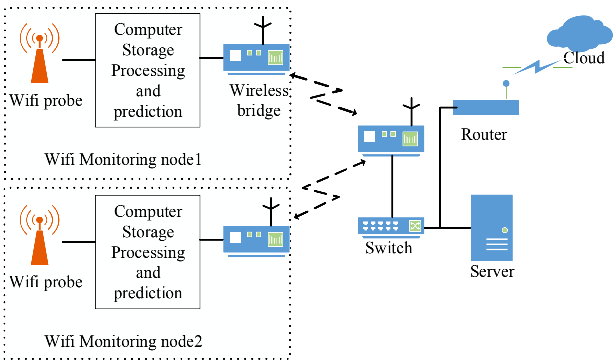

Figure 1. Architecture of the system

When the number of real-time users exceeds the predicted threshold, the Wifi monitoring node sends the abnormal information to the server. Then the server performs alerts and regularly collects abnormal information, with which to make data analysis to achieve the purpose of monitoring the gathering and activity status of personnel through WIFI signals.

3. The crowd behavior monitoring system

3.1 Web application

Web applications for both Wifi monitoring node and the back-end server are developed based on Django framework. A pilot monitoring system consisted of two monitoring nodes and a back-end server is deployed at Donglu Campus of Yunnan University. Node1 and the server is installed at Huaizhou Building, while Node2 at the Science Museum, as shown in Figure 2.

Figure 2. The monitoring node installed at the Science Museum of Yunnan University.

The system interface is shown in Figure 3. It is divided into many functional regions. Region 4 is a 3D online map based on ArcGIS that displays the location of AP nodes. The number of real-time person (WiFi user), new arrivals and departures detected by the current node are displayed

Figure 3. The system interface

on the top left corner of the map. The interface will display the data of the corresponding monitoring node by clicking on the node icon on the map. The photograph and MAC address of some target person can be stored in the database of the system in advance. When the person appears in the monitoring area of the node, the photograph will be displayed in Region 1. Region 2 displays the MAC address of the most active person near the current monitoring node. The statistical results are obtained by recording all RSSI of each MAC address within ten minutes, and judging the activity according to number of RSSI variation for each person. Region 3 is distance information statistics, which is used to count the number of people at different distances near the current node. The abscissa is the distance from 0m to 280m. A large red dot means that more people are gathered at that distance. The yellow line and red line in Region 5 represent the relation between the detected number of person and time, and the prediction results. Region 6 is the visit duration statistics, which is used to record the stay duration of a person near the current node, and the top 15 Wifi users are displayed. Region 7 is the histogram of the visit duration, which shows the stay duration distribution of all user detected by the current node. Region 8 is the MAC address statistical table, which records the users' MAC address, last access time, the distance to the monitoring node and RSSI.

3.2 Method of prediction

In the prediction part, we use the LSTM model to predict the number of WiFi user. The LSTM consists of an input gate i_t, a forget gate f_t, an output gate O_t, a memory cell C_t, and a hidden state h_t: the forget gate determines what information is removed from the cell state; the input gate stores information at the current moment; Output gate controls whether the current time information is output to the hidden state h_t. Finally, combining the current time with past information, the LSTM unit has the ability to save, read, reset, and update long-distance historical information [9].

$$f_t = \sigma\left(W_f \times [h_{t-1}, x_t] + b_f\right) \quad (1)$$
$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \quad (2)$$
$$u_t = tanh(W_c \times [h_{t-1}, x_t] + b_c) \quad (3)$$
$$O_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \quad (4)$$
$$h_t = O_t \times tanh(C_t) \quad (5)$$
$$C_t = f_t \times C_{t-1} + i_t \times u_t \quad (6)$$

In the above equations, x_t represents the input time series, W_* represents the connection weight, σ and tanh are activation functions. In this work, the training model of LSTM has 5 layers, first is 3 LSTM layers, each layer has 200 neurons, then there is a dropout layer, the dropout rate is 0.3, and finally a fully connected layer outputs prediction data. The training process has a total of 250 epochs. Using the Adam optimizer, the initial learning rate is lr = 0.001, and the learning rate is reduced by 20% for every 100 epochs.

3.3 Result

Figure.4 shows the raw data of WiFi users recorded by the Wifi monitoring node at the Science Museum of Yunnan University from December 17, 2019 to December 25, 2019, and the prediction results obtained based on LSTM algorithm. It can be seen that the number of person in the vicinity of the Science Museum changes periodically, which is related to their activities around the monitoring node. The statistical characteristics of the raw data from Monday to Thursday is nearly the same, the other three days are different.

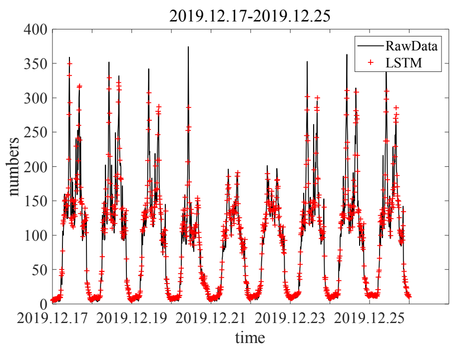

Figure 4. Raw data and predicted curve for WiFi users.

Figure 5 (a) shows the number of Wifi User around the Science Museum on Thursday. It can be seen that there are 11 characteristic peaks at 4: 30-24: 00. We find that since there is a school bus station and a library nearby the Science Museum, these characteristic peaks are closely related to the departure time of the school bus, the meeting time of the Science Museum and the opening hours of the library, which cause a large gathering of people. 7:00, 9:00, 12:30, 14:30, 17:40 are the departure times of the school bus. 8:30, 10:30, 13:00, 16:00, 17:30, 18:00 and 21:00 are the arrival times. It is obvious that, the characteristic peaks at 12:30 and 17:40 are the highest, indicating more people choose to take school buses in these two time periods, which is in consistent with the activities of the crowd behavior in campus.

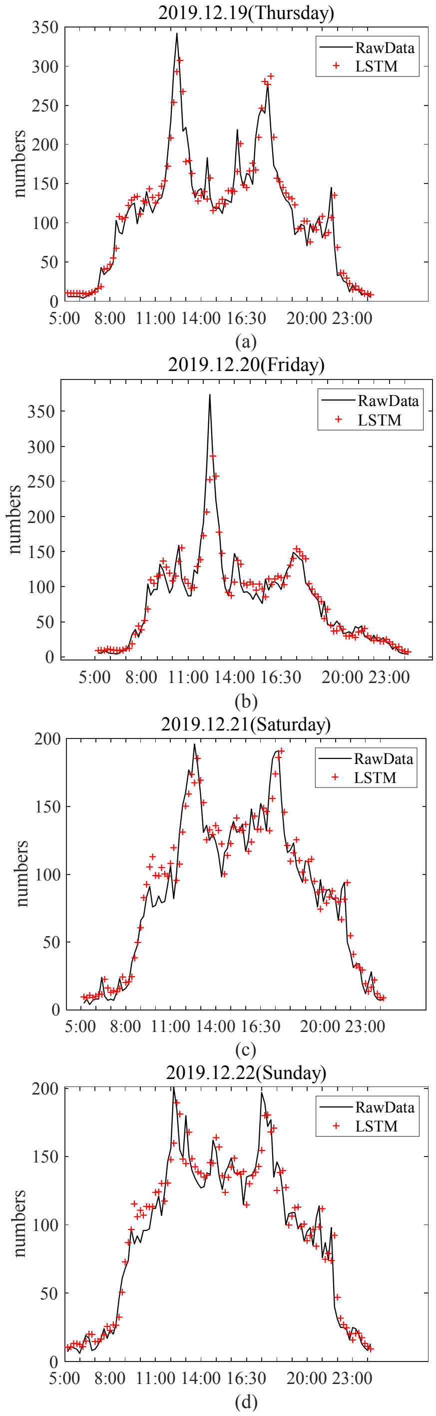

Figure 5. Raw data and predicted curve for WiFi users. (a)Thursdays; (b) Friday; (c) Saturday; (d) Sunday.

Besides, we have compared the performance of LSTM with XGboost and ARIMA, and the results show that LSTM has the best prediction effect. The root mean square error, mean absolute error and the R-squared of LSTM model are 20.7340, 13.1661 and 0.9256, respectively.

4. Conclusion

In this paper, an architecture of the Wifi-based crowd behavior monitoring system is proposed. A pilot monitoring system consisted of monitoring nodes and a back-end server is deployed at Donglu Campus of Yunnan University. The application software for the monitoring node and the server is developed. The correlation between the number of Wifi users and time is predicted and analyzed. It reveals the crowd behavior in campus, and may have potential application in public safety.

Acknowledgement

This work was funded by the National Natural Science Foundation of China (Grant Nos. 61963037, 61863035, 11564044).

References

[1]C.Marta, A.Cesar, A.Barabasi, Understanding individual human mobility patterns, *Nature*, **453**, June 2008, pp.779-782, doi: https://doi.org/10.1038/nature06958
[2] Z. Chen, L. Zhang, C. Jiang, Z. Cao and W. Cui, "WiFi CSI Based Passive Human Activity Recognition Using Attention Based BLSTM, " in *IEEE Transactions on Mobile Computing*, 18, 11, Nov. 2019, pp. 2714-2724, doi:10.1109/TMC.2018.2878233
[3] Z. Wang *et al.*, "A Survey on Human Behavior Recognition Using Channel State Information, " in *IEEE Access*, **7**, 2019, pp. 155986 - 156024, doi: 10.1109/ACCESS.2019.2949123
[4] Y. Cao *et al.*, "Contactless Body Movement Recognition during Sleep via WiFi Signals," in *IEEE Internet of Things Journal*. doi: 10.1109/JIOT.2019.2960823
[5] J. Liu, H. Liu, Y. Chen, Y. Wang and C. Wang, "Wireless Sensing for Human Activity: A Survey," in *IEEE Communications Surveys & Tutorials*. doi: 10.1109/ COMST.2019.2934489
[6] P. Fuxjaeger, S. Ruehrup, T. Paulin and B. Rainer, "Towards Privacy-Preserving Wi-Fi Monitoring for Road Traffic Analysis," in *IEEE Intelligent Transportation Systems Magazine*, **8**, 3, Fall 2016, pp.63-74, doi:10.1109/MITS.2016.2573341
[7]M.Traunmueller, J. Nicholas, M Awais, et al. Digital footprints: Using WiFi probe and locational data to analyze human mobility trajectories in cities," *Computers, Environment and Urban Systems*, **72**, 2018, pp.4-12, doi:10.1016/j.compenvurbsys.2018.07.006
[8] M.Cunche, M.Kaafar, R.Boreli, "Linking wireless devices using information contained in Wi-Fi proberequests," *Pervasive & Mobile Computing*, **11**, April 2014, pp.56-69
[9] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, **9**, 8, 1997, pp. 1735-1780.