Traffic Congestion Level Prediction Based on Recurrent Neural Networks

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***Abstract*—In recent years, traffic congestion has become a global concern. Many researchers work on the development of Intelligent Transportation Systems (ITS) to reduce traffic congestion and improve transportation efficiency. Traffic Information such as vehicle speed, traffic volume, and inter-vehicle spacing are common indicators to determine traffic congestion situation. However, most existing studies only use a single indicator to estimate traffic congestion status. In this paper, we propose the Road-condition-based Congestion Prediction System (RCPS) that uses both traffic volume and vehicle speed to predict traffic congestion. The proposed solution collects real-time road images taken from camera drones to extract traffic volume and vehicle speed on the road. The extracted traffic indicators are then used to predict the congestion level in the future. Using two traffic indicators instead of one, the RCPS achieves high accuracy in congestion level prediction. The RCPS predictions can also been shown on the APP developed for it. It is expected that the road congestion level prediction provided by the RCPS will provide valuable information for drivers to choose the best route.**

***Index Terms*—Traffic Prediction, Congestion prediction, Deep Learning, Image Recognition, Drone.**

I. Introduction

The use of Intelligent Transportation Systems (ITS) to predict traffic-related information is a hot topic in the smart transportation field. A well-designed ITS can inform drivers the locations and time spans of congested road sections, such that drivers can avoid them. There have been many studies focus on traffic congestion prediction [1] [2]. Some studies calculate the number of vehicles on the road, some analyze the real-time images of intersections, and some use big data or artificial intelligence techniques to analyze and predict traffic congestion [3]. Among the existing solutions, applying deep learning to build a neural network (NN) is popular because a complex neural network structure can usually extract traffic information characteristics to predict future traffic conditions. For example, if traffic information is organized into two-dimensional information (similar to the representation of a picture), the Convolution Neural Network (CNN) architecture can be used to predict future traffic conditions. Traffic information is chronological, so many studies use the Recurrent Neural Network (RNN) architecture to predict traffic conditions. There are also some studies that use the Multi-Task Learning (MTL) approach in NN to improve the prediction accuracy.

Because camera drones have many advantages such as low cost, high mobility, and fast deployment, using camera drones has gradually become a popular way to acquire traffic information. Most existing ITS studies use only a single traffic indicator (such as vehicle speed or traffic volume) to identify whether congestion occurs. However, because traffic congestion is not in proportional to a single traffic indicator, it is not easy to accurately determine the congestion level using only a single indicator. To accurately determine the congestion level, it is necessary to consider more than one traffic indicator. In this paper, the Road-condition-based Congestion Prediction System (RCPS) is proposed to classify road congestion level. The RCPS uses camera drone to obtain traffic information (such as traffic volume, vehicle speed, and traffic light duration) and then apply deep learning to predict future congestion level. The road congestion is divided into four levels in the RCPS. Extensive field tests have been conducted to verify the performance of the RCPS. To facilitate drivers to obtain the congestion prediction easily, an APP is also developed to display the predicted road congestion level.

The contribution of the paper can be listed as follows:

1) Derive road traffic volume correctly based on the actual number of passing vehicles, the capacity of the road, and the duration of traffic lights.
2) Propose a traffic congestion level prediction system using image analysis techniques and the RNN architecture.
3) Develop an APP to provide visualized traffic congestion level.

II. Related Works

Recently, many researchers have used regression models, neural networks, and time series models to predict road congestion. Most of the congestion classification methods divide congestion into three levels (smooth, normal, and congestion). Typical classification methods include Markov model [4], fuzzy inference [5] [6], adaptive neuro-fuzzy inference [7] and decision trees [8]. However, the accuracy of these methods can be improved. Pongpaibool et al. uses image analysis software to analyze road images to obtain traffic volume and vehicle speed. Then, the fuzzy logic and adaptive neural network are applied to define the traffic congestion level (high, normal, or low) [7]. An issue of this method is that the road image capture and analysis are offline and thus cannot support real-time applications. Given the driving distances of vehicles and the assumption that the vehicle trajectory is continuous, some researchers use the Autoregressive Integrated Moving Average (ARIMA) regression model to predict the future traffic volume changes of road sections [9]. A limitation of the ARIMA model is that it is suitable only for linear-varying traffic volume predictions. Some works utilize a deep learning architecture consisting of a CNN and Gated Recurrent Units (GRU) to identify vehicles and then to obtain the traffic volume. The features of images is extracted by a CNN and feed into the GRU to get the temporal characteristics [10] [11]. A problem of using a CNN to extract feature vectors is that the recognition accuracy is not good enough when the images changes dramatically. RNN is another neural network suitable for predicting the driving time of a vehicle. For the traffic prediction methods using RNN, those using the Long Short-Term Memory (LSTM) model achieve the best performance [12] [13]. Kang et al. uses the LSTM model to predict traffic volume and vehicle speed [14]. The proposed method can accurately predict the traffic volume and vehicle speed of the target road section but does not provide associated congestion level to drivers.

The traffic predicting methods mentioned above either fail to provide traffic prediction correctly or do not provide drivers a traffic indicator that is easy to be understood. This motivate us to correctly predict traffic condition and then map to a traffic congestion level to provide drivers usable traffic information.

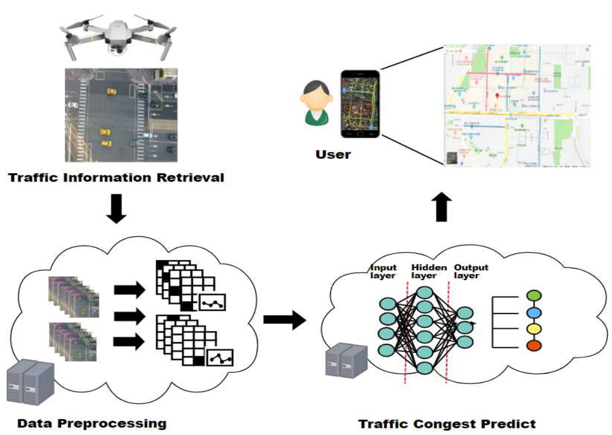


Fig. 1. System Structure

III. The Proposed RCPS System

To perform the congestion level prediction, three tasks must be handled in the RCPS: (1) define the traffic congestion level, (2) perform data preprocessing and establish a deep learning model, and (3) predict traffic congestion in the future through the traffic information obtained from camera drones. The system structure of the RCPS is shown in Fig. 1. The camera drones send the captured image of the target road segment to the RCPS. Based on the collected traffic information of the road segment, the RCPS predicts the future congestion level through the deep learning model. The congestion level prediction will also be plotted on the map such that drivers can access the prediction easily through the APP developed for the RCPS.

In the following, the three tasks of the RCPS are described in detail.

A. Traffic congestion level definition

Using only a single traffic indicator is not easy to accurately determine the congestion level of a road segment. For example, if only the vehicle speed is considered, three vehicles travel at an average speed of 50 km/h may have different congestion levels: depending on the three vehicles being driven in a single lane or in three lanes. If only the traffic volume is considered, there may be a large amount of traffic on a certain road but vehicles can still be driven at a high speed. That is, a large traffic volume does not necessarily imply that congestion occurs.

To determine the congestion level of road sections, the RCPS uses two traffic indicators: the average vehicle speed and the traffic volume. The traffic volume on road segment i in time interval T, denoted as $CF_{i,T}$, is defined as

$$CF_{i,T} = \frac{F_{i,T}}{L_i \times \; F_T}$$

where $F_{i,T}$ is the number of vehicles passing segment i in time interval T, L_i is the number of lanes of segment i, and F_T is the maximum number of passing vehicles in a single lane with safe distance between vehicles in the time interval T. F_T is defined as

$$F_T = \frac{S_i \times T}{D_{SL}} \times \frac{G_i}{R_i + G_i}$$

where S_i is the speed limit of road segment i, D_{SL} is the safety distance between two vehicles plus the average length of a vehicle, and R_i and G_i is the red light and green light duration of the road segment i, respectively. The safety distance is set to 25 meters in the RCPS [15]. The congestion level of road segment i in time interval T, denoted as $C_{i,T}$, is represented by two binary bits: indicating the average vehicle speed and traffic volume of the road segment i in time interval T. The first bit of $C_{i,T}$ is set to 1 as the average vehicle speed is greater than 70% of the speed limit of road segment i [16]. The second bit of $C_{i,T}$ is set to 1 as the number of vehicles actually passing road segment i in time interval T is greater than the maximum number of vehicles that can pass road segment i with safe distance maintained. According to the value of $C_{i,T}$, the RCPS divides congestion level into four levels: 00, 01, 10, 11 representing extremely congested, congested, light, and normal, respectively.

B. Data preprocessing and model training

With the current congestion level of a road segment, the RCPS uses the LSTM model to predict the congestion level in the future [14]. Specifically, the congestion levels of the road segment i at different time periods are represented by a sequence $[(C_{1,1})\ (C_{1,2})\ (C_{1,3})\ \cdots\ (C_{i,T})]$. Using the LSTM model, a multi-layer analysis of these data can be used to predict the congestion level of the road segment. For example, assume that the congestion levels obtained at different time periods in a single road segment are [(11)(10)(00)(01)(00)(11)], the RCPS prediction may look like [(11)(10)(00)(01)(00)(11) *(11)(10)(01)(00)*...] where the italicized values indicate the estimated congestion levels. The congestion level at the seventh time unit is *(11)* which means the estimated congestion level is *normal* then.

The RCPS uses the traffic data provided in "Taichung City Real time Traffic Information" to train the prediction model [17]. The traffic data from January 2017 to August 2018 are used as training data set while the traffic data from September to December 2018 are used as validation data set. Finally, the traffic data in January 2019 is used to verify the accuracy of the trained model. Note that the public traffic data are collected hourly and thus the RCPS only predict the congestion level next hour. As traffic data with smaller intervals are available, the RCPS can also predict congestion level with smaller time intervals.

To evaluate the effectiveness of the prediction model of the RCPS, the Mean Absolute Error (MAE), Mean squared Error (MSE), and Root Mean Squared Error (RMSE) were used as the evaluation metrics. The three evaluation metrics are defined as follows:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - \hat{f}_i|$$
$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(f_i - \hat{f}_i)^2$$
$$\text{RMSE} = [\frac{1}{n}\sum_{i=1}^{n}(|f_i - \hat{f}_i|)^2]^{\frac{1}{2}}$$

where f_i and $\hat{f}_i$ is the actual and the predicted congestion level, respectively. For all the three metrics, a smaller value indicates a better accuracy of the prediction. The single segment vehicle speed and traffic volume comparison between the prediction and the ground truth is shown in Fig. 2(a) and Fig. 2(b), respectively. The horizontal dashed lines in Fig. 2 represent the threshold of setting the first and second bit of the road congestion level, respectively.

TABLE I
PREDICTION RESULTS OF THE RCPS

	MAE	MSE	RMSE
single-segment traffic volume	195.824	69684.16	263.98
single-segment speed	2.09	8.43	2.90
multi-segment traffic volume	136.02	28859.82	169.88
multi-segment speed	1.77	5.24	2.29

In reality, road sections are interconnected and the traffic flow of different road sections will affect each other. Therefore, it is difficult to accurately predict future traffic congestion level of a road by using only the traffic condition of the road itself. In order to improve the prediction accuracy, the RCPS also use traffic information of multiple road sections to predict the congestion level of the target road segment. Multiple segment prediction results are shown in Fig. 3. Traffic information at different time periods for p different road segments is extended to a matrix:

$$\begin{bmatrix} (C_{1,1}) & (C_{1,2}) & (C_{1,3}) & (C_{1,4}) & \cdots & (C_{1,T}) \\ (C_{2,1}) & (C_{2,2}) & (C_{2,3}) & (C_{2,4}) & \cdots & (C_{2,T}) \\ (C_{3,1}) & (C_{3,2}) & (C_{3,3}) & (C_{3,4}) & \cdots & (C_{3,T}) \\ (C_{4,1}) & (C_{4,2}) & (C_{4,3}) & (C_{4,4}) & \cdots & (C_{4,T}) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \\ (C_{p,1}) & (C_{p,2}) & (C_{p,3}) & (C_{p,4}) & \cdots & (C_{p,T}) \end{bmatrix} \quad (1)$$

The congestion level of a road segment can still be predicted by using LSTM model. The prediction error rate can be significantly reduced when using the information of multiple road segments as the correlation between the road segments (upstream and downstream) is available. TABLE. I. is the prediction results of the RCPS using single and multiple road sections. Specifically, for RMSE, the prediction error rate of traffic volume and vehicle speed is reduced by 35% and 21%, respectively, when considering multiple instead of a single road segment information. Fig. 3(a) and Fig. 3(b) show the RCPS prediction performance using multiple road segments.

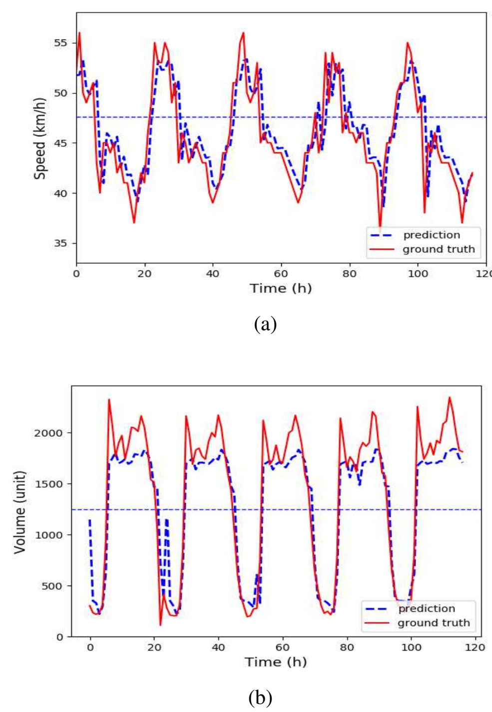
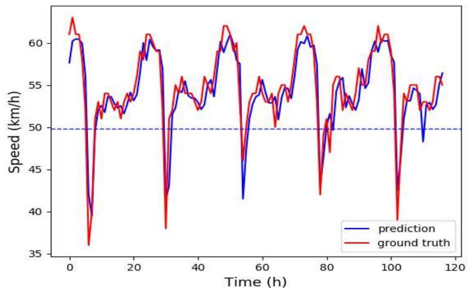


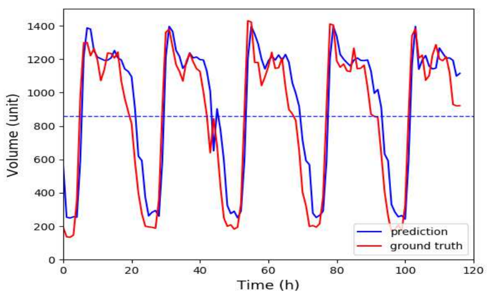
Fig. 2. Single segment traffic prediction result of the RCPS and the ground truth of vehicle speed and traffic volume

C. Road congestion level prediction

Road congestion usually begins at the entrance of the road [18]. Therefore, in the RCPS, the intersection traffic informa-



(a)



(b)

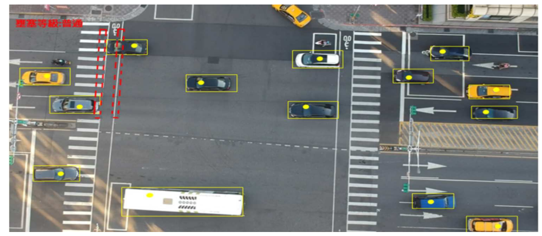
Fig. 3. Multiple segment traffic prediction result of the RCPS and the ground truth of vehicle speed and traffic volume

tion of the road segment to be predicted is analyzed. The RCPS identifies the moving vehicle in the road intersection image in real time. In addition to tracking the moving vehicles, the RCPS sets two virtual gateways to record the time passing the first and second gateway such that the vehicle speed and traffic volume can be collected. The RCPS can predict the congestion level of the road section based on the vehicle speed and traffic volume. In order to allow drivers to get the road congestion level easily, we have also implemented an APP to present the predict results of the RCPS. The roads are marked with red, yellow, blue, and green on the map to indicate the congestion level of extremely congested, congested, normal, and light, respectively.

IV. Experimental result

The accuracy of the RCPS prediction is verified using the traffic information of a single road (Wenxin road) on January 12, 2019. During 3 p.m. to 4 p.m., an average of 15 vehicles per minute drove through the observed section, with an average speed of 55 kilometers per hour. During 4 p.m. to 5 p.m., an average of 22 vehicles per minute drove through the section, with an average speed of 48 kilometers per hour. The RCPS predicted the congestion level of the road for 4 p.m. to 5 p.m. and 5 p.m. to 6 p.m. is light and normal, respectively. The snapshot of Wenxin Road at 4:10 p.m. and 5:10 p.m. on January 12, 2019 is shown in Fig. 4(a) and Fig. 4(b), respectively. We can see that the predictions of the RCPS meet the actual traffic conditions. There are still some errors in the traffic indicator prediction when using only single

(a)



(b)

Fig. 4. A snapshot of the observed intersection at (a) 4:10 p.m. and (b) 5:10 p.m.

road segment information. However, the experimental results show that the prediction error on traffic volume and vehicle speed has little effect on the results of the final congestion classification. In other words, using only a single segment of information is sufficient to achieve an acceptable congestion classification. If there are multiple segments of information that can more accurately predict the speed and traffic volume, it can be expected that the classification of the congestion can be further enhanced. The prediction results are also displayed on the APP developed for the RCPS, as shown in Fig. 5.

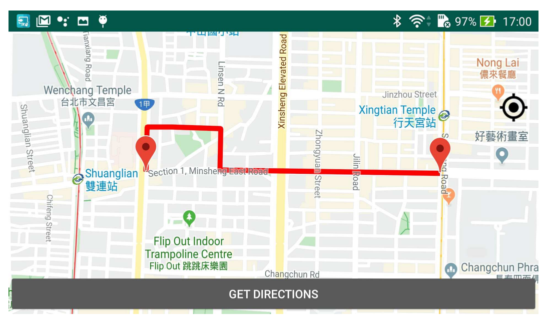


Fig. 5. A snapshot of the APP for the RCPS

V. Conclusion

In this paper, a traffic congestion prediction system (RCPS) that considers both average vehicle speed and traffic volume is proposed. The RCPS uses LSTM to build the prediction model to classify the traffic congestion into four levels. Experimental results verify that the prediction of the RCPS is pretty good and can be applied to the real world. A user can easily access the prediction of congestion level by the APP designed for the RCPS. We believe that RCPS can provide immediate and intuitive information for drivers so as to improve their driving experience.

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REFERENCES

[1] P. Chhatpar, N. Doolani, S. Shahani, and R. Priya, "Machine learning solutions to vehicular traffic congestion," *2018 International Conference on Smart City and Emerging Technology (ICSCET)*, 2018.

[2] Y. Liu and H. Wu, "Prediction of road traffic congestion based on random forest," *2017 10th International Symposium on Computational Intelligence and Design (ISCID)*, vol. 2, 2017.

[3] M. M. Chowdhury, M. Hasan, S. Safait, D. Chaki, and J. Uddin, "A traffic congestion forecasting model using cmtf and machine learning," *2018 Joint 7th International Conference on Informatics Electronics and Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision and Pattern Recognition (icIVPR)*, 2018.

[4] F. Porikli and X. Li, "Traffic congestion estimation using hmm models without vehicle tracking," *IEEE Intelligent Vehicles Symposium*, pp. 188 – 193, 2004.

[5] J. Lu and L.Cao, "Congestion evaluation from traffic flow information based on fuzzy logic," *Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems*, vol. 1, pp. 50 – 53.

[6] B. Krause, C. von Altrock, and M. Pozybill, "Intelligent highway by fuzzy logic: congestion detection and traffic control on multi-lane roads with variable road signs," *Proceedings of IEEE 5th International Fuzzy Systems*, vol. 3, pp. 1832 – 1837, 1996.

[7] P. Pongpaibool, P. Tangamchit, and K. Noodwong, "Evaluation of road traffic congestion using fuzzy techniques," *TENCON 2007 - 2007 IEEE Region 10 Conference*, pp. 1–4, 2007.

[8] T. Thianniwet and S. Phosaard, "Classification of road traffic congestion levels from gps data using a decision tree algorithm and sliding window," *Proceedings of the World Congress on Engineering 2009*, vol. 1, 2009.

[9] Z. Zhao, W. Chen, H. Yue, and Z. Liu, "A novel short-term traffic forecast model based on travel distance estimation and arima," *2016 Chinese Control and Decision Conference (CCDC)*, pp. 6270 – 6275.

[10] X. Cao, J. Wang, Y. Zhong, C. Zhu, Y. Zhou, and W. Zhang, "Interactive temporal recurrent convolution network for traffic prediction in data centers."

[11] R. Fu, Z. Zhang, and L. Li, "Using lstm and gru neural network methods for traffic flow prediction," *Proc. 31st Youth Academic Annu. Conf. Chin. Assoc. Automat. (YAC)*, pp. 324–328, 2016.

[12] Y. Tian and L. Pan, "Predicting short-term traffic flow by long short-term memory recurrent neural network," *Proc. IEEE Int. Conf. Smart City/SocialCom/SustainCom (SmartCity)*, pp. 153–158, 2015.

[13] X. Ma, Z. Tao, Y. Wang, H. Yu, and Y. Wang, "Long short-term memory neural network for traffic speed prediction using remote microwave sensor data," *Transp. Res. C Emerg. Technol.*, vol. 54, pp. 187–197, 2015.

[14] D. Kang, Y. Lv, and Y. Chen, "Short-term traffic flow prediction with lstm recurrent neural network," *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, 2017.

[15] "Highway and expressway traffic control rules," *Ministry of Transportation and Communications, ROC*.

[16] Y. Liao and H. Chu, "A study of setting up speed limit on the urban roads- a case for chiayi city," *2014 Road Safety and Law Enforcement Seminar*, 2014.

[17] T. C. Government, "Taichung city realtime traffic information," march 8, 2019. [Online]. Available: http://e-traffic.taichung.gov.tw/ATIS_TCC/

[18] S. Surya and N. Rakesh, "Flow based traffic congestion prediction and intelligent signalling using markov decision process," *2016 International Conference on Inventive Computation Technologies (ICICT)*, vol. 3, pp. 1–6, 2016.

[19] Y.-J. Duan, Y.-S. Lv, J. Zhang, X.-L. Zhao, and F.-Y. Wang, "Deep learning for control: The state of the art and prospects," *Acta Automatica Sinica*, vol. 42, pp. 643–654, 2016.

[20] L. Li, Y. Lv, and F.-Y. Wang, "Traffic signal timing via deep reinforcement learning," *IEEE/CAA J. Automatica Sinica*, vol. 3, pp. 247–254, 2016.