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ARTICLE

Using the CVP Traffic Detection Model at Road-Section Applies to Traffic Information Collection and Monitor — the Case Study

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ABSTRACT

This paper proposes a using Cellular-Based Vehicle Probe (CVP) at road-section (RS) method to detect and setup a model for traffic flow information (info) collection and monitor. There are multiple traffic collection devices including CVP, ETC-Based Vehicle Probe (EVP), Vehicle Detector (VD), and CCTV as traffic resources to serve as road condition info for predicting the traffic jam problem, monitor and control. The main project has been applied at Tai # 2 Ghee-Jing roadway connects to Wan-Li section as a trial field on fiscal year of 2017-2018. This paper proposes a man-flow turning into traffic-flow with Long-Short Time Memory (LTSM) from recurrent neural network (RNN) model. We also provide a model verification and validation methodology with RNN for cross verification of system performance.

1. Introduction

Advanced traffic information collection can provide an efficient, reliable, instant and mass traffic info at instant governmental road information publication. It can also be used for traffic managing strategies, monitor and control. This paper provides a trial area at Tai # 2 Gee-Jing Roadway connecting to Wan-Li section on the fiscal year of 2017-2018[1,2]. This project provides a new increased CVP detecting road-section (RS) from Man-flow turning into vehicle-flow Model applying to Traffic Information Collection and Monitor for 7 days per week with 5 minutes interval traffic info. Via the new improved man-flow turning to vehicle flow model, we proposed a Long-Short Time Memory (LTSM) recurrent neural network (RNN), to rapidly setup several trained into big data model for regular daytime.

This paper provides proposed traffic monitoring resources from CVP, EVP, VD, and CCTV, etc. This model combines a LTSM RNN structure to rapidly setup and validate with RNN several trained into model with peak and non-peak model for one year.

The main project combines Tai # 2 Gee-Jing Roadway connecting to Wan-Li section and Mai-Kin road (RD) as RS collection area. It includes Tai #2 northern costal RD (Emerald Bay to Gee-Jin 2nd RD), Gee-Jin 3rd RD, Gee-Jin 2nd RD, Gee-Jin 1st RD, Mai-Jin RD, and An-Ler RD. Figure 1 shows the flowchart of CVP road condition detection procedure. This paper just includes the above area as shown 56 RS in total at Figure 2 [1] (24 RS) and Figure 2a [2] (32 RS). Thus, there are 56 RS in total at

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Figure 2 (a) & (b) and 5 minutes traffic info for CVP with RS traffic travelling time, vehicle flow, and RS-turning vector updated periodically. Figure 3 shows the detected CVP Road Condition detection flowchart. The flowchart is designed to have 5 procedures, which is the first step, CVP signal command original; data collection; the second step is related traffic info collection, like CVP, EVP, VD, and CCTV. The third step is merged from step 1 and step 2. Then, the major work of this project is traffic flow trajectory modelling setup and Analysis. The deployed at the trial region is shown at Figure 2a & b.

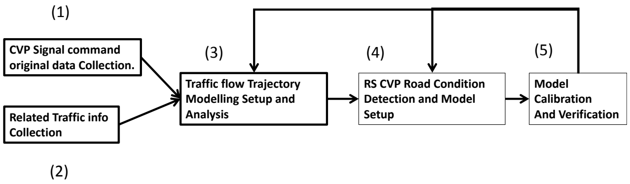

Figure 1. CVP Road Condition Detection Flowchart

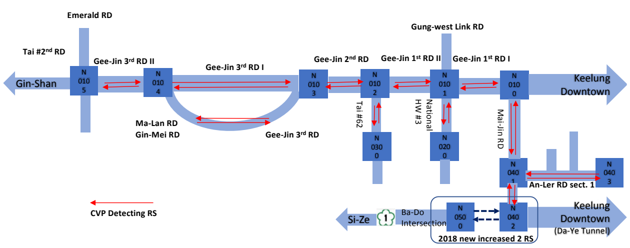

Figure 2 (a). 2017 de facto CVP Detecting RS Demo Project [2]

Figure 2 (b). 2018 newly increased CVP Detecting RS Demo Project [2]

Figure 3 demonstrates the signal timing at selected intersection points during the weekday / holiday morning, evening, and holidays with major investigated intersection. Table 1 shows the peak and non-peak traffic modes at different types of Intersection.

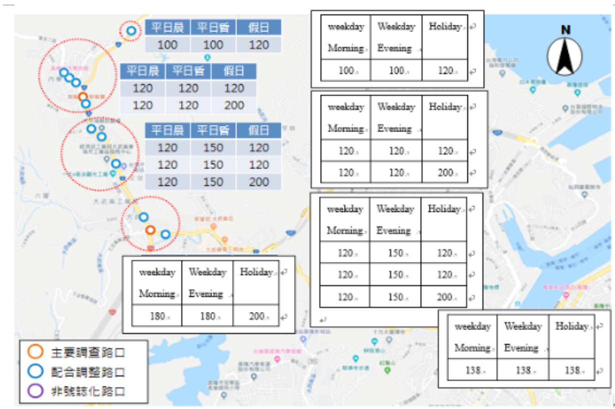

Figure 3. Signal timing at selected intersection points

Table 1. Peak and Non-peak Traffic modes at different types of Intersection

RD #	Intersection	Figure	Flow Direction	weekday Morning		weekday Evening		Holiday Peak time	
				Peak-time interval	Traffic flow (PCU/HR)	Peak-time interval	Traffic flow (PCU/HR)	Peak-time interval	Traffic flow (PCU/HR)
I04	Gee-Gin 3rd RD (GG) | North Coastal HW		A	07:00 | 08:00	454	16:30 | 17:30	907	13:00 | 14:00	907
			B		1103		886		1275
			C		-		-		-
			D		591		546		451
I10	NC HW Gee-Gin 2nd RD | Tai #62 LN JS RD		A	07:15 | 08:15	817	16:45 | 17:45	737	02:00 | 03:00	891
			B		0		0		0
			C		603		504		643
			D		134		214		74
			E		0		0		0
			F		1198		1198		1560
I12	Jong-Shan 1st RD | Chen-Kung 2nd RD		A	07:15 | 08:15	449	17:15 | 18:15	454	11:15 | 12:15	383
			B		381		456		361
			C		872		826		993
			D		586		445		566
I13	Jong-Shan 1st RD | Xi-Ding High Structure		A	07:15 | 08:15	799	17:15 | 18:15	707	11:15 | 12:15	686
			B		917		844		1,025
			C		937		858		921
			D		344		362		279
I14	Chen-Kung 1st RD | 133 LN		A	07:30 | 08:30	-	17:30 | 18:30	-	11:00 | 12:00	-
			B		865		881		1,041
			C		109		174		133
			D		831		899		919

Resource: CHT Data Division Company

2. CVP Road Condition Detection and Model Setup

Road condition detection is defined as to include the traffic flow and travelling time detection together. Based on the traffic flow volume, one can postulate the instant signaling data and related position of actual position. We can use statistics to calculate each individual timing on the certain road-section (RS) for every customer. Then, we use customer volume and actual real traffic volume to setup a postulated model. Thus, we can probably postulate this RS traffic flow volume. Simultaneously, based on one customer's adjacent instant signal interval difference, one can postulate the traffic volume at that RS moving traffic flow. When we calculate all of the mobile customers individually contribute the traffic volume by statistics, one can induct an embedded road-user related reference value at RS traffic volume. However, Telecom signal will have an averaged 5 minutes delay from signal reception, cleaning, making a pair, model analysis, and providing a operation result.

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2.1 Traffic-flow Model Setup and Analysis

Via the mobile signal info, we can estimate the traffic-flow volume at that RS from the historical info by neural network training data module to postulate the RS traffic volume. When the system receives the instant traffic mobile data, one can use this module to postulate traffic-flow volume. Furthermore, when each accumulated period of time from the historical data, one can increase the accuracy of traffic-flow volume. For analyzing the CVP road- condition to postulate the trend of traffic-flow volume. This paper uses the supervised learning from machine learning model. The training procedure is to tell the true value of that RS to let them learn themselves. The training model is used to postulate the future change of traffic flow. This paper uses the model of long short- term memory, (LSTM) to be an extended model, as shown in Figure 4 for system architecture. It is an artificially recurrent neural network (RNN) architecture. LSTM has feedback connections and not only process single data points (such as images), but also entire sequences of data. The compact forms of the equation for the forward pass of an LSTM with a forget gate are: [7,8]

$$f_t = sigmoid(W_f * x_t + U_f * h_{t-1} + b_f) \quad (1)$$

$$i_t = sigmoid(W_i * x_t + U_i * h_{t-1} + b_i) \quad (2)$$

$$O_t = sigmoid(W_o * x_t + U_o * h_{t-1} + b_o) \quad (3)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c * x_t + U_c * h_{t-1} + b_c) \quad (4)$$

$$h_t = o_t \circ \sigma_h(c_t) \quad (5)$$

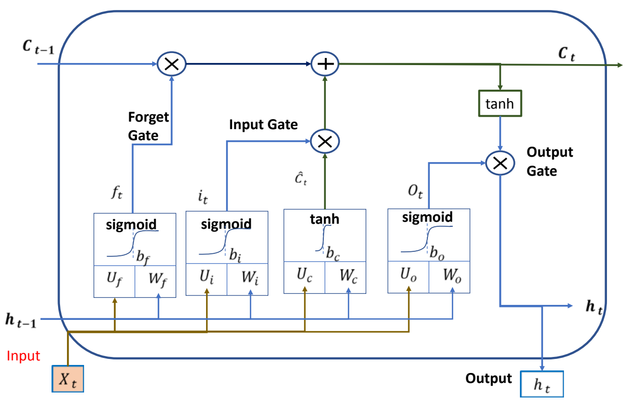

Figure 4. LSTM system architecture

Where the initial values are $c_0 = 0$ and $h_0 = 0$ and the operator o denotes the Hadamard product (element-wise product). The subscripts t indexes the time step. LSTM handles the cell memory to be a controlled gate state. That is it can delete, increase, and output the message. f_t is defined as forget gate, which message is deleted, increased, and outputted from cell. And, i_t is defined as the input gate which message is deleted, increased, and inputted from cell. O_t is defined as the output gate which message is deleted, increased, and outputted from cell.

It can memorize the time-series info of traffic volume and serve as the reference point of next time stamp. Compared with RNN model, LSTM model has more gates such as forget gate, input gate, and output gate. They can be used as a more complicated parameters to be used memorize and forget to reach a better postulated capability. We compare the experimental models of CNN, BPNN, and LSTM from simulation. The LSTM has a better result [2].

2.2 Traffic-flow Estimation

Via the mobile signal info, this paper proposes a postulated estimated traffic –flow volume estimation from neural network training RS during a historical info module over a period of time. For accumulated historical data, one can reconstructed the model of RS to increase the accuracy of traffic-flow estimation.

To analyze the trend change of road condition for the variation of CVP to postulate the traffic-flow. This paper adopts the supervised learning style of machine learning. That is at the training level to input the true value of traffic-flow to let if self-adjust at the training model. One just see the MSE error of training model enter the allowance range to reach the accepted setup model.

We can use this model to postulate the variation of traffic flow in the future. In the model, we propose the major structure of RNN because the info of time-series model can record the past info change from memory and use this model to postulate the future change of traffic flow. There are five major elements in the RNN model:

(1) The input of RNN is an X, which is the Telecom signal info. Those contain man-flow, date, time (5 minutes as one units), and traffic-flow, etc.

(2) The output of RNN is a postulated traffic-flow.

(3) The parameters of RNN are the weightings of U, V, W with the final recursive trained values.

(4) The hidden state is to represent the RNN's memory's S.

(5) A series of continued periods of time from t-1, t, t+1.

(6) The traffic-flow postulated model is based on the time-series recurrent neural network, which is based on the info of CVP, can be regarded the input of RNN and the trend of traffic-flow is regarded as the output of RNN; where the hidden state at the time instant of t-1 and the hidden state of time t. The formula is written as

$$S_t = f\left(\left[U\right]\right)X_t + \left[W\right]S_{t-1} \quad (6)$$

The Timing Sequence of RNN can be depicted as Figure 5.

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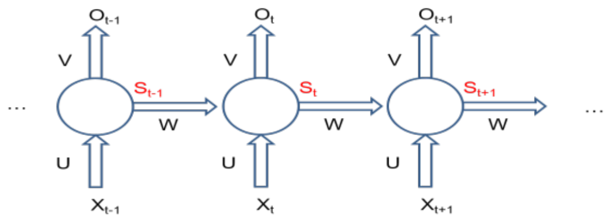

Figure 5. Timing Sequence of RNN [3,4]

Because the traffic-flow is a continuous state; thus, it is quite to refer the past-timing state to change the current state to reach a more postulated state for the trend of variation. To reduce the effects of the irregular states, one needs to pretreat the traffic info. The pretreatment of traffic info include the info become a time-series info; which contains 4 stages, sort out time-series info, combine RS, info standardization, and correspond to CVP info, respectively. The total flowchart is depicted as figure 6.

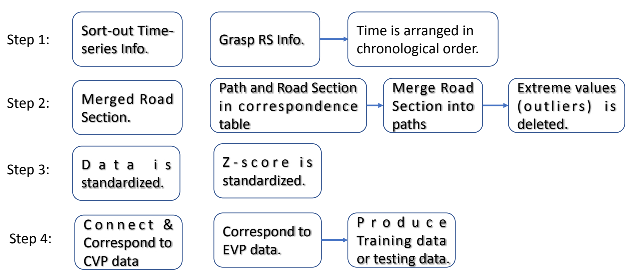

Figure 6. Pretreatment of Man-flow turning into traffic-flow

The procedure is arranged into the following stages:

(1) The 1st stage:

The 1st stage is to arrange time-series data and telecom user individual time-series data.

(2) The 2nd stage:

The 2nd stage is to combine RS. At first is to investigate the path road section in correspondence table and find out the needed RS info of required path and combine them and delete the outlier's value and vacant value.

(3) The 3rd stage:

The 3rd stage is to standardize data and proceed the data to meet standard normal distribution. That is, the mean value is 0, standard deviation error is 1, and, its transfer function is

$$z = \frac{(x-\mu)}{\sigma} \tag{7}$$

where x is needed to be standardized score, μ is the average value, σ is the standard error and σ ≠ 0, z represents the original score and the distance of population mean.

(4) The 4th stage:

The 4th stage is the correspondence of EVP info and produces the training data and test data. Then, provide the CVP man-flow turning into traffic-flow model with cross-validation by RNN. The flowchart of construction of model and testing procedure is given at Figure 7.

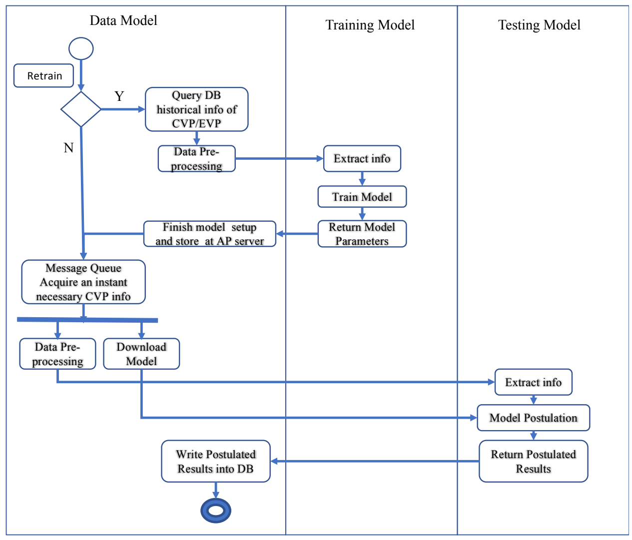

Figure 7. Man-flow turning into traffic-flow postulated framework

The framework of human-flow given at Figure 8 turning into vehicle-flow contains input layer, LSTM layer, hidden layer and output layer; where t represents time stamp, t-5, represents a priori 5 time stamp. X_1 – X_4 represents different characteristics, j_1 to j_n represents a hidden neural unit, y(t) represents the traffic-flow. At input layer, there are numerous characteristics such as the total signal numbers, travel time, a rough estimated total number of vehicles at that RS to be a set of input info. Furthermore, one-time estimated info needs to be input 6 sets data from (t_0)~(t-5). After passing numerous long-term memory LSTM layer (as shown in Figure 7) and one hidden layer, it finally come out an estimated traffic-flow result. The flowchart of human-flow turning into vehicle-flow postulated model is given in Figure 8. Mainly, it can be casted with three folds. There are data model, training model, and testing model, respectively. Their responsibilities are data processing at data model, training model at trained model, and executing vehicle-flow postulation at testing model. At first, one comes into data model. They execute the judge of retrain to decide those data whether needs to be retrained. If, it is 'yes', it shall enter to query the historical data and proceed to handle data preprocessing. Via the training

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model, one can get the extracted trained model to be the input model of neuron. After finishing the setup model, we store it into Application (AP) server. Furthermore, from the data model, one can acquire the necessary postulated CVP data and similarly proceed info pre-processing. Therefore, we can get a better capability from that kind of reference record. The individual training and parameter adjustment are important to reach an expected result.

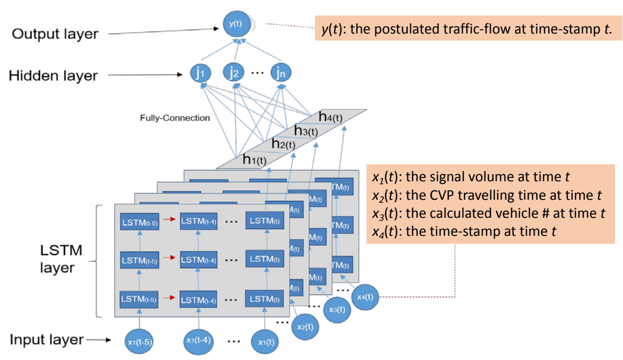

Figure 8. the flowchart of man-flow turning into vehicle-flow model

3. Model Verification and Validation

3.1 Signal Info Analysis

Although collecting traffic signaling info, it can promote the comprehensiveness and integrity of traveling info. However, the signal info is restricted to the law of Privacy Act. Due to different geometrical geospatial base station coverage, the market share of telecom operator and user habit are different. The possibility of accuracy of signal may produce prejudice. Therefore, we need to proceed model verification and validation through other transportation info to increase the accuracy of analytical results.

3.2 Model Verification and Validation

The major RS have implanted electronic tag (eTag) detectors at the described deployed testing area. Thus, we want to use eTag's info to proceed the verification and validation. This paper wants to use neural network to train the traffic-flow and use eTag detector RS to get cross validation and then calculate the error rate. If the error rate is larger enough than expected, we need to calibrate the module to reach the required accuracy. Furthermore, if the RS has no eTag detector or vehicle detector (VD), this project will use the traveling time from Google Map to be reference point for cross validation. About the Traffic-flow, we use AI image recognition to analyze the verification result.

This paper adopts the Lewis [7] as the accuracy of evaluation criteria with MAPE. If, when the value of MAPE is between 10%-20%, it the model has high accuracy; when the value is 20%~50%, it means the prediction is reasonable.

Table 2. MAPE Evaluation criteria [7]

MAPE(%)	illustration
<10	High accuracy prediction
10-20	Good prediction
20-50	Reasonable prediction
>50	Not accuracy prediction

Resource: Lewis, C.D. (1982) [7].

3.3 Cross Validation by Neural Network

The cross validation by RNN is given in Figure 3.1 (a). When the values of characteristics (include man-flow, date, time (5 minutes as a unit), traveling time, etc. the output of o for traffic-flow), times weighting W and add it together. Then, one can get the mapping value from activation (sigmoid) function f; that is, the postulated traffic-flow volume. Then, we get final value of t via eTag detecting traffic-flow volume. Finally, we use the Adam [6] algorithm to optimize the weightings of W. The compared adjusted postulated value of a with true value of t is very close. This procedure is called a one-time calibration cycle. Through various trainings, the error of MSE will gradually reduce to the wanted results as shown in Figure 3.1 (b) at Gee-Gin 1st RD and 2nd RD during holiday model.

Figure 9 (a) and 9 (b) were executed at the last fiscal year of 2017 results. The weekday's and holiday's verification results of independent CVP model at Gee-Gin 1st RD-2nd RD were given respectively. The CVP traffic-flow verification at National HW #1 (From Bar-do to Mai-Gin RD) and the Manual Computing Unit (MCU) vs. CVP are given at Figure 10 (a) and 10 (b), respectively. The CVP traffic-flow postulated verified testing results at Gee-Gin RD at Table 2. Using EVP traffic-flow has the same result as CVP did it before. According to [7], If, MAPE is less than 20%, it is a good prediction; the value of MAPE between 20~50 % is a reasonable prediction. Thus, if we found that the newly increased detecting are has no the resources of EVP or VD at this project of 20, we will use CCTV instead as vehicle detector. Using image to transfer into traffic-flow and then compare/validate with the result with CVP model.

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Table 2. The CVP traffic-flow postulated verified testing results at Gee-Gin RD

Road Section	Independent Model		Shared Model	
	Weekday MAPE	Holiday MAPE	Weekday MAPE	Holiday MAPE
Gee-Gin 1st RD-2nd RD	20.4%	15.5%	40.1%	32.2%
Gee-Gin 2nd RD-1stRD	18.9%	16.7%	32.4%	28.6%
Gee-Gin 2nd RD-3rd RD	14.4%	14.8%	25.0%	27.3%
Gee-Gin 3rd RD-2nd RD	18.2%	12.2%	25.1%	24.3%
Average	17.9%	14.8%	30.6%	28.1%

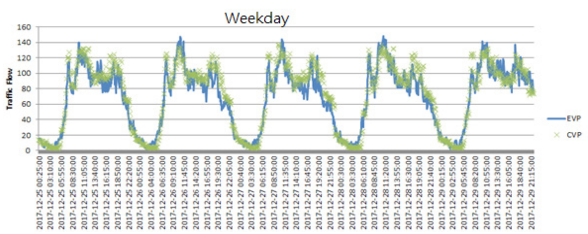

Figure 9 (a). the weekday's verification result of independent CVP model at Gee-Gin 1st RD-2nd RD

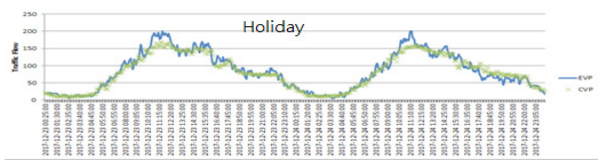

Figure 9 (b). the holiday's verification result of independent CVP model at Gee-Gin 1st RD-2nd RD

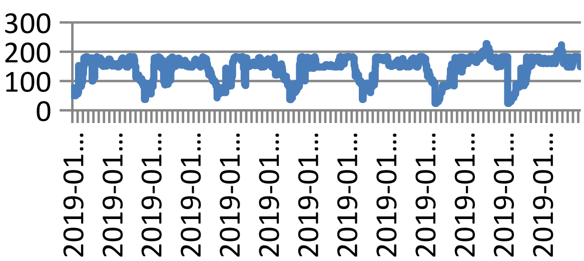

Figure 10 (a). The CVP traffic-flow verification at National HW #1 (From Bar-do to Mai-Gin RD)

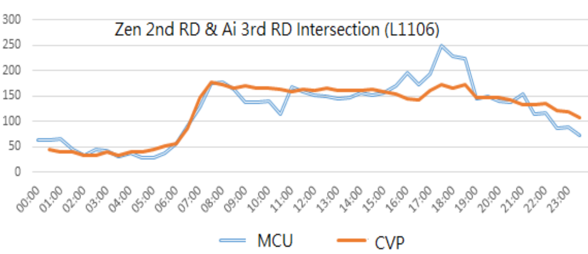

Figure 10 (b). The Manual Computing Unit (MCU) vs. CVP

4. Conclusion

This paper proposes a using CVP method at RS to detect and setup a model for traffic flow info collection and monitor. Via the new improved man-flow turning to traffic-flow model, we proposed a LTSM with RNN to validate data model for regular daytime and peak and non-peak model for one year.

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