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Perception-based Road Traffic Congestion Classification using Neural Networks

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***Abstract*—In this study, we investigated an alternative technique to automatically classify road traffic congestion with high accuracy aligning with travelers' opinions. The method utilized an intelligent traffic camera system orchestrated with a web survey system to collect the traffic conditions and travelers' opinions. A large number of human perceptions were used to train the artificial neural network (ANN) model that classify velocity and traffic flow into three congestion levels: light, heavy, and jam. The learning parameters were heuristically optimized to gain highest prediction accuracy. The outcomes were a practical method and the model achieving as high as 94.99% accuracy. The model was then compared to the Occupancy Ratio (OR) technique, currently in service in the Bangkok Metropolitan Area. The comparison indicated that our model could determine the traffic congestion levels 12.15% more accurately than the existing system. The analysis revealed that the derived model classified congestion levels based mainly on the vehicle velocity, suggesting that the model could be modified and broadly used with various types of traffic sensors. The methodology, though conceived for use in Bangkok, is a general Intelligent Transportation System (ITS) practice that can be applied to any part of the world.**

***Index Terms*—traffic congestion level determination, intelligent transportation system (ITS), human judgment, artificial neural network (ANN), occupancy ratio (OR).**

I. Introduction

Accurate traffic reports are essential for congested and overcrowded cities such as Bangkok. Without traffic information, commuters might not be able to choose a proper route and might get stuck in traffic for hours. Intelligent Transportation System (ITS) with automated congestion estimation algorithm can help produce such reports. Several initiatives from both private and government entities have been proposed and implemented to gather traffic data to feed the ITS. According to our survey, most efforts focus on limited installation of fixed sensors such as intelligent traffic cameras with image processing capability. Although the investment for large-scale deployment of such camera system is capital intensive, it is desirable to have it installed due to the ability to provide visualization of real traffic conditions. It is also able to provide basic information that is essential to generate traffic reports, such as the average vehicle velocity and the volume of vehicles. Traffic congestion levels can also be derived from such parameters calculated by the traffic camera with image processing capability. The current system used to classify the congestion level is by an image processing system utilizing the Occupancy Ratio (OR) technique. A study [1] by Charusakwong et al. showed that the results from existing techniques may not be consistent with the travelers' perception. In contrast, our results show a significant improvement on consistency and suggest that a well-trained neural network using velocity and traffic flow is a promising candidate to provide an automated congestion classification.

In this paper, we proposed a method to automatically classify the traffic congestion level that was consistent with motorists' perceptions by imitating their visual judgments using an artificial intelligence technique. To accomplish this, we captured a large amount of traffic conditions, and then let the motorists indicate the congestion level for each captured image selected from the image pool. The relation patterns of these ratings along with each of their corresponding image processing information were used to train an artificial neural network model. The trained neural network model was later used to automatically classify the traffic congestion level. This approach would lift the confidence that the congestion level on the traffic reports would be consistent with motorists' perceptions. It was virtually costless when this approach had been implemented, and was in operation. This paper focuses on the accuracy optimization of the neural network model and its accuracy when compared to the working system in Bangkok. The congestion levels that we studied were limited to three levels: light, heavy and jam, which was appropriate [2].

This paper is organized as follows: In Section II, we provide an overview of related works concerning traffic congestion reports. The methodology is explained in Section III. In Section IV, we analyze and discuss the results, and Section V offers a conclusion and the possibilities of future works in this realm.

II. Related Works

Many techniques to estimate traffic congestion levels were investigated to suit each type of collected data. Traffic data could be gathered automatically from two major types

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of sensors: fixed sensors and mobile sensors. The study in [3] applied the neural network technique to the collected data using mobile phones. It used Cell Dwell Time/CDT, the time that a mobile phone attaches to a mobile phone service antenna, which provides rough journey time. Our work employed a similar technique but on the data captured from existing traffic cameras. The study in [4-5] estimated the congestion level using data from traffic cameras by applying fuzzy logic, and hidden Markov model, respectively. Our work applied neural network techniques and we expected higher accuracy. The works in [6] considered traffic density and highway speeds, but our measurements reflect traffic conditions on an expressway. Studies in [7-8] used fuzzy logic to determine continuous and six discrete levels of congestion while our method focuses on three discrete levels of congestion.

In some countries, for example, as in the study of [9] and [10] found out that the main parameters used to define the traffic congestion levels are time, speed, volume, service level, and the cycles of traffic signals that delay motorists. Our work would locally investigate whether the congestion degrees are subjective to other factors, including type of roads, the time of day, the day of week, and so on. The congestion levels that we studied were limited to three levels: light, heavy and jam, which was sufficient and appropriate according to the study of [2].

In this study, we evaluated the accuracy of our technique against that of the existing system currently operating in Bangkok. In Bangkok, the processing of the traffic camera images utilizes the Occupancy Ratio (OR) technique [1]. The working principle of the OR technique is measuring the time that vehicles use to occupy a virtual indicated frame, from entering until leaving it. If the time that vehicles used to travel through the frame is short, the traffic is light. The methodology of the work was presented in the following section.

III. Methodology

A. Data Collection & Tools

The traffic data was captured by traffic cameras every minute. As stream video was processed, the average speed (km/h) of the vehicles and traffic volume (cars/min) were calculated. Then, the captured images and related information were presented to participants who then rated the traffic congestion levels. In order to ensure that the determined congestion levels were consistent with the road users' perception, we needed a large amount of samples. A web survey was used to collect the road users' opinions.

Fig. 1 illustrates the web survey we developed to collect congestion levels judged by users corresponding with the image shown to the user. On the left side of the web survey, the participants were allowed to select from several traffic cameras mounted around congested areas of Bangkok. In this study, we focused on only one camera located at one of the most crowded expressways in Bangkok. The captured still images, shown one at a time, along with the matching information including date and range of time were shown on the right of the screen. The participants were asked to rate the traffic congestion level according to the provided information on both in-bound and out-bound directions. The web survey was implemented by the Google Map APIs, PHP, AJAX and the PostgresSQL database. The targeted participants were general road users. The judgment data was collected between the period of Jan 10th and Jan 30th, 2009. The number of total participants was 146 and there were 3,456 records of judgments. The data was used to learn by the neural network models; explanatory details are given in the following section.

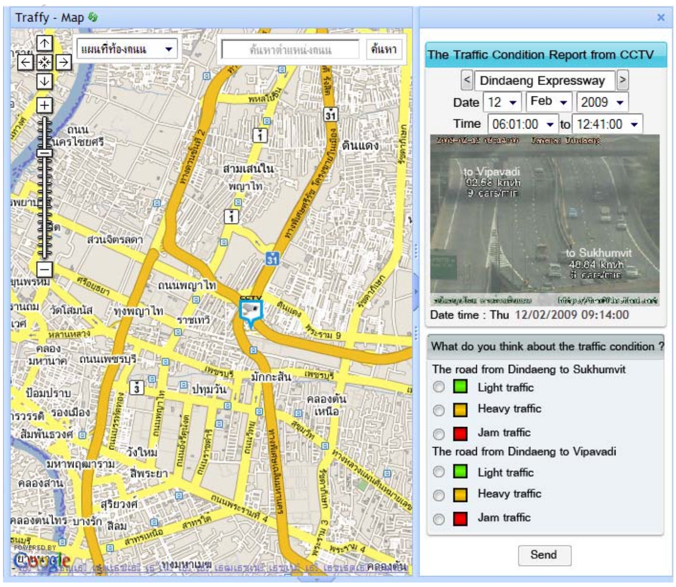

Fig. 1. The web survey screen consists of a traffic image and data with the options for the participants to rate the congestion level.

B. Data Classifications

In general, the architecture of a neural network consists of three node layers: one input layer, one hidden layer, and one output layer, all fully connected as shown in Fig. 2. The neural network model will adjust the weight of each node to reflect the patterns of the trained data [11].

The features of input data consist of 1) the day of the week (DW): monday through sunday, 2) the time of the day in terms of the minute of the day (MT), 3) average speed (SP) in km/h, and 4) traffic volume (VOL) in cars/min, in the input layer. the input layer is composed of 10 nodes as shown in fig 5. the day of week variable constructed 7 variable nodes due to its nominal status. the output layer is the targeted congestion level (CL) judged by the participants. WEKA, a machine learning program with Multilayer-Perceptron (Neural Network) Model was used to train and create a learned model. Samples of training dataset are shown in Table I.

TABLE I
SAMPLES OF TRAINING DATASET

DW	MT	SP	VOL	CL
Mon	471	12.78	5	3
Mon	472	12.88	2	3
Mon	473	11.94	4	3
Mon	474	15.37	4	3
Mon	475	17.18	3	3

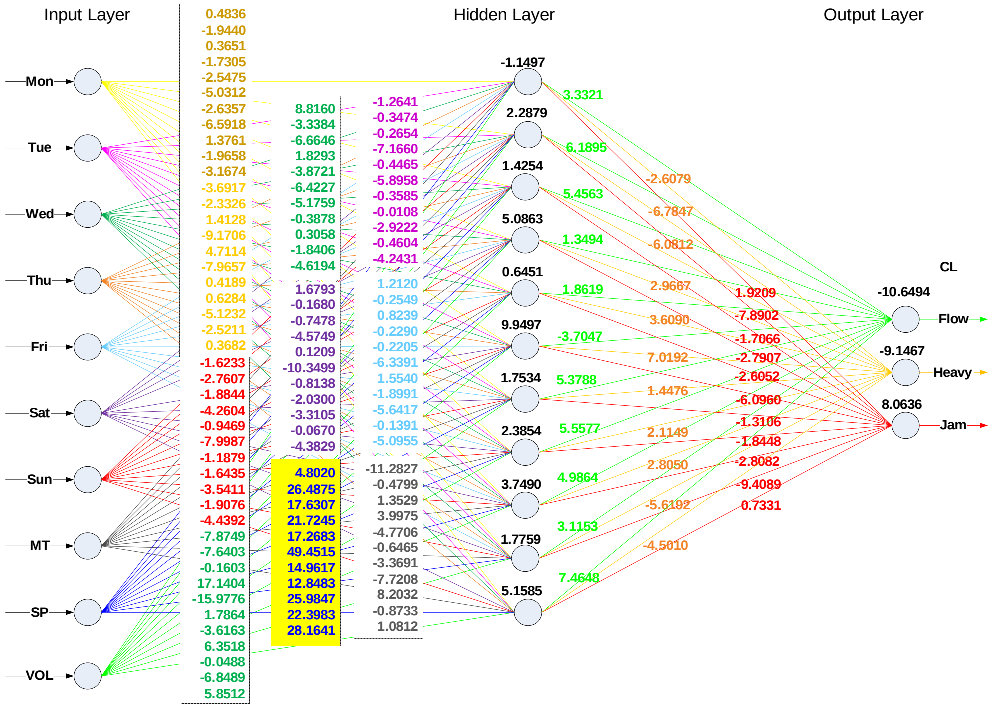

Fig. 2. The learned neural network model configurations.

C. *Optimization*

In order to obtain the best model configurations, three parameters of the model, i.e., the number of hidden nodes, learning rates, and momentum, were optimized. In the experiment, the number of hidden node was varied from 1 to twice the number of input nodes plus one, 23, as suggested in the literature. By comparing Root Mean Square Error (RMSE), the appropriate number of hidden nodes that gave the best performance will be found.

The momentum parameter is the weight of each training cycle. The momentum was tuned by values raging from 0.1 to 0.9. The optimal RMSE and accuracy were used to decide the best value. This adjusted configuration then was configured for the proper learning rate. The learning rate value is responsible for the time the model uses to learn. It ranged from 0.1 to 0.9.

The optimization yielded the configuration showed in the next section. Priorities of the input parameters were determined, and the classification performance was evaluated against the working system.

IV. Results and Evaluations

A. *Model Configurations*

The model parameters—number of nodes in the hidden layer, learning rate, and momentum—were adjusted and provided the neural configurations as shown in Fig. 2. According to the experiment of adjusting the number of nodes in the hidden layer from 1 to 23 nodes, the optimum number of nodes was 11, which provided the lowest error (RMSE), and, at the same time, provided the highest accuracy. Fig. 3 depicts the relations between the number of nodes in the hidden layer and the RMSE. The RMSE was lowest when the number of nodes was 11. Fig. 4 indicates that the learning rate of 0.3 would achieve the lowest RMSE, and the optimum momentum was 0.2 as shown in Fig. 5.

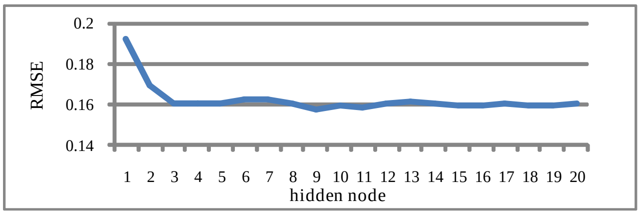

Fig. 3. The relations between the number of nodes in the hidden layer and the root mean square error.

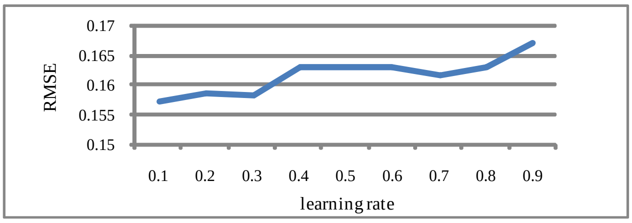

Fig. 4. The relations between the learning rate and the root mean square error.

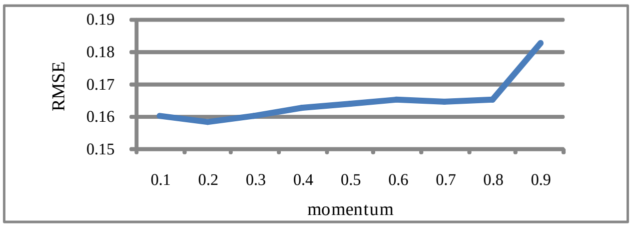

Fig. 5. The relations between the momentum in the hidden layer and the root mean square error.

B. *Performance Evaluations*

Fig. 2 represents the derived neural network model configurations labeled with the weight of each node in each layer. According to high and positive value of weights, the vehicle speed (SP) has the highest influence to classify the congestion followed by the traffic volume, the time of the day and the day of the week. The vehicle speed associated with congestion levels can be illustrated as shown in Fig. 6. The distribution of speed of each congestion level is subject to further investigation.

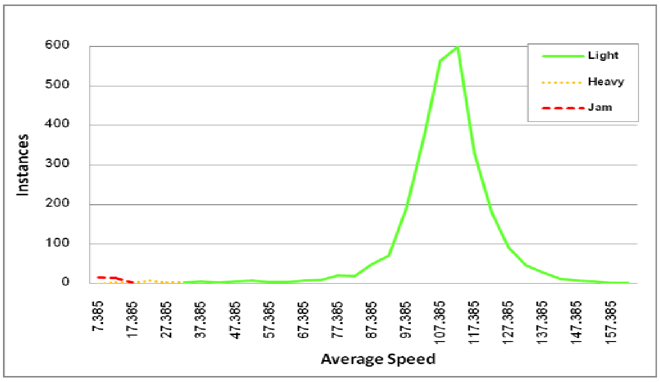

Fig. 6. The chart shows the number of road users' rated instances (y-axis) according to the speed of the vehicles (x-axis) along with classified congestion levels.

The structure of the optimized neural network was 10-11-3 for the number of input nodes, hidden nodes, and output node, respectively; the learning rate was 0.3; and the momentum was 0.2. This model achieved an overall accuracy of 94.99% with 0.1583 root mean square error.

By examining the accuracy for each output class, i.e., the congestion level, the model can classify light traffic condition with the highest accuracy of 99.60%, heavy traffic conditions with the lowest accuracy among the output class with an accuracy of 72.40%, and the jam traffic with an accuracy of 82.30% as shown in Table II. The model was then evaluated against the existing system in Bangkok, which is described in the next section.

TABLE II
THE OPTIMIZED NEURAL NETWORK CLASSIFICATION ACCURACY

Accuracy	Correctly Classified %			RMSE
	Light	Heavy	Jam	
94.99	99.60	72.40	82.30	0.1583

C. *Evaluations with the Existing System*

We evaluated our model against the existing system using occupancy ratio (OR) by comparing the congestion levels classified at the exact same points of time. As per Table III, 84.71% of traffic incidents were classified into the same congestion level by both models. The confusion matrix showing the congestion level classification of both models can be found in Table II. The columns of the confusion matrix show the congestion levels classified by ANN while the rows of the confusion matrix show the congestion levels classified by OR.

TABLE III
THE CONFUSION MATRIX BETWEEN THE CLASSIFIED CONGESTION LEVELS USING THE NEURAL NETWORK MODEL AND THE OCCUPANCY RATIO (OR) TECHNIQUE FROM THE BMA SYSTEM

		Artificial Neural Network (ANN) Classification (%)		
		Light	Heavy	Jam
Occupancy Ratio (OR) Classification (%)	Light	83.66	0.30	0.11
	Heavy	2.43	0.00	0.00
	Jam	12.04	0.41	1.05

For example, the first column on the left was classified as light traffic by the ANN. 83.66% was classified as light traffic the same as the OR technique. However, 2.43% and 12.04% were classified as heavy and jam using the OR

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technique. The values in shaded cells show the percentage of mutual classification by both models.

We investigated the causes of different classification using the recorded traffic images, processed data and the road users' ratings. Single step differences in classification, e.g., light to heavy and heavy to jam, are due to the different points of view on congestion of motorists, in which definitive conclusions cannot be drawn. Additionally, the percentage of these differences is relatively low. We will focus our attention on the significant differences from light to jam or vice versa.

In the first case, i.e., light to jam (0.11%), the analysis revealed that the speed is between 6.04 to 14.27 km/h. All of recorded images, as one example shown in Fig. 7 (to Sukhumvit), clearly confirm that the traffic was in jam condition.

Fig. 7. Image classified as jam traffic by ANN and as light traffic by OR technique.

In the second case, i.e., jam to light (12.04%), the analysis revealed that the speed is between 70.19 and 129.41 km/h. All of recorded images, as one example shown in Fig. 8, clearly confirm that the traffic was in light condition, in which our model classified accurately.

Fig. 8. Image classified as light traffic by ANN and as jam traffic by OR technique.

We further investigated the relationship between speed and congestion level of the existing system as shown in Fig. 9. In Fig. 6, the speed range of each congestion level clearly separates one from each other, especially for light and heavy traffic. However, the speed ranges of three congestion levels in Fig. 9 largely overlap. This makes it difficult and confusing to distinguish the congestion level using only speed attributes. Additionally, the figure shows a counter-intuitive relationship between speed and congestion level. For example, the speed range of jam is between 87 to 127 km/h. The preliminary results suggested that the opinion-based ANN exhibits a more concrete classification pattern.

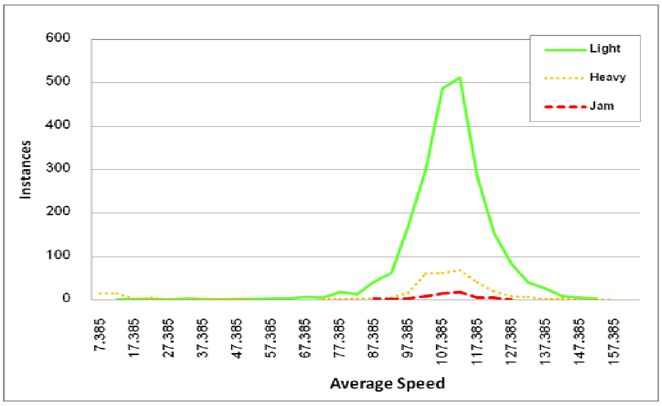

Fig. 9. The congestion classification derived from the BMA system.

Thus, it safe to claim that this neural network model could achieve higher accuracy in the determination of the traffic congestion level than the current system operating in Bangkok using OR technique; consistencies were greater by as much as 12.15% with the overall accuracy of the model itself reaching 94.99%.

V. Conclusion

The study employed the artificial neural network technique to automatically determine the traffic congestion levels achieving an accuracy of 94.99% and the root mean square of 0.1583, based on motorists' perceptions, with the 10-11-3 node configurations. The weighting priorities of the input were speed (km/h), traffic volume (car/min), the time of day, and the day of week. The optimized learning rate and the momentum parameters were 0.3 and 0.2 respectively. The model was 12.15% more consistent with the motorists' perceptions than the Occupancy Ratio method used by the existing system in the Bangkok Metropolitan Area. This model can be implemented to increase the accuracy of the system. Since the vehicle speed most affected the congestion level determination, it can then be modified and used to classify the traffic congestion levels of the data collected from various kinds of sensors besides traffic camera, which should be a worthwhile investigation.

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