A Neural Network Model for Road Traffic Flow Estimation

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Abstract Real-time road traffic state information can be used for traffic flow monitoring, incident detection and other related traffic management activities. Road traffic state estimation can be done using either data driven or model based or hybrid approaches. The data driven approach is preferable for real-time flow prediction but to get traffic data for performance evaluation, hybrid approach is recommended. In this paper, a neural network model is employed to estimate real-time traffic flow on urban road network. To model the traffic flow, the microscopic model Simulation of Urban Mobility (SUMO) is used. The evaluation of the model using both simulation data and real-world data indicated that the developed estimation model could help to generate reliable traffic state information on urban roads.

Keywords Neural network · State estimation · In-vehicle mobile phone · Simulation of urban mobility (SUMO)

1 Introduction

Real-time road traffic information is important for road traffic management activities like incident detection, traffic monitoring and so on. Road traffic state estimation is a fundamental work in Intelligent Transport System (ITS). It is applicable for

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N. Pillay et al. (eds.), *Advances in Nature and Biologically Inspired Computing*,
Advances in Intelligent Systems and Computing 419,
DOI 10.1007/978-3-319-27400-3_27

dynamic vehicle navigation, intelligent transport management, traffic signal control, vehicle emission monitoring and so on. The two major components of ITS, Advanced Traveller Information System (ATIS) and Advanced Traffic Management System (ATMS) particularly need accurate current road traffic sate estimation and short term prediction of the future for smooth traffic flow [1].

Existing road traffic state estimation techniques can be grouped into model based approach, which are used for offline traffic state estimation and data driven approach for online state estimation [2]. Model based traffic state estimation approaches use the analytical traffic model Lighthill-Whitham-Richards (LWR) model [3] or simulation based models which are more suitable to model complex road traffic flows [4] or hybrid approaches. However, data driven approaches are preferable for real-time road traffic state estimation [2].

From all data-driven methods, Artificial Neural Networks have been applied extensively in short term traffic forecasting field and acknowledged to be a promising approach because of its superiority in modelling complex nonlinear relationships [5, 6]. Artificial Neural Networks have other advantages over other methods that make researchers choose them as road traffic modelling tool [7]. The first is the strong adaptability of Artificial Neural Networks, which enabled them to learn from past data. As they are data driven models, their transferability is strong and also need little experience when applied to different road traffic networks. Moreover, Artificial Neural Networks are very flexible in producing accurate multiple step-ahead forecast with less effort. Artificial Neural Networks have also some limitations like their "black box" nature, there are so many types of Artificial Neural Networks and as existing researches proved, appropriate network topologies and configurations can greatly affect performance of Artificial Neural Networks models [8].

Road traffic state estimation is a complex activity which cannot be done using a single forecasting method [9]. To use the data-driven approach, for example neural network, deployment of data collection infrastructure on road segments need high investment [10]. To train the neural network, model based traffic state estimation methods like microscopic or macroscopic simulators can be used [11]. Hence, application of hybrid model based and data-driven road traffic state estimation reduces computational delay and also increases forecasting accuracy [12]. For example, Habtie et al. [13] proposed hybrid method of combining Neural Network (data driven approach) and Microscopic simulator SUMO (model based approach) to estimate road traffic flow at real-time on urban road networks.

The traffic data used for estimation can be gathered from several sources like loop detectors, microwave radars and more recently from mobile users [14]. These days, road traffic information estimation from cellular networks has received much attention because of the widespread of the cellular network, its low cost, all-weather traffic information collection and with large number of mobiles to be used as location probes covering the whole road network. In order to estimate road traffic information from cellular network, the basic steps like location data collection, cell phone mobility classification, map matching, route determination and road traffic condition estimation are included [15]. In this study in-vehicle mobile phone, as it is proposed in [13], is used as road traffic data source.

In this article, a Neural Network Model is developed to estimate real-time road traffic state estimation. The model performance is evaluated through simulation. To represent road traffic flow the microscopic simulator SUMO is utilized. The reminder of this paper is organized as follows. Section 2 discusses the Artificial Neural Network Model. Section 3 presents the model application and the conclusion is shown in Sect. 4.

2 Artificial Neural Network Model for Urban Arterial Road Traffic State Estimation

Different types of artificial neural networks (ANN) have been proposed in the past few years for estimation purpose. The most popular connected multilayer perceptron (MLP) neural network architecture is chosen in this study as it is extensively applied in transportation applications [16].

In-vehicle mobile phones are used as a probe to collect traffic data and the data collected contain vehicle position, time stamp and vehicle speed on the road link. Hence position, time stamp and speeds are used as input data in the ANN model and the structure of the ANN model, which is experimentally proved with different traffic demand (free flow, 20 % demand increase, 50 % demand increase, 100 % demand increase) is adapted from Zheng and Zuylen [26] as shown on Fig. 1.

The mathematical model for the input layer, hidden layer and output layer is as follows. Input layer:

$$
\begin{gathered}
\mathrm{x}\ (\mathrm{i}) = \begin{bmatrix} x_1(i) \\ \vdots \\ x_n(i) \end{bmatrix} = \begin{bmatrix} p(i) \\ r(i) \\ t(i) \\ v(i) \end{bmatrix}, p(i) = \begin{bmatrix} p_1(i) \\ \vdots \\ p_n(i) \end{bmatrix}, r(i) = \begin{bmatrix} r_1(i) \\ \vdots \\ r_n(i) \end{bmatrix}, \\
t(i) = \begin{bmatrix} t_1(i) \\ \vdots \\ t_n(i) \end{bmatrix}, v(i) = \begin{bmatrix} v_1(i) \\ \vdots \\ v_n(i) \end{bmatrix}
\end{gathered}
\tag{1}
$$

where $p(i)$ is position vector, $r(i)$ is link id vector, $t(i)$ is time stamp vector and $v(i)$ is speed vector. Hidden layer:

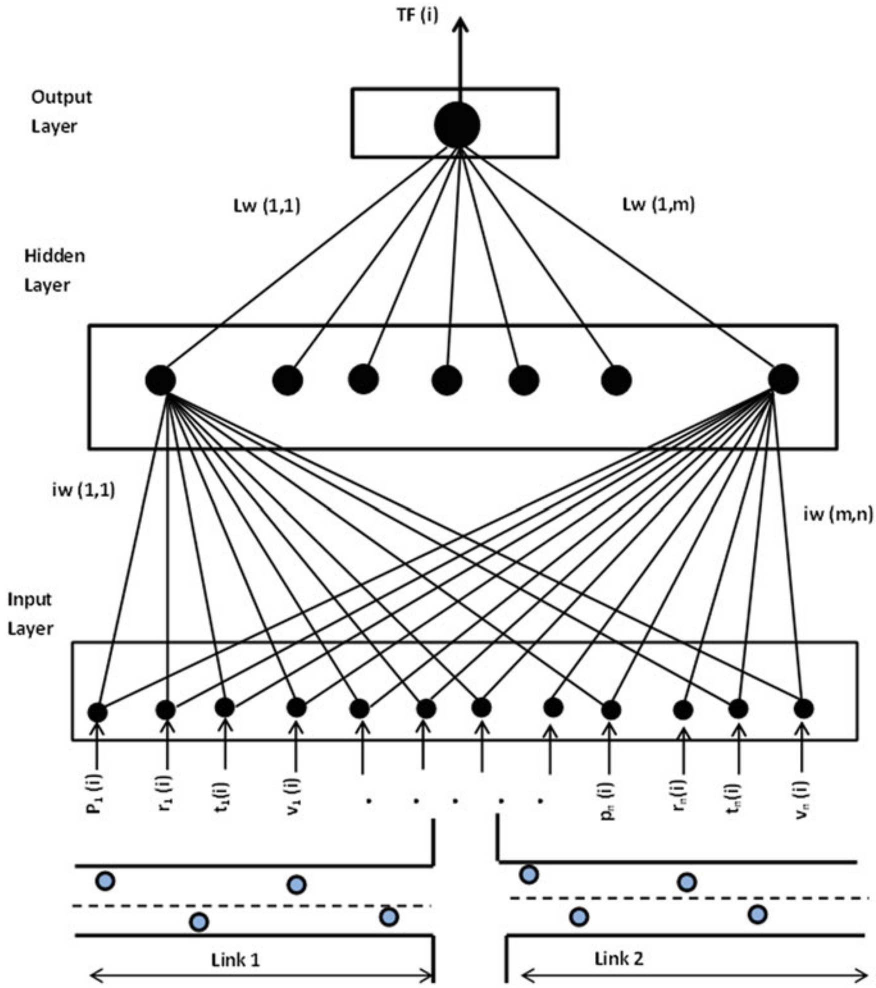

Fig. 1 Artificial neural network for road traffic state estimation [17]

$$H(i) = \begin{bmatrix} h_1(i) \\ \vdots \\ h_m(i) \end{bmatrix} = \begin{bmatrix} \varphi(\sum_{j=1}^{N} w_{j,1}x_j(i) + b_1) \\ \vdots \\ \varphi(\sum_{j=1}^{N} w_{j,m}x_j(i) + b_m) \end{bmatrix} \tag{2}$$

where $h_m(i)$ denotes the value of the mth hidden neuron, $w_{j,m}$ represent the weight connecting the jth input neuron and the mth hidden neuron, b_m is bias with fixed value for the mth hidden neuron and φ is the transfer function.

Output layer

$$y(i) = TV(i) = \varphi\left(\sum_{k=1}^{m} w_k h_k(i) + b\right) \tag{3}$$

where $y(i)$ and $TV(i)$ denote estimated traffic speed of probe vehicle i on the link under consideration, w_k represent the weight connecting the kth hidden neuron and the output neuron, b is bias for the output and φ is the transfer function.

3 Model Application

3.1 Sample Road for Testing

The sample road, depicted on Fig. 2, used for testing the model is taken from Addis Ababa city road network. The OpenStreetMap (OSM) xml file of the selected road network is edited using Java OpenStreetMap (JOSM) [18] to remove road edges that can't be used by vehicles like road ways to pedestrian etc., and also for simplicity all road edges are set to one-way. The simplified road network consists of 13 nodes, 12 links with length range from 169 to 593 m and 4 traffic lights.

Fig. 2 Sample road network for simulation

To model the arterial road traffic, a microscopic simulation package “Simulation of Urban Mobility” (SUMO) [19] is employed. To generate road network and vehicle route, the SUMO packages NETCONVERT and DFROUTER are used. From the 1 h SUMO simulation, the simulation output file, FCD output, generates large amount of simulated mobile probes at real time. At every second location updates (in terms of x, y or longitude, latitude) for the mobile probes is recorded. There are in total 437 probes and the time they spent range from 10 to 202 s. The FCD output file contains detail information of each vehicle/mobile and grows extremely large. Hence converting this location data into more compressed one is necessary [20]. Accordingly, to degrade location data, one can set up a specified percentage of simulated vehicles/mobiles to be traffic probe. Previous studies suggest that for arterial roads reliable speed estimation, a minimum penetration rate of 7 %, i.e. at least 10 probe vehicles traversing a road section (every road link) successfully is required [21–23] although factors like road type, link length and sample frequency affects the minimum sample size. In this research work, the sample is taken considering the road link length as indicated in Table 1 and sampling frequency is based on Pinpoint-temporal method [17].

3.2 *Neural Network Training*

A training process is needed before the ANN model can be applied to estimate traffic state. In the process, three procedures including training, testing and validation were conducted. The total training data set (110 probe data) were divided

Table 1 Number of probes taken for the sample from the FCD output based on road link length

Link # (street name)	Link length (m)	Number of sample probes	Number of location updates per probe
1 (Tesema Aba Wekaw Street)	274.6	10	15
2 (Tesema Aba Wekaw Street)	233.4	10	15
3 (Tesema Aba Wekaw Street)	258.8	10	15
4 (Tesema Aba Wekaw Street)	194.2	10	15
5 (Sudan Street)	194.2	10	15
6 (Sudan Street)	695.8	20	15
7 (Churchill Avenue)	593.9	15	15
8 (Churchill Avenue)	233.3	10	15
9 (Churchill Avenue)	531.4	15	15
10 (Zambia Street)	484.3	15	15
11 (Nigeria Street)	69.5	10	15
12 (Yared Street)	601.7	20	15
13 (Ras Damtew Street)	214.6	10	15

into three subsets [24] which are 88 probe data (80 %) for training, 11 probe data (10 %) for testing and 11 probe data (10 %) for validation. During the training process different hidden neurons like 10, 15, 20, 25 were chosen. During testing the performance in terms of Mean square error (MSE) for the case of 10, 15, 20 and 25 neurons is compared and 15 hidden neurons were used to build the network. Levenberg-Marquardt algorithm [25] was chosen for training. The trained ANN model is applied to estimate link traffic state under free flow but proved even in over saturated condition [26].

3.3 Evaluation

To evaluate how the ANN model performs, the performance indicators Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used and defined as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(v_{pv,k} - v_{true,k}\right)^2} \tag{4}$$

$$MAPE = 100 * \frac{1}{n}\sum_{k=1`}^{n}\left|\frac{v_{pv,k} - v_{true,k}}{v_{true,k}}\right| \tag{5}$$

where $v_{pv,k}$ the estimated travel speed of the kth is probe vehicle and $v_{true,k}$ is the true link speed of the kth probe vehicle recorded by data collection points.

3.3.1 Results Based on Simulation Data

The trained ANN model is used to estimate link travel speed with a simulation data input. A correlation between the estimated link travel speed based on ANN model and the true link travel speed which is computed from the simulation data using the integration method (IM) of calculating vehicle speed is performed [17]. As depicted in Fig. 3, the estimated link travel speed has very high correlation with the true link travel speed (R^2 > 99 %). The linear regression between the estimated and true (simulated) link speed that predicts the best performance among these values has an equation y = 0.997*x + 0 indicating the trained ANN model performs reasonably well, where x represents true speed and y for estimated link travel speed.

The performance of the estimation method in terms of RMSE and MAPE is 0.029325 and 0.127 % respectively with average speed of 7.191 m/s.

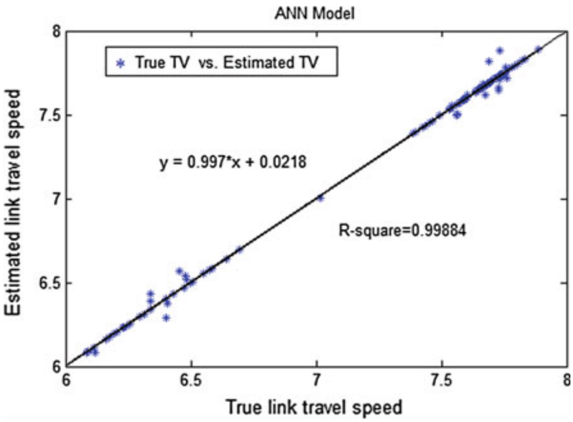

Fig. 3 Correlation between estimated link travel speed and true link travel speed

3.3.2 Results Based on Real A-GPS Data

The trained ANN model was also applied to estimate travel speed based on real A-GPS data. To collect field based data, a car with A-GPS based mobile phone travelled on the sample road network and location updates in terms of longitude, latitude, timestamp, speed and accuracy is recorded at every 3 s for about 45 min (see Fig. 4).

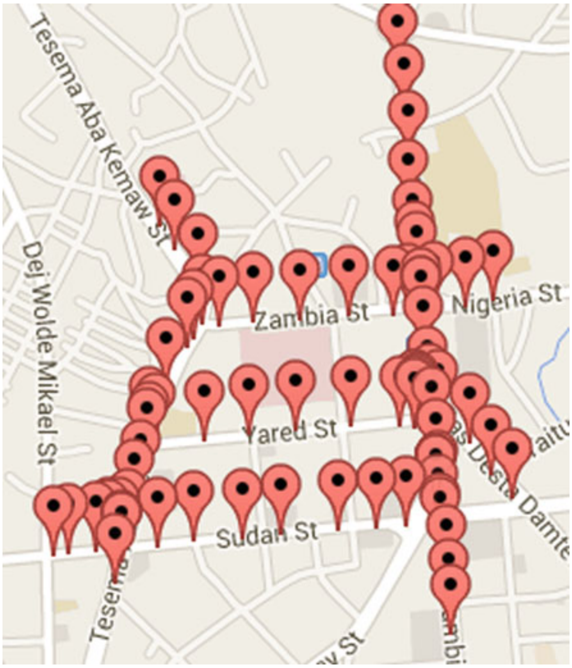

Fig. 4 Real A-GPS based moving vehicle location data

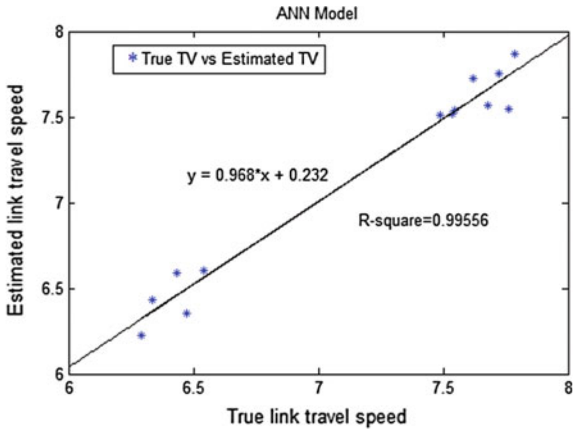

Fig. 5 Correlation between estimated link travel speed and true link travel speed using real A-GPS data

A sample using Pinpoint-Temporal method [17] with 10 s time interval is taken and at every road link for 15 location points i.e. total of 195 A-GPS based vehicle location points are taken. The estimation result is shown on Fig. 5. Each point represents travel speed on each trip i.e., at every road link. From the regression formula of Fig. 5, it can be seen that the trained ANN model performs very good. The RMSE and MAPE are 0.101034 and 1.1877 % respectively, which show the possible application of the ANN model to real link travel speed measurements.

4 Conclusions

This paper presents a neural network model used for estimating urban road traffic flows at real-time. To evaluate the performance of the model a simulation data using the microscopic simulator SUMO was employed. Besides a real world data gathered using in-vehicle A-GPs enabled mobile phone was also used to validate the trained neural network performance. The performance of the developed model based on the performance matrices RMSE and MAPE are 0.029325 and 0.127 % based on simulation data and 0.101034 and 1.1877 % using the real A-GPS based data respectively.

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