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A Long Short-Term Memory Neural Network Approach for Traffic Density Estimation with Sensor-equipped Probe Vehicles

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Abstract

More accurate density estimation techniques are needed to effectively utilize data from alternate sources of traffic data such as probe vehicles, which do not depend on expensive and invasive infrastructure such as loop detectors. From previous experiments, we found that traffic density estimation using probes has an issue of overestimation of traffic densities when traffic is in transition (periods from free-flow to congestion and vice versa). This pattern of overestimation exhibits certain correlations, and at the same time is highly non-linear in nature by time. Closed-form analytical tools used in previous research are incapable of dealing with these complex non-linearities, justifying the use of high-order machine learning algorithms. We propose an algorithm to tackle the nonlinearity of traffic flow according to time and time-lag characteristics. Our research employs LSTM neural network to estimate traffic density by utilizing data gathered from sensor equipped vehicles and road geometry. We evaluated our proposed method by using a microscopic simulation program (PARAMICS). 100 days of one peak hour traffic data are generated in the simulation and the dataset is divided into training set and test set. These experiments confirm that our proposed model outperforms the previous model and efficiently solves the overestimation problem in traffic transition period.

Keywords:Traffic Density Estimation; Radar Sensors; Probe Vehicles; Neural Network; LSTM

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1. Introduction

Estimating traffic density is of critical importance in understanding current traffic conditions and predicting future traffic congestion conditions. Developing vehicle sensing technologies and the concept of "Internet of things" give many opportunities to measure traffic density more accurately. Traffic density estimation using sensor equipped probes is emerging as a valuable tool in research and practice (Herring et al. 2010, Seo and Kusakabe, 2015, Seo et al. 2015, Al-sobky and Mousa 2016, and Nam et al. 2017). This is apparent when we consider the fact that modern cars are now being equipped with advanced on-vehicle sensors. These sensors can be camera-vision, lidar and radar, which were originally installed for Advanced Driver Assistance Systems (ADAS). The number of vehicles equipped with these advanced functionalities will significantly increase in the near future, specifically with the emergence of autonomous vehicles. A side benefit of these technological advancements is that we can now have a sufficient number of vehicles traveling on the road at any given time to obtain a large amount of sensor data which can then be harnessed to get much improved estimates of traffic densities. Nam et al. (2017) propose the Simulation-based TRaffic density Estimation AlgorithM (STREAM) that applies Edie's definition in order to utilize data from sensor-equipped vehicles to estimates traffic density. Although STREAM yielded highly accurate estimation results, simulation analysis also opened further lines of inquiry. The primary issue is overestimation of traffic densities when traffic is in transition (periods from free-flow to congestion and vice versa).

Methodologies using probe vehicles suffer from a few limitations, which merit further research. Although a probe vehicle can capture traffic states during stationary traffic conditions such as non-congested and fully congested conditions, it is vulnerable during flow transition periods. Specifically, the performance deteriorates during the onset of congestion and queue-clearing conditions, in comparison with its performance in other states. Figure 1 shows a simplified illustration of overestimated traffic density during the onset of congestion, when a simple local density estimation algorithm is applied. The number of cars on the road section can be suitably thought of as a proxy for road density. The purple vehicles indicate probes, each having a sensing area shown in blue. Faster-moving and slower-moving vehicles are depicted in green and red, respectively. Depending on the sensor positions, the congestion build-up or clearing conditions can move through the sensing zone and cause a time-lag effect. A simple algorithm will naturally capture travel hours and travel distances of all vehicles in the sensing area of the probe vehicles to calculate densities, but during times of congestion there is a greater proportion of slower vehicles in the sensing area in each time step, which can cause oversampling. This oversampling of slower moving vehicles from time step to time step can lead to overestimation of traffic density. To correct for this overestimation, the algorithm needs a certain time-step to time-step memory. Moreover, sensing areas from different probe vehicles tend to overlap in these conditions, which can also add to the overestimation. In this paper, we describe a scheme using Long Short-Term Memory (LSTM) neural networks that overcomes this problem.

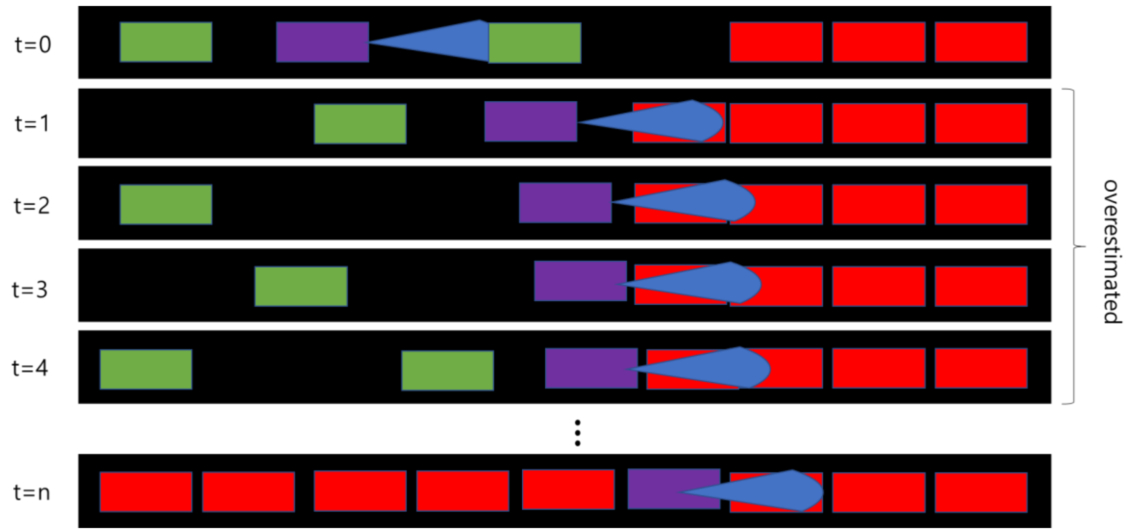

Figure 1. Overestimation pattern in time of onset of congestion

2. STREAM-LSTM Model

Traffic dynamics are highly non-linear, and traffic dynamics in transitional periods even more so. The combination of non-linearity with a large amount of data to be analysed leads us to propose Machine Learning (ML) algorithms as appropriate tools to identify these patterns. ML algorithms excel in extracting relationships between different variables in large datasets. In this research study, the data to be analysed are a fusion of probe vehicle data and road geometry data. This fusion is not trivial, as we need to formulate innovative ways to combine these disparate sources of data.

The capabilities of Deep Learning algorithms are increasingly being recognized in the fields of traffic estimation and prediction (Ma et al. 2015, Tian and Pan, 2015, Polson and Sokolov, 2016). One common conclusion that has emerged in the field of traffic flow prediction is that deep learning methods are successfully able to point out nonlinearity of traffic flow according to time and time-lag characteristics, and that deep learning algorithms can accurately predict traffic fundamentals. LSTM is a scheme within the broad category of deep learning methods.

Figure 2 shows the conceptual framework of the proposed LSTM network. Hereinafter, we will call the proposed model as STREAM-LSTM (Simulation-based TRaffic density Estimation AlgorithM-Long-Short Term Memory). A traffic management center collects various pieces of information from probes passing a road section every 0.5 seconds and stores the data in a moving horizon window vector of *n* time steps. In this study, we set the moving horizon to be 5 time steps. Actual traffic density of a road section can be determined only with the traffic pattern seen in the whole time horizon. This implies that traffic density is highly affected by prior traffic conditions that are captured by sensor probes. We call this pattern a “Sensor Signature”. The LSTM network recognises the current signature and previous time step’s layer pattern. The advantage of employing LSTM networks in this context is that they do not suffer from the well-known “vanishing gradient” problem. Simply stated, this means that they can consider not only very recent prior conditions but also relatively longer prior conditions, just as the phrase “Long Short-Term memory” implies. This property becomes crucial in probe vehicle-based traffic density estimation to avoid the problem shown in Figure 1.

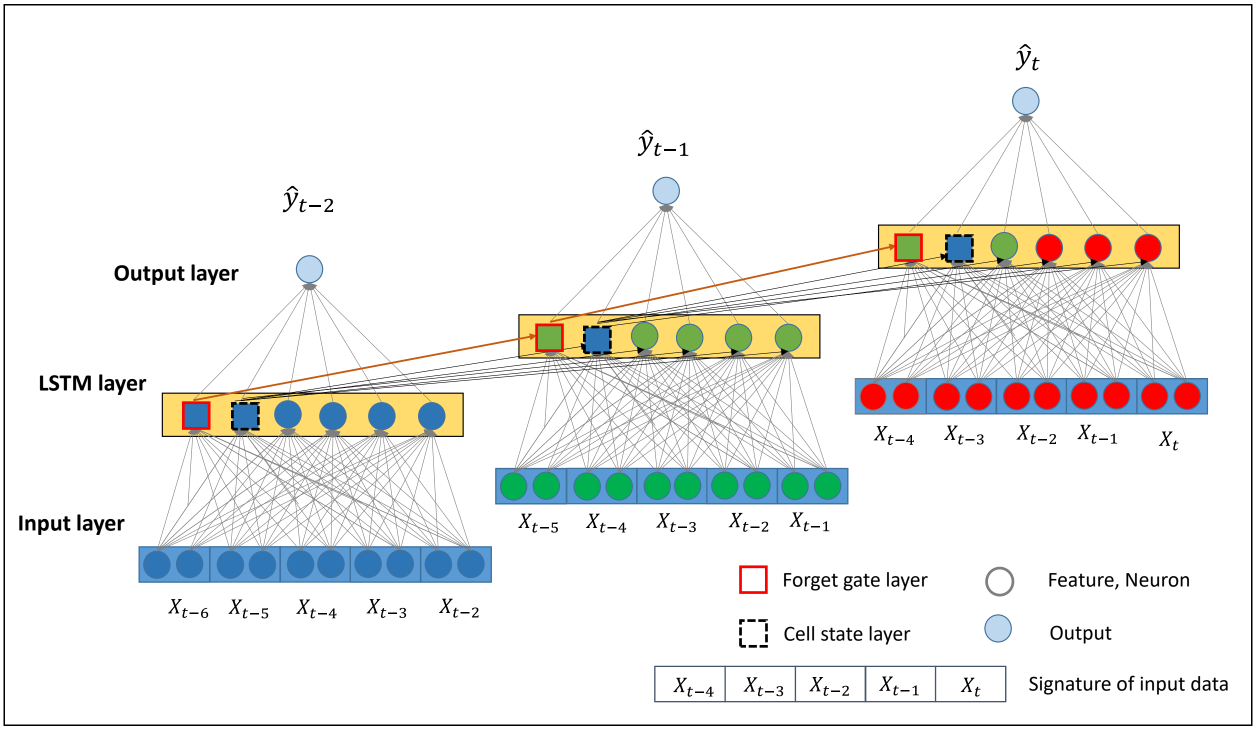

Figure 2 Design of LSTM for signature data from sensor equipped vehicles

This model can take multiple features as input variables from sensor probes as shown in Figure 3. The input layer at time t (i_t) consists of an input vector (x_t), a hidden vector of previous time step (h_{t-1}), weights for the two vectors, and a bias b_i. To reflect time-relevant characteristics in the data, this model uses a “forget layer” and a “cell state layer” to store temporal information which is the output of neuron states in the previous time step. Forget layer f is called a transfer function that is determined to be forgotten or alive from the previous states by cell state layer. If the states do not affect the current output values, the cell state layer decides to not use the forget layer. The function can take any form such as linear, sigmoid, tanh, or ReLU. From each neuron state, density is estimated by Equation (3)

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \qquad \text{Eq (1)}$$
$$f_t = \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right) \qquad \text{Eq (2)}$$
$$c_t = f_t \circ c_{t-1} + i_i \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \qquad \text{Eq (3)}$$
$$\hat{y}(t) = f\left(\sum_i^I w_i n_i(t) + b\right) \qquad \text{Eq (4)}$$

where

x_t: Input vector
$\hat{y}_t$: Estimated output
σ_h, σ_y: Activation function
W_h, U_h: Weights of a layer h (it plays a role in connecting perceptrons among layers)
b_h: Bias vector

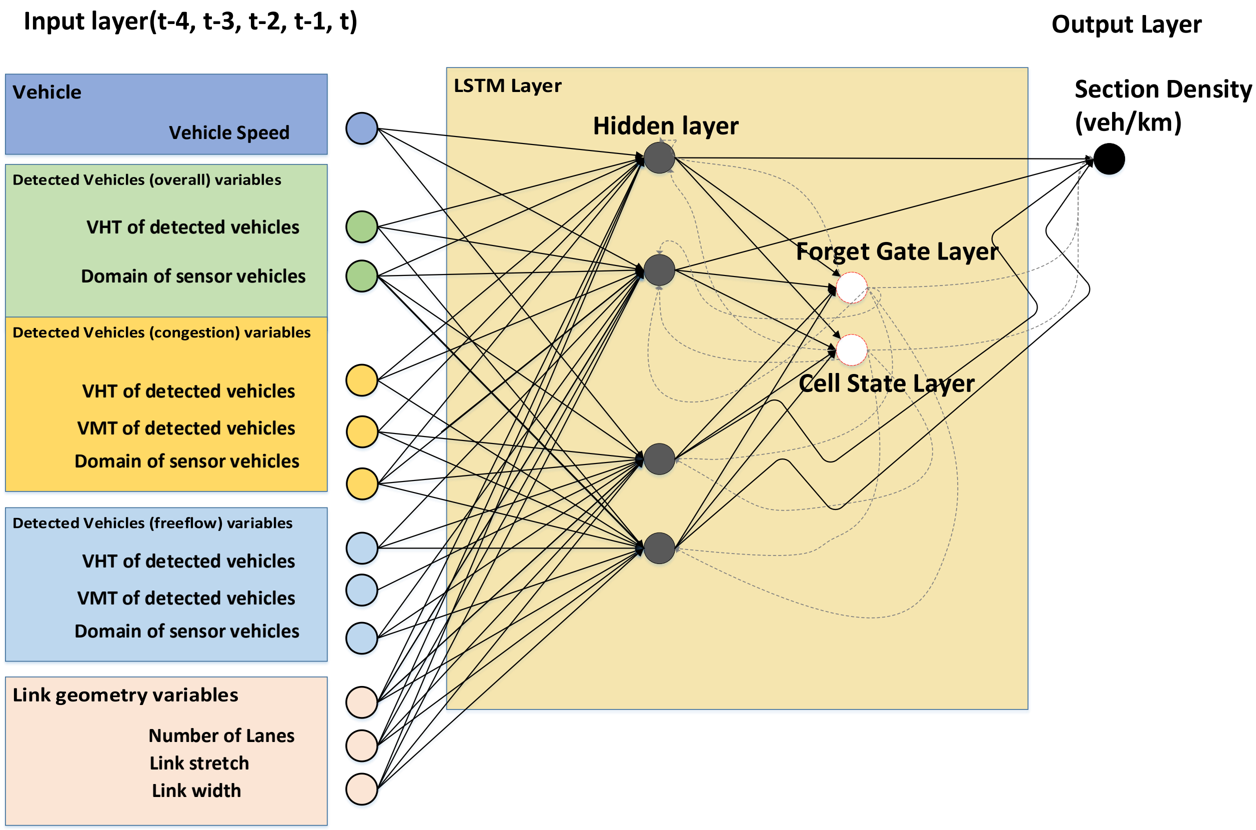

Figure 3. Input-output variables and LSTM network design

3. Data Description

The deep neural network model has a mechanism of probabilistic learning methods that incorporate the uncertainty of numerous factors such as parameter, network structure, input data and actual value (y). Learning and prediction can be regarded as a form of inference. This means that as more datasets are trained, the model would get more accurate until a certain ceiling is reached. In other words, the deep neural network model can learn various traffic situations from the large datasets available to it as input.

The developed simulation can generate multiple scenarios by changing a random seed number. Given a network and OD demands, a random seed number determines all stochastic decisions taking place in the simulation environment, such as vehicle departure time in origin, lane change/ acceleration/ deceleration behaviours and vehicle composition. In this research, we developed a python batch programming module to automatically generate 100 sample scenarios, implying 100 days of a peak hour, by controlling the PARAMICS Processor.

Furthermore, the mechanism of Deep learning has various random terms. Each output of the STREAM-LSTM model could be slightly different across multiple trials. We randomly divide the samples into 70 days for training and 30 days for evaluation.

After multiple experiments, we select the input variables that are known to have an effect on traffic density. First of all, we consider travel speed of a sensor vehicle. We refer to the well-known Edie's definition that traffic density is a function of vehicle travel time over a time-space domain. As can be seen in the Figure 4, the traffic pattern in non-congested conditions is significantly different from that in congested conditions. With this insight, we categorize the traffic condition into the two regimes and calculate the variables (VHT, VMT, Sensor time space domain) in each traffic regime. We set the congestion criterion of the expressway in this research to 80 km/hour.

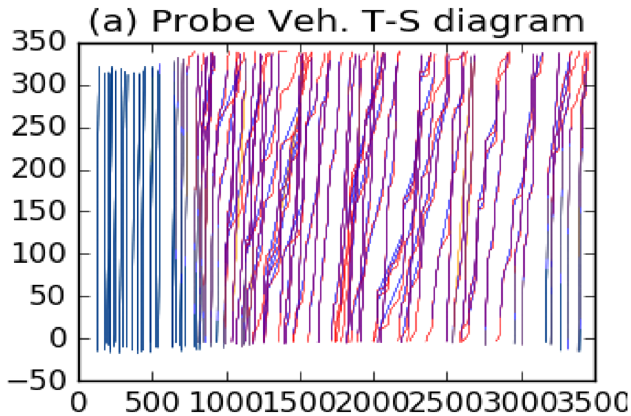

Figure 4 Vehicle trajectory variation according to the congestion level

4. Evaluation

We evaluated our proposed method by using a microscopic simulation program (PARAMICS). The testbed for our evaluation is a simple traffic network shown in Figure 5, hereafter called toy network. This network contains one single stretch of freeway, with 3 lanes, and one origin-destination pair. For our study, congestion is artificially induced in the network by dropping the number of lanes abruptly from 3 lanes on Link13 to 2 lanes on its immediate downstream Link11. The entire simulation period is set to be 1.5 hours, out of which the first 0.25 hours and the last 0.25 hours are discarded due to the peculiarities of the simulation software where we have previously observed erratic vehicle behaviour around the boundary conditions (beginning and end of the simulation). The period of evaluation is set to be the middle 1 hour.

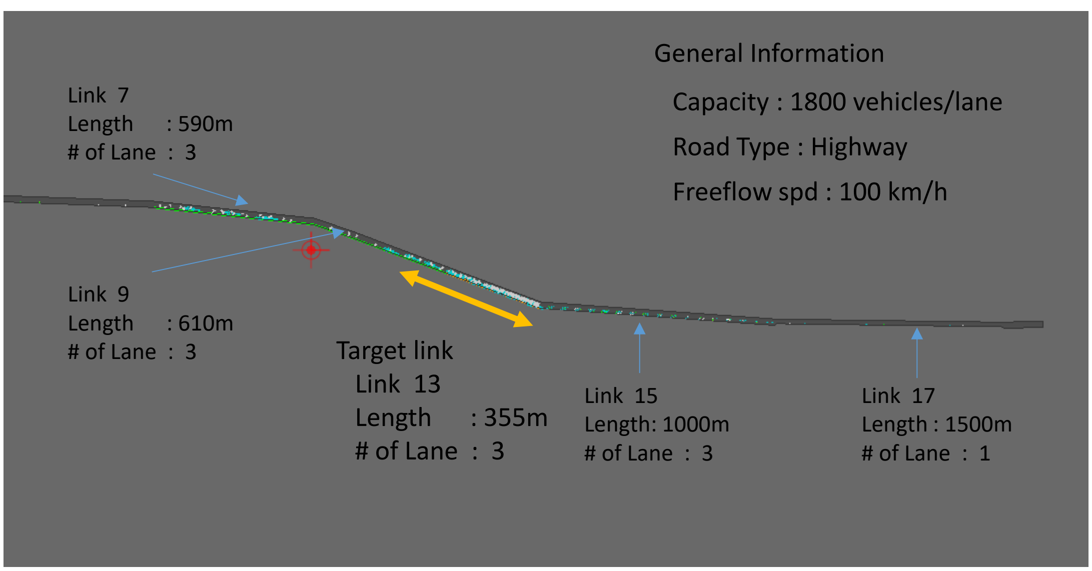

Figure 5 The overview of Toy Network

Table 4.1 and Table 4.2 indicate the sensor configuration in the simulation and evaluation configuration respectively.

Table 1 Sensor configuration

Sensor Code	Name	Target Angle	Range	Distance
1	Front Long	0	10	30
2	Front Short	0	60	10
3	Rear Left	160	40	10
4	Rear Right	200	40	10
5	Rear Center	180	20	20

Table 2 Configuration for Density Estimation

Type	Name	Configuration
Simulation	Simulation time	1.5 hours
	Warm up time	First 0.25 hour
	Analysis time	1 hour
	Updating time step of simulation	0.1 second
	Vehicle compositions	- Sensor vehicle - Regular vehicle
	Generated samples	100 days of morning peaks
Density Estimation	Updating time step	30 seconds
	Congestion criteria	80 km/hour
	Size of the moving horizon	5 time step (2 min 30 sec)
	Dataset composition	Training : 70 days Test : 30 days

These datasets contain information collected by the probe vehicles and have both static (link geometry) and dynamic (vehicle sensed, link flow, etc.) information. The training dataset is used to by the model to build relationships between link density and probe data. The trained model is then deployed on the test data to evaluate its accuracy. This procedure is repeated for different market penetration ratios.

The performance of the STREAM-LSTM method is compared with that of a density estimation method of STREAM which does not employ a memory scheme to correct for oversampling. As expected, STREAM tends to estimate traffic density poorly at the onset of congestion and during queue clearing conditions.

Detailed results are shown in Table 3 and Figure 6. The proposed methodology shows an improvement over STREAM. Moreover, its performance gets better as the penetration rate increases, with an almost 45% improvement in RMSE and 66% improvement in Relate Error in the 25% market penetration scenario. As shown in Figure 6, STREAM tends to estimate traffic density poorly at the onset of congestion and during queue clearing conditions. Our method accurately estimates traffic density in Free-flow, Transition, and Congested conditions. During the Queue clearing conditions, the LSTM method finds the actual density faster than STREAM, although it still overestimates density in comparison with its performance in all other traffic conditions.

Table 3. Evaluation for the proposed method: Numerical Results

Penetration rate	RMSE			Relative Error		
	STREAM-LSTM	STREAM	Improvement (%)	STREAM-LSTM	STREAM	Improvement (%)
1%	32.69	49.15	33.50	0.36	0.50	27.80
5%	14.08	16.29	13.54	0.18	0.30	40.14
10%	12.12	15.69	22.74	0.15	0.30	49.68
25%	8.88	15.97	44.36	0.11	0.34	66.11

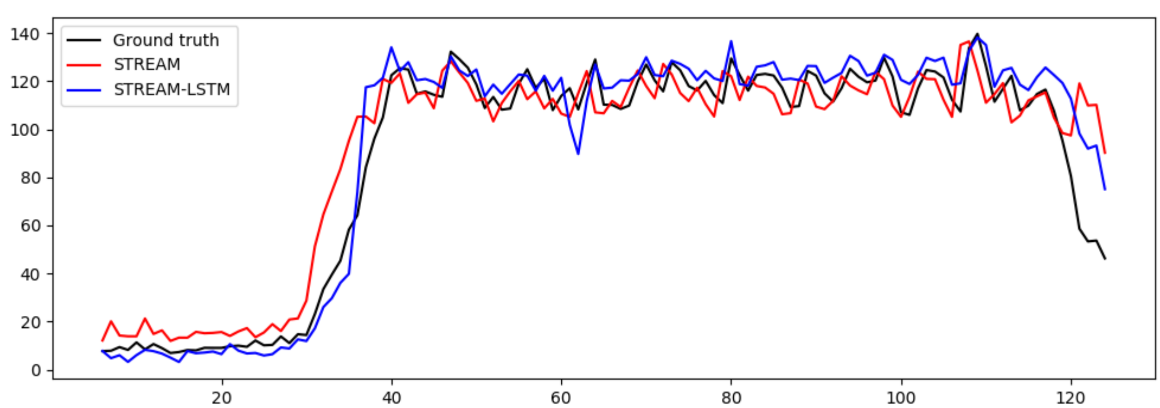

Figure 6 Comparison of results of the density estimation methods

5. Conclusion

In this research, we propose an STREAM-LSTM approach which is a non-parametric method to estimate traffic density. This research was partially motivated by our previous work on probe-based traffic estimation research (STREAM, Nam et al., 2017), in which we identified that a method without proper corrections using observation memory can have a tendency to overestimate density in certain traffic conditions. Our evaluation results indicate that the proposed method has better performance than previous methods, and shows significant improvement over STREAM in all market penetration scenarios. This is because our proposed method fully utilizes the signature of multiple information gathered from multiple sensor equipped probes.

Our model accurately estimates traffic density in Free-flow, Transition, and Congested conditions. Although overestimation still remains a problem in the Queue clearing condition, the STREAM-LSTM method converges to the actual density faster than STREAM. The primary reason for this performance is that LSTM Neural Networks can efficiently memorize the relationship between the signature and time-lag characteristics of traffic densities.

Current efforts are underway to improve the performance of our algorithm even further. It is evident that, in a transportation network, the traffic flow characteristics on any link influence the traffic characteristics on nearby links. Therefore, it stands to reason that if we formulate these relationships between links and present them as additional input data to our LTSM model, its accuracy can be expected to improve.

Acknowledgements

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