Data-driven prediction of experienced travel times for freeways

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1 Introduction

Travel time prediction is one of the most important features to support successful Intelligent Transportation System (ITS). Accurate travel time prediction not only can help for a traveller to make decisions about their trip by giving them which route would take the least travel time under the dynamic transportation system but also enable operators to establish dynamic control strategies. In this paper, therefore, we introduce a prediction method for the experienced travel time.

We predict the travel time based on the predicted velocity field. Velocity field is defined as the collections of velocity measurements through the time in a period, e.g., day, week, or month. For example, the velocity field of 20^{th} July,

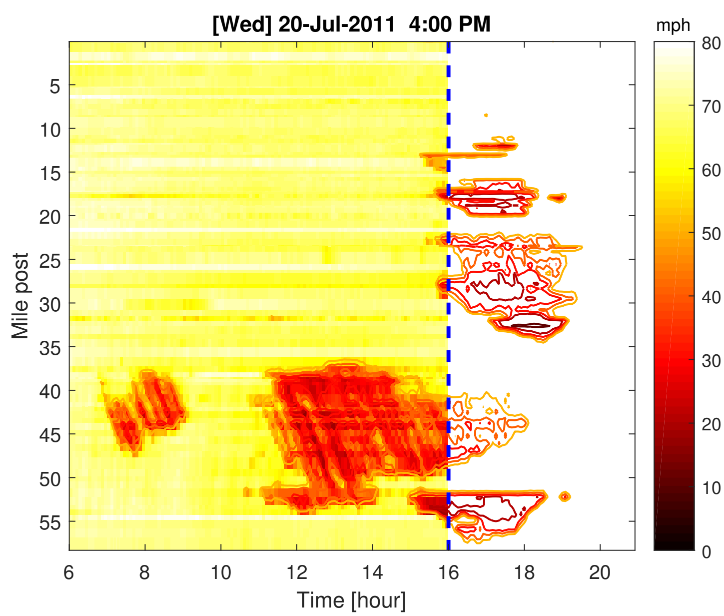

Fig. 1. The speed profile of July 20^{th} (Wednesday), 2011.

2011 from 6 am to 4 pm is shown in the left area of dashed vertical line of Fig. 1. The x-axis and y-axis represents the time and distance, respectively, and the value of each pixel represents the velocity at the time of the section.

Intuitively, the prediction of a velocity field is just fill the image corresponding to the future (of course, this intuition is only valid for the case of a link. For a network, the velocity field cannot be drawn as a image). For example of the Fig. 1, the right side of the vertical dash line at 16:00 hours is the field where we want to fill. In this figure, the contour plot represents the velocity field of the ground truth that can be a good target of the prediction.

What data can we use to draw the white box? Naturally, the historical data and real time measurements are essential ingredients to draw it. The most important thing is that how to use the ingredients. For example, we can draw the white box by replicating the current measurement for the rest of the future. The instantaneous travel time is calculated based on the predicted velocity profile.

However, the instantaneous travel time has relatively huge error with real travel time especially when the congestion starts or ends, since the fundamental assumption is that the current state will be continued infinitely. Actually, the major deficiency of the instantaneous travel time comes from the truth that the historical data is not considered to predict velocity profile.

Naturally, many researchers have been dedicating to use both ingredients in a smart way. Yildirimoglu and Geroliminis [1] grouped the historical data set to three clusters (weekdays, Friday, and weekend), and build the stochastic map for

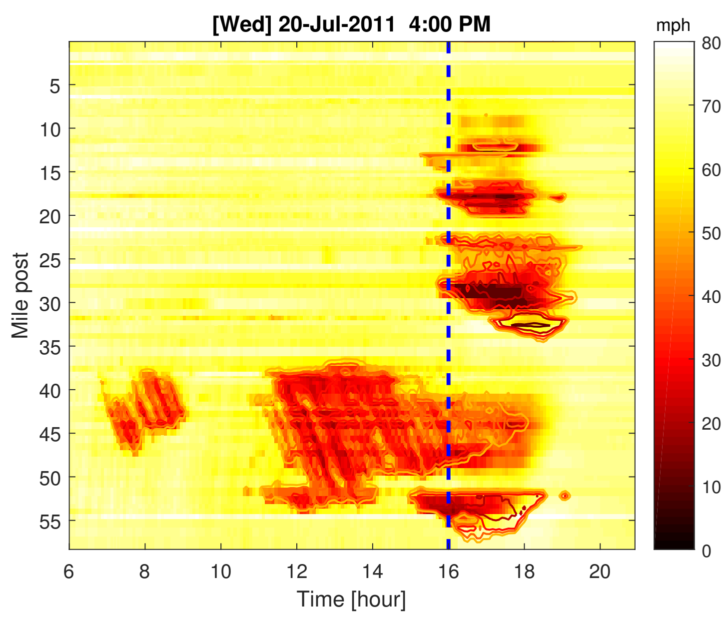

Fig. 2. The prediction of the velocity field at 4 PM of July 20^{th} (Wednesday), 2011.

each cluster. Based on the stochastic map, Yildirimoglu and Geroliminis matched the real-time measurement to one of them with a threshold and predict future velocity field. Zhang and Rice [2] build a dynamic linear regression model with the relationship between instantaneous travel time and experienced travel time. They calculated the relationship (coefficient) with historical dataset and with the optimal coefficient and real-time measurement, predicted the travel time. Park and Rilett [3] applied Neural network and Chien and Kuchipudi [4] used Kalman filter to predict travel time. Further information about former studies are well organized in the review paper [5].

2 Piecewise linear state model

We build a piecewise linear state model with white Gaussian noise which represents the relationship between current velocity vector (e.g., the blue-dashed line in the figure) and the next one:

$$\mathbf{v}_{t+1} = \mathbf{H}_{t+1,t}\mathbf{v}_t + \mathbf{n} \tag{1}$$

The transition matrix contains the relationship and the key point to predict future velocity profile is how to calculate the transition matrix with the historical data set. Here, the transition matrix is calculated under the maximum likelihood sense:

$$\hat{\mathbf{H}}_{t+1,t} = \mathbf{V}_{t+1}\mathbf{V}_t^T(\mathbf{V}_t\mathbf{V}_t^T)^{-1} \tag{2}$$

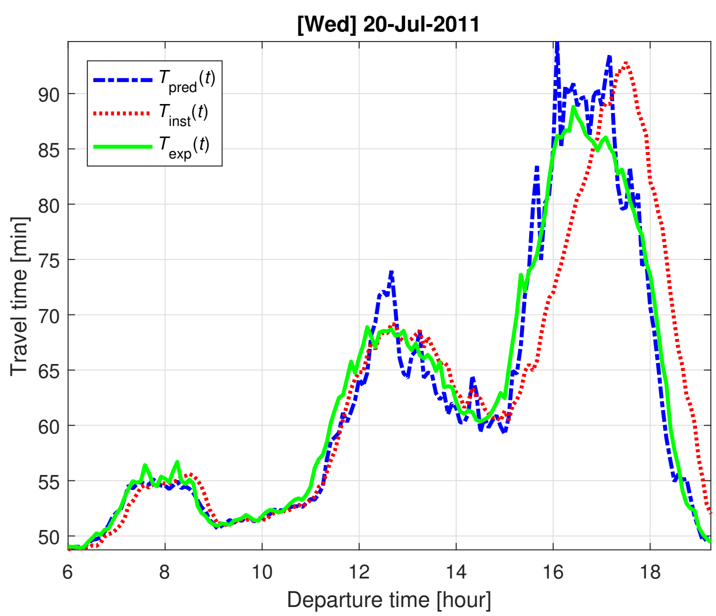

Fig. 3. Travel times of 20^{th} July (Wednesday), 2011.

where the matrix $\mathbf{V}_t$ represents the collection of velocity vectors which corresponds the time t in the historical data set.

With the trained transition matrix, we draw the white box by plugging the real-time measurements in the equation (1) (the velocity profile which corresponds to the time from 6 am to 4 pm in the figure). The prediction result is shown in the Fig. 2. As shown in the figure, the result is similar to the contour plot, which is the ground truth.

We also calculate the travel time based on the prediction, and compare to the instantaneous travel time which can be interpreted as a naïve predictor of travel time by assuming that the current state is the solution of the predictor for the future state. Figure 3 shows that the predicted travel time is closer to the experienced travel time, which is the travel time based on the ground truth velocity profile, compare to the instantaneous travel time. As we discussed on the previous section, the difference between the instantaneous travel time and experienced travel time is huge when the congestion starts (16 hours) and ends (18 hours).

3 Conclusive remarks

In this paper, we study a prediction method for travel time by suggesting a linear state model for velocity field. The main contribution of the work is design the state model as a linear state model. The transition matrix is trained by historical data within the maximum likelihood sense. This simple model not only enables to learn the transition matrix fast with huge amount of historical data but also predict velocity fields. The full paper will contain the detailed explanation of how to calculate the transition matrix with the historical data set and the optimal predictor. More test data will be examined to evaluate the performance of the travel time predictor and be compared with the state-of-the-art technologies. Also, how the performance depends on the choice of training set will be studied. For the future work, the generalization of the method to network can be an option. Dimensionality reduction method such as clustering, principal component analysis can be plugged in the model.

References

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