Within-day prediction of path travel times with use of multi-source of traffic data

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Introduction

Under the big data arena, various models and advanced techniques have been developed in recent years for intelligent transportation systems (ITS) with taking account of different sources of traffic data. As an essential component of ITS, predicting the traffic conditions of near future offers supportive information for pre-trip planning and traffic control. Based on historical and current available data, the short-term traffic prediction provides valuable information and have been studied in recent years (Vlahogianni et al., 2014). Since travel time is an essential indicator for evaluating the performance of the road network as well as the level of service (EI Faouzi et al., 2010), the short-term travel time prediction has increasingly received much attention of scholars and practitioners.

In practice, various types of traffic detectors have been developed and installed on the roads. There are two major types of traffic detectors as classified by Mori et al. (2015). The first type is point detectors including loop detectors and video image detectors (e.g. Autoscope). They are fixed at given locations of the roads. By sensing the vehicles passing through them, they can measure and collect the spot speed data as well as the traffic flow data. The second type is interval detectors, which contains probe vehicles, floating cars as well as automatic vehicle identification (AVI) detectors. They can directly measure and collect the vehicular travel times of the road segments under observation. For point detectors, the temporal evolution of traffic conditions is properly captured. At these locations of point detectors, the vehicle flow rate, mean, and variance of vehicle spot speeds are collected at a pre-determined time interval. For the AVI detectors, the spatial information of travel time on the study path are sampled as the AVI detectors can provide a better spatial coverage on the road segments along the path.

The technics pertinent to short-term traffic predictions have been developed and matured in the past decade. Most of the related studies focus on traffic flow-based and data-based approaches (Mori et al., 2015). Traffic flow theory-based models make traffic predictions via regenerating future traffic conditions and deriving the predicted travel times (Celikoglu, 2007; Papageorgiou et al., 2010). However, these models may simplify some realistic features in the process of simulations, the performance of regenerating future traffic conditions is therefore limited. Data-based approaches include parametric approaches and non-parametric approaches. Parametric approaches like linear regression, Bayesian network, and time series models have more understandable structures and comprehensive mathematical foundations. However, they are computationally extensive and have more difficulty dealing with nonlinear data (Du et al., 2012; Fusco et al., 2016) in reality. For non-parametric approaches, families of neural networks, decision trees, support vector regression and other local regression models are often adopted for traffic prediction. These methods can deal with nonlinear data but with black-box procedures in applications (Vlahogianni et al., 2014; Li and Rose, 2011).

In reality, single source traffic detector may not be able to collect sufficient data for providing reliable travel time estimations and predictions due to low penetration rate or other reasons. With multi-source of different traffic data, it is vital to integrate various information from these sources and fusing them to provide a more consistent and reliable travel time predictor. Faouzi et al. (2011) demonstrated the application of data fusion in traffic forecasting. There are three categories of data fusion structures including decision level (detector level), central-level and hybrid (Faouzi and Klein, 2016). Each detector provides corresponding estimates based on their measurements for further fusing at decision level. At the central level, measurements from different detectors are sent to the fusion processors directly for data analysis. In literature, hybrid approach has been proposed to integrate both processes in the fusion processors. The existing data fusion methods adopted for traffic forecasting consist of weighted average method, Kalman filter, machine learning, fuzzy set theory, and Bayesian methods etc. Zhao et al. (2018) fused traffic data from the dedicated short-range communications (DSRC) and remote transportation microwave sensors (RTMS) by Gated Recurrent Unit (GRU) neural network to achieve path travel time prediction. Heilmann et al. (2011) fused speed data from local detector and Electronic Toll Collection (ETC) system for a short-term speed prediction by a nonparametric kernel predictor. Soua et al. (2016) predicted the traffic flow from streams of data and event-based data and fused them by Dempster's conditional rule.

Methodology

This study proposes integrated fusion predictors with use of multi-source of various traffic data for the short-term path travel time prediction by time of day. The structure of data fusion at decision level is extended on the basis of the previous related approach. It is similar with the fusion of predictors based on single data source (Zheng et al., 2006; Guo et al., 2018), which aims to provide a more reliable and robust travel time prediction. Since reliable estimations make great contributions for prediction (Diaz et al., 2016), this study forecasts within-day path travel times based on estimates obtained from two different types of detectors. The path travel time estimates from AVI detectors are based on a dynamic travel time estimation algorithm (Dion and Rakha, 2006). The path travel time estimates from point detectors based on the extrapolation of spot speed measurements. The prediction approach for AVI and point detector data is extended on the basis of the **functional principal component analysis (FPCA)**, which has been proved to be an out-performing travel time predictor even for abnormal traffic conditions. (Chen and Müller, 2014; Zhong et al., 2017). Compared with other predictors, the FPCA method provides an efficient way to examine the variance-covariance structure of samples, and fuses both historical and within-day information for dimension reduction and prediction (Zhong et al., 2017). Suppose that the mean and variance of travel time function following the conditional Gaussian distributions, the corresponding predictors for AVI and point detectors can provide mean and variance of path travel time predictions for each time step.

The fusion algorithm adopted in the study is the Bayesian fusion (Maskell, 2008), which fuses the predicted travel time distributions from multi-source of data according to Bayes' rule. With the assumption of Gaussian travel time distribution, the fused predicted travel time distribution is then a conditional Gaussian distribution.

Results

The case study is performed on a Hong Kong urban road network. The travel times of a path connecting Island Eastern Corridor (H3) in Hong Kong Island and West Harbour Tunnel (WH) in Kowloon are predicted. The path is installed with six point detectors (Autoscope) and a pair of AVI detectors. The detail of this studied path (H3-WH) is shown in Figure 1. Two types of travel time estimates of path H3-WH are obtained from two corresponding detector systems every 2 minutes by the adopted estimation methods. Two FPCA models regarding travel time estimates from AVI and Autoscope system are established for providing sperate path travel time predictions. The fusion step of these predictions is performed thereafter.

Figure 1. Map of the studied path.

The time interval for each time step is 2 minutes hence the prediction of 30 minutes later is a multi-step prediction task. The rolling horizon approach is adopted for real time predictions similar as Pan et al., (2013). The predictions are updated once every 2 minutes. With the application of FPCA and Bayesian fusion, the fused path travel time predictions are evaluated and compared with single source predictor and naïve fusion algorithm to test the fusion performance. Also, the other widely used predictors including long short-term memory neural network (LSTM NN), gated recurrent unit neural network (GRU NN), k-nearest neighbor (KNN), and random forest (RF) are applied for benchmark comparison. The actual experienced path travel times in the next 30 minutes intervals from AVI detectors with supplementary information from Autoscope system are regarded as the ground truth. The mean absolute percentage error (MAPE) and mean absolute error (MAE) are adopted for describing the percentage difference and absolute difference between predicted and observed values. The results were shown in Table 1. It could be observed that the performance of the proposed method is better than both single source data and other predictors. The 95% confidence intervals of fused travel time predictions from 7:00 to 23:00 are plotted with the assumed ground truth. It can be observed that the actual means of experienced travel times are within the predicted confidence interval as shown in Figure 2.

Table 1. Performance evaluation of travel time prediction results.

	Morning period (8:00 – 10:00)		Evening period (19:00 – 21:00)		Overall	
	MAPE (%)	MAE (minutes)	MAPE (%)	MAE (minutes)	MAPE (%)	MAE (minutes)
AVI detector only	13.54	2.69	12.72	1.88	13.13	2.29
Point detector only	14.04	2.75	15.01	2.18	14.53	2.47
Weighted average	13.71	2.81	13.8	2.02	13.76	2.42
LSTM NN	14.32	2.89	13.60	2.00	13.96	2.45
GRU NN	14.58	2.91	13.54	2.02	14.06	2.47
KNN	16.41	3.23	15.02	2.19	15.72	2.71
RF	16.74	3.34	14.59	2.14	15.67	2.74
Proposed method	12.11	2.51	11.78	1.73	**11.95**	**2.12**

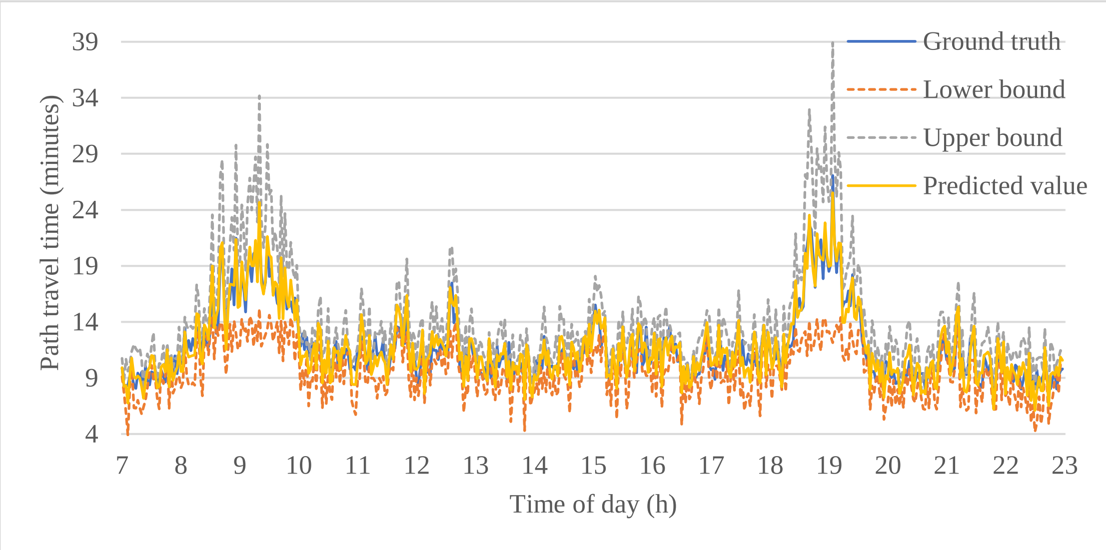

Figure 2. Predicted path travel time distributions from 7:00 to 23:00.

Conclusion

This study proposes a novel approach to fuse multi-source traffic data with use of the Bayesian fusion theory. The traffic data from point detectors (Autoscope) and interval detectors (AVI data) are fused for within-day path travel time prediction. A Hong Kong urban road network is chosen for path travel time predictions of the next 30 minutes by time of day. The results provide a satisfactory performance of the proposed approach with a benchmark comparison study. The future work will further improve the quality of the fused predictions with use of other data sources.

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