Transportation Research Part C 92 (2018) 90–100

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Predictor fusion for short-term traffic forecasting

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1. Introduction

Short-term traffic prediction can be defined as the process of estimating the anticipated traffic conditions in the short-term future given historical and current traffic information (Vlahogianni et al., 2014). A wide variety of Intelligent Transport Systems (ITS) applications require predictive information regarding aspects of the transport network state. For example, in the case of network management applications predictive information enables the development of proactive (rather than reactive) network and incident strategies (Van Arem et al., 1997). Similarly, individual travellers can use the predictive information to plan their mobility decision more efficiently (Dia, 2001). Therefore, accurate short-term traffic prediction is one of the key components in ITS applications, and has been the subject of extensive research in recent years (Vlahogianni et al., 2014).

Traffic conditions in urban areas exhibit recurrent patterns over time (Williams and Hoel, 2003). Most traffic prediction methods make use of this periodicity. However, recurrent traffic conditions are affected by planned incidents such as road works, sports events and unplanned incidents and accidents, resulting in a deviation from the recurrent patterns. Short-term prediction is arguably more important during such abnormal conditions because of uncertainty about how the traffic state will evolve into the future. These factors also make it substantially more challenging.

The challenges of short-term prediction during disruptions resulting in abnormal conditions are not unique to transport. In a number of other fields including bioengineering, computer science and power networks, an effective approach to such problems has been found in the idea of prediction fusion (Bonissone et al., 2011; Ishida and Kinoshita, 2008; Loh and Henry, 2002; Mizianty and Kurgan, 2009). The central concept underlying prediction fusion is based on the observation that different prediction methods will have different strengths and weaknesses in different contexts of normal and abnormal operation (Chan and Stolfo, 1997). Therefore rather than relying on a single prediction methods, it is potentially desirable to combine or fuse the predictions arising from different methods, in a manner that is analogous to sensor data fusion. A key issue in prediction fusion is clearly the method used.

This paper applies similar ideas to the problem of short-term prediction in the transport domain. In particular, the main objective of this paper is to develop a fusion-based framework to improve the accuracy of traffic prediction based on a combination of multiple stand-alone predictors that work accurately under different traffic conditions. We evaluate fusion-based frameworks using three different fusion strategies: averaged, weighed and k-Nearest Neighbour (kNN) methods, applied to three different machine learning methods, Neural Networks (NN), Support Vector Regression (SVR) and Random Forests (RF). We select these three methods as the stand-alone predictors, not only because they are widely used in short-term traffic prediction under different conditions (Guo et al., 2017; Guo et al., 2010) but also because they are very different techniques resulting in model diversity (Mitchell, 1997). The stand-alone and fusion based methods are compared against each other using traffic flow and travel time data from Central London under different traffic conditions.

2. Related work

2.1. Previous short-term traffic prediction studies

Short-term traffic prediction is an active research area. However, most of the literature only considers prediction under normal

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https://doi.org/10.1016/j.trc.2018.04.025
Received 13 September 2017; Received in revised form 25 April 2018; Accepted 30 April 2018

traffic conditions, using recurrent traffic information. A common characteristic of these studies is that the recorded traffic data that had been influenced by abnormal conditions are detected and removed from the database used in traffic prediction applications (Castro-Neto et al., 2009). A wide range of different statistical and machine learning prediction models have been applied to such scenarios. For example, many early traffic prediction models use the basic Auto-Regressive Integrated Moving Average (ARIMA) (Box and Jenkins, 1970) method (Hamed et al., 1995; Szeto et al., 2009; Van Der Voort et al., 1996). More recently, machine learning methods have been widely used to predict future traffic variables. Commonly used methods include Neural Networks (NN) (Abdulhai et al., 1999; Ishak and Alecsandru, 2004; Park and Rilett, 1999; van Hinsbergen et al., 2009; Zheng et al., 2006), Support Vector Regression (SVR) (Wu et al., 2004), k-Nearest Neighbours (kNN) (Clark, 2003; Habtemichael and Cetin, 2016; Krishnan and Polak, 2008; Smith and Demetsky, 1997; Smith et al., 2002) and Random Forest (RF) (Guo et al., 2017; Guo et al., 2014; Leshem and Ritov, 2007). More recently still, deep learning methods such as Convolutional Neural Networks (CNN) and stacked auto-encoders (SAE) have been applied in short-term traffic prediction (e.g. Lv et al. (2015), Polson & Sokolov (2017)).

Comparison of prediction accuracy between these above methods was made in many studies (e.g. Guo et al. (2010); Guo et al. (2017); Smith & Demetsky (1997); Smith et al. (2002); Vlahogianni et al. (2004)). In general, these comparisons show that there is no single method that can best predict traffic states in all types of datasets and under different conditions (Tan et al., 2009; Vlahogianni et al., 2014; Zheng et al., 2006). Some studies discussed the reasons why a combination of individual forecasting methods might improve accuracy (Clemen, 1989; Makridakis, 1989). In recent years, researchers have begun to investigate strategies to combine predictors for traffic forecasting to increase accuracy under normal traffic conditions. The Bayesian approach was used in Zheng et al. (2006) to combine short-term predictive results from two single neural network predictors. Both training and testing data were collected from four locations under typical normal traffic conditions on an expressway in Singapore. A neural network based approach was used in Tan et al. (2009) to aggregate the results of three time-series forecasting methods. They used one-hour traffic flow data collected from one site on a highway in China. The results showed that the aggregation method could improve one-step ahead prediction accuracy. The authors stated that the developed model in their research only worked under normal traffic conditions because only simple time series prediction methods were used. More recently, a probabilistic method was used in Djuric et al. (2011) to fuse results from four single traffic speed predictors. Data used in their study was collected from a loop detector on a freeway in the USA. However, the developed aggregation models could not provide accurate prediction results during abnormal traffic conditions caused by incidents, sports events and severe weather. More recently, Tselentis et al. (2015) tested both linear regression and Bayesian combination methods with individual time series methods for short-term freeway traffic speed prediction. Both spatio-temporal and exogenous information such as rainfall and volume were considered in the proposed models. Similarly, Qiu et al. (2016) proposed an integrated precipitation-correction model for freeway traffic flow prediction using fusion techniques with four basic forecasting models. Vlahogianni (2015) proposed the surrogate model using three prediction methods for combination in short-term freeway traffic speed prediction. These studies have demonstrated that the combination of different predictors can improve the final accuracy of traffic prediction under normal traffic conditions on freeways and motorways. Table 1 shows the summary of the key features of traffic fusion literature reviewed above, under a number of headings covering the characteristics of the prediction context (such as urban/freeway), the fusion method and the traffic conditions (normal/ abnormal) within which the models were implemented.

The challenges of prediction under abnormal traffic conditions (such as non-recurrent traffic congestion that is caused by planned events such as road works or unplanned events such as incidents or accidents) have received much less attention in the literature, despite their significance, especially in urban areas. However, in the past decade interest in prediction under abnormal traffic conditions has grown. For example, Tao et al. (2005) used NN to predict short-term travel time during incidents using data collected from a highway corridor in the United States. Castro-Neto et al. (2009) proposed an Online-Support Vector Regression (OL-SVR) model to forecast traffic flow variables during holidays and traffic incidents using data collected from the United States_ENREF_5. Random Forests (RF) was used in Guo et al. (2014) to predict travel time under incident conditions using data collected in urban areas in the United Kingdom.

Because different machine learning tools use different strategies to learn relationship from the training dataset, different predictors have differential performance in different circumstances. There is no single method that best all traffic variables under all traffic conditions. The strategy of predictor fusion is widely used to improve prediction accuracy in many fields, such as power (e.g., Bonissone et al., 2011), computer science (e.g., Loh & Henry, 2002) and biology (e.g., Chan & Stolfo, 1997). Motivated by this, a fusion-based framework is proposed to leverage the strengths of different machine learning tools using the same inputs for traffic prediction under a range of traffic conditions.

Table 1
Categorisation of available literature in existing traffic prediction fusion models.

Author	Context	Input data resolution (min)	Prediction step	Input variables	Traffic condition	Fusion model
Zheng et al. (2006)	Highway	15 min	1	Flow	Normal	Bayesian
Tan et al. (2009)	Expressway	60 min	1 and multi	Flow	Normal	NN
Djuric et al. (2011)	Freeway	5 min	Multi	Speed	Normal	Probabilistic
Qiu et al. (2016)	Expressway	5 min	Multi	Flow and Rainfall	Normal /Heavy rain	Precipitation-correction
Tselentis et al. (2015)	Freeway	5 min	1	Speed and Flow/ Rainfall	Normal /Heavy rain	Statistic and Bayesian
Vlahogianni (2015)	Freeway	5 min	1	Speed	Normal	Surrogate model