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Traffic state estimation is an important task that has attracted a lot of research effort in recent decades. The main goal of traffic state estimation is to turn measured data, which is normally noisy and incomplete, into meaningful information for further investigation, either offline or online (e.g. traffic management and control).

Traffic state estimation is mainly encompassed of three ingredients: raw data from sensors; relationships between observed data and the underlying desired state variables; and data assimilation techniques to combine the former two. Classic approaches use full-fletched traffic flow models in combination with recursive Bayesian data assimilation methods such as Kalman filters (Wang Y. et al., 2006, van Hinsbergen et al., 2012) and particle filters (Chen et al., 2011, Hegyi et al., 2006) to fuse and assimilate any sensor data related to the underlying state variables. The advantages of these approaches are tractability and the fact that such methods are very suitable to support "what-if" analysis and prediction on entire networks. On the downside, they contain many parameters and inputs that often require prediction themselves with data that is in many cases not available. More recently, predominantly statistical approaches are proposed estimate link speeds based on correlations between link conditions (speed or flow) over a network (Yang et al., 2016, Lv et al., 2015). The data-driven nature of these approaches make them flexible and more easily maintainable, however, there are also disadvantages. Without observation equations relating observed data to underlying state variables (e.g. density), such latent variables cannot be reconstructed. Moreover, it is not always easy to relate outcomes of data-driven processes to the actual traffic processes that led to these outcomes. Therefore, combining these two approaches to take advantages of them is highly motivated.

The proposed method constitutes two main phases, namely offline learning and online estimation. In the offline learning phase, congested traffic patterns are classified into different congestion states (Krishnakumari et al., 2017). Research has revealed several noticeable states, such as wide moving jams; heterogeneous traffic states with oscillations, which result in the emergence of moving jams of different amplitude; and homogeneous congestion, which expands over time and space. From these congestion patterns, shockwaves can be extracted and labelled as traffic states upstream, downstream and inside congested areas. Moreover, speeds of these shockwaves can be calculated directly according to their vectors in spatiotemporal data. On the other hand, according to shockwave theory, there is an indirect method to compute these speeds given traffic flow and density values. A data-driven framework is implemented to investigate the consistency of these speeds derived from the two methods.

Given traffic congestion, the online estimation phase is responsible for quickly estimating current traffic states and predicting how the congestion area grows for short time horizon. This phase consists of four steps: (i) current traffic classification, (ii) space-time region separation, (iii) region state estimation and (iv) prediction. The main drawback of most theory-based estimation techniques is the high number of degrees of freedom. The proposed hybrid method aims at using data pattern recognition from historical data as a solution for this situation. Traffic state information can be inferred from historical traffic patterns when physical sensor data is insufficient. Deriving on-ramp and off-ramp flow data is a typical example of this. As a result, it can alleviate the number of parameters required by estimation models, while maintaining model precision.

In addition, quickly determining likely current congestion states can also improve the accuracy of data fusion in estimating future traffic states. Needless to say, similar congestion patterns can be expected to occur under similar circumstances, e.g. for similar infrastructure design or similar incident events. Therefore, accurate classification of current traffic congestion assists the use of embedded data-driven method to derive most related historical patterns. For ongoing congestion, this method proposes using a (partial) pattern recognition approach to match current traffic with a corresponding congestion state.

In the second step, traffic congestion will be separated into different space-time regions for analysis. Similarly to what is described in the offline learning phase, this is performed using basic first order traffic flow theory. Figure 1 gives an example describing the idea of separation of congested traffic flow states. The currently observed shockwaves are shown by two red lines. They are formed by changes in traffic states between downstream and upstream in congested areas, which are denoted by number 1, 2 and 3 respectively. For computing efficiency, these areas are discretized in time, which is denoted by two dotted vertical lines. The third step is for estimating the states of those separated space-time regions. The state of each region is defined as an average value of states of all “points” (e.g. any space - time moment in the region). Accurately estimated results are extremely important as they are underlying features for traffic prediction.

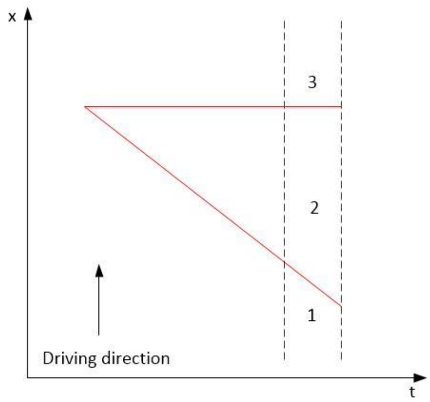

Figure 1: An example of congestion and separation of space-time area

The final step is the prediction step, in which the future states of different regions (upstream, downstream and congested area) are forecasted. At this moment, there are different reasonable solutions to resolve this requirement. Firstly, the classifying step using pattern recognition, which was mentioned previously, provides a number of similar traffic situations. They can be considered as rough representations for the forecast of the traffic states in the next time period. Another possible solution is applying traffic flow theory to future traffic states to infer the speeds of shockwaves between those estimated regions. This determines how the congestion propagates over the prediction horizon.

In determining the performance of the proposed method, two validating systems are implemented for testing the data model and the prediction results. The data model in the offline learning phase is examined based on its qualification of representing relationships between traffic states and shockwave speeds on a test dataset. With regard to the traffic prediction scheme, forecasted shockwave speeds are compared with ground truths of shockwaves from data to validate its forecasting accuracy.

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