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Network-wide traffic state estimation using a mixture Gaussian graphical model and graphical lasso

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ABSTRACT

This study proposes a model that estimates unobserved highway link speeds by a machine learning technique using historical probe vehicle data. For highway traffic monitoring, probe vehicle data is one of the most promising data source. However, since such data do not always cover an entire study area, we cannot measure traffic speeds on all links in a time-dependent manner; quite a few links are unobserved. To continuously monitor speeds on all links, it is necessary to develop a technique that estimates speeds on unobserved links from historical observed link speeds. For this purpose, we extend the current Gaussian graphical model so as to use two or more multivariate normal distributions to accurately estimate unobserved link speeds. In general, since the number of unknown model parameters (mean parameters and covariance matrices) is enormous and also unobserved links always exist, the EM algorithm and the graphical lasso technique are employed to determine the model parameters. Our proposed model was applied to the Bangkok city center in Thailand as well as to the Fujisawa city in Japan. We confirmed that the model can estimate the unobserved link speeds quite reasonably.

1. Introduction

Real-time traffic monitoring is required on a highway network for effective highway management and providing beneficial information to highway users. However, the installation of infrastructure sensors such as traffic detectors on many highway links to monitor the network-wide traffic state is expensive and inefficient for information provision. One of the promising alternatives is to utilize probe vehicle data which can be used to track trajectories of vehicles along their routes by measuring their positions every few seconds. Unlike traffic detectors, little infrastructure is required to acquire probe vehicle data. Hence, the use of vehicle probe data to monitor traffic has attracted attention not only in developed countries where the maintenance of infrastructure sensors has become burdensome but also in developing countries where few infrastructure sensors have been installed.

However, network-wide monitoring using vehicle probe data and the existing methods for implementing it have several unresolved problems.

1. The available data is spatially sparse. Except arterial highways, many road links in a road network are unobserved by probe vehicles. As we discuss later, at most 30–40% of all road links are observed in 5 min in central Bangkok. As a result, network-wide traffic monitoring is substantially difficult.

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2. Road networks have complex characteristics. For example, parallel road links, despite not being directly connected, have a complex relationship. It is difficult to model such complex relationships.
3. The spatial interpolation problem is essentially different from the temporal forecasting problem. To solve the temporal forecasting problem, we can use both physical models based on traffic flow theory and statistical models based on historical data. On the other hand, to solve the spatial interpolation problem in a road network, we need to infer the traffic state of spatially separated locations from the observed road traffic state. Therefore, the role of statistical models is more important and we need more sophisticated statistical models.

Most existing methods infer the traffic state of an individual road segment. Currently, there are two types of traffic state estimation approaches: One based on the statistical method and the other on traffic flow theory (Lighthill and Whitham, 1955; Daganzo, 1994). In the statistical approach, observed data that are either temporal-neighboring (collected from the same detector at the same time period but in neighboring days) or pattern-neighboring (collected from the same detector at the same time period but in other days with similar daily flow variation patterns) are used for interpolation (Zhong et al., 2005; Yin et al., 2012). Nakata and Takeuchi (2004) developed a travel-time prediction method using auto regression model with historical statistical and real-time data. Li et al. (2013) used probabilistic principle component analysis for capturing traffic state patterns and interpolating the missing data. Jenelius and Koutsopoulos (2013) estimated the travel time between two points on a road network using low sampling rate trajectory data. Their approach considers the correlation between different road segments in terms of their historical traffic patterns to infer the travel time on a road segment and the delay at intersections. Using the approach based on traffic flow theory, Hellinga et al. (2008) proposed a highly accurate travel-time estimation on a road segment by decomposing probe travel time into free flow travel time, congestion time, and stoppage time based on traffic flow theory. Herring et al. (2010) proposed a travel-time estimation method using a Coupled Hidden Markov Model based on traffic flow theory. Their approach combined traffic flow theory and the statistical approach. These studies focused on a specific road segment or the relationship between connected road segments.

The statistical approach has also been used for network-wide traffic estimation. Furtlehner et al. (2007) proposed a spatial interpolation method using belief propagation in a Markov random network by treating the traffic state as a binary variable (congested or free flow). Kataoka et al. (2014) developed a traffic state estimation method using a Gaussian Markov random field model by treating variables such as travel time, average road link speed, and density as continuous. Wang et al. (2014) calculated link travel time and path travel time by tensor decomposition using a tensor constructed with road link set, driver set, and time. This approach requires individual path trajectory data. Sun et al. (2012) proposed the network-scale traffic forecasting method using graphical lasso and neural network.

Our approach focuses on network-wide traffic estimation using sparse probe data and it is similar to the approach of Furtlehner et al. and Kataoka et al. As the daily travel behavior of people is repetitive to some extent, the traffic state generated by these travel behaviors contains certain patterns and statistical properties. Therefore, even if there are many unobserved road links in the network, the statistical model learned from real data can infer the network-wide traffic state, solving the first problem. Furtlehner et al. and Kataoka et al. had assumed a simple relationship between connected road links and Kataoka et al. had used a Gaussian graphical model as a generative model. In contrast, we propose a mixture Gaussian graphical model (mixture GGM) using a mixture of multivariate normal distribution and assume a complex relationship between road links. Our approach can estimate the complex relationship reasonably from observed data using the graphical lasso method and it can achieve a higher accuracy of network-wide traffic estimation than the existing methods. The difference between Sun et al. (2012) and our approach is that the objective of our approach is the interpolation of unobserved road links and we propose the mixture GGM which can express traffic states more flexibly. Using historical observed data for estimating model parameters, our method can interpolate the traffic state of unobserved road links from partially observed real time data. By applying the model to the Bangkok city center in Thailand and Fujisawa city in Japan, we confirmed that the model can estimate the unobserved link speed quite reasonably.

Our key contributions are as follows:

- We obtain the missing values of traffic state in the road network by interpolation. The interpolation is executed using both a statistical model learned by historical data and partially observed data at that time. In addition, the parameter estimation of the statistical model requires only partially observed historical data because of the use of the EM algorithm (Dempster et al., 1977).
- We propose a mixture GGM as a generative model, which is a flexible model because it consists of a mixture of multivariate normal distributions. The existing method uses GGM and can express only a single peak distribution, whereas the mixture GGM can express more complicated distributions. The mixture ratio can be implicitly interpreted as the shift of the traffic state within a day.
- The covariance matrices of our mixture GGM are more complex than those of the existing methods. The existing methods assume that connected road links are related but the other pairs of road links are conditionally independent. This assumption is too strong to express the traffic state in a road network. The number of parameters in the covariance matrix is enormous and the amount of observed data may not be sufficient. In our method, the covariance matrix of each GGM can be estimated by the graphical lasso method (Friedman et al., 2008; Banerjee et al., 2008), which can extract the complexity of the covariance matrices efficiently from small sample data.
- We evaluate the accuracy of our method with real probe data in both a developed country and a developing country. The accuracy of our method is shown to be higher than those of the existing methods.