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Short communication

Tensor based missing traffic data completion with spatial–temporal correlation

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HIGHLIGHTS

- We use tensor pattern to fully cover the spatial–temporal correlation of corridor freeway traffic volume.
- Various tensor patterns are tested on the traffic volume data collected from PeMS open database.
- We suggest that the tensor based method with spatial correlation achieves better performance than that without spatial information.
- The experimental results show that the proposed method can address the extreme case where the data of a long period of one or several weeks are completely missing.

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ABSTRACT

Missing and suspicious traffic data is a major problem for intelligent transportation system, which adversely affects a diverse variety of transportation applications. Several missing traffic data imputation methods had been proposed in the last decade. It is still an open problem of how to make full use of spatial information from upstream/downstream detectors to improve imputing performance. In this paper, a tensor based method considering the full spatial–temporal information of traffic flow, is proposed to fuse the traffic flow data from multiple detecting locations. The traffic flow data is reconstructed in a 4-way tensor pattern, and the low-n-rank tensor completion algorithm is applied to impute missing data. This novel approach not only fully utilizes the spatial information from neighboring locations, but also can impute missing data in different locations under a unified framework. Experiments demonstrate that the proposed method achieves a better imputation performance than the method without spatial information. The experimental results show that the proposed method can address the extreme case where the data of a long period of one or several weeks are completely missing.

1. Introduction

With the steady increase in travel demand, urban freeways worldwide have experienced increased congestion, but the problem can no longer be addressed by building new highways for economical and environmental reasons [1]. As a consequence, the optimization of existing traffic network [2] has increasingly become a more desirable alternative to the management of traffic congestion. Intelligent transportation systems (ITS) play a significant role in optimizing the existing

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transportation networks. As a key input for ITS, real-time collected traffic data enable the optimization of transportation networks, ITS applications such as route planning and driver assistance systems [3]. With the development of data collection technology, traffic data that collected from multiple sources such as loop detectors, GPS and video sensors become more and more important in ITS [4–6].

Unfortunately, missing data problems are inevitable due to detector faults or transmission distortion [7,8], which seriously restricts the application and generalization of intelligent transportation system. For example, the traffic control system requires sufficient traffic flow data (i.e., traffic volumes, occupancy rates, and flow speeds) to generate appropriate traffic management strategies [9]. In traffic forecast areas, if there exists missing data, the predicting performance will reduce sharply [10,11]. Without proper imputation methods, traffic counts with missing values are usually either discarded or simply estimated, which may seriously affect the performance of ITS. Consequently, it is urgent to develop a method of better effect on estimating the missing data.

A considerable amount of literature has been published on missing traffic data imputation. These studies to date have tended to focus on missing traffic data imputation with temporal correlations rather than imputation with global information. For example, Smith et al. [12] studied several temporal imputation methods such as Historical Average and Average of Surrounding Time Periods. They concluded that missing traffic data could be imputed by sophisticated statistical techniques using global information. Zhong et al. [13,14] modeled traffic data of a single location as time series and then impute missing data based on the relationship identified from historical past-to-future data pairs. Ni and Leonard [15] use a Bayesian network to learn the temporal correlations encoded within traffic variables to solve the incomplete ITS data issue. Qu et al. [16] propose PPCA-based imputation method makes use of daily periodicity and interval variation for traffic flow volume data incompleteness. Tan et al. [17] developed a RPCA-based imputation method that not only utilizes the temporal correlation, but also considers the physical limitation of traffic data. While all the previously mentioned imputation approaches are powerful and useful methods in some special cases, a serious weakness of these methods, however, is that they do not cover the spatial information of traffic data. Another problem with these approaches is that they could not impute missing data from a different location in a unified framework.

The recent missing traffic data imputation studies have shown that spatial information could help reduce estimation errors. Zhang and Liu [18] demonstrated that making good use of the spatial and temporal information greatly helps the data imputation based on SVM. Yin et al. [19] analyzed and compared temporal and spatial Interpolation-based imputation methods and found that spatial method is robust under various conditions. Li et al. [20] have showed that spatial information could help reduce imputing errors significantly for PPCA and KPPCA methods. Recent evidences of traffic prediction area also suggest that spatial information is helpful for short-term traffic prediction [21,22]. However, most studies in the field of missing data imputation have only focused on utilizing spatial information for single point missing data imputation in transportation networks. Few studies have been able to draw on the development of unifying missing data imputation method for multiple detecting locations in transportation networks. Most studies have only been carried out by using information from a limited number of locations (upstream and downstream). Thus, the modeling and fusion of spatial correlation requires stronger mathematical tools.

Recently, tensor (multi-way array) based methods [23–27] have been introduced to traffic data processing. The tensor based methods construct traffic data into multi-way matrices to accurately capture the underlying multi-mode structure (day, week, time and space mode) of traffic data. For example, the global information of traffic data can be simultaneously taken into account by the $day \times week \times time \times space$ tensor pattern [23]. Then the missing data within the tensor can be solved by tensor completion algorithm, which takes advantage of the global property of the data. Compared with traditional imputation methods, the tensor based method can combine and utilize more multi-mode correlations. Consequently, the tensor completion method is more accurate and robust. Despite the success achieved by tensor based imputation methods, however, there has been limited in-depth discussion about the use of spatial information to upgrade imputation performance.

To date, various methods have been developed and introduced to the tensor completion. As tensor decomposition gives a concise representation of the underlying structure of the tensor [28], a variety of tensor decomposition based methods are applied to the tensor completion. For instance, Acar et al. [29] proposed a method based on CANDECOMP/PARAFAC decomposition. Since CANDECOMP/PARAFAC decomposition is a special case of Tucker decomposition, numerous Tucker decomposition based methods [23,30,31] have been proposed. For low-rank matrix completion, the nuclear norm was used as a convex envelop for the rank function [32]. Generalizing this program to tensor case, the tensor nuclear norm is defined as the weighted sum of unfolding modes of tensors and applied to the tensor completion [33,34]. The previous studies show that the nuclear-norm based methods outperform tensor decomposition based methods particular to high-rank problem and high missing ratio [34]. The goal of this paper is to apply the tensor completion for imputing missing data on multiple locations on a unified framework. The framework uses the spatial information to upgrade missing data imputation performance under the tensor completion. Considering the missing ratio is high in some special cases, and traffic data could not be approximated as a very low-rank tensor due to its intrinsic characteristics [17]. The nuclear-norm based method—HaLRTC [34] is selected in this paper.

This paper is organized as follows: The Related tensor completion backgrounds are provided in Section 2. Theoretic background of the method is presented in Section 3. Various tensor models for a freeway corridor is conducted and analyzed in Section 4. In Section 5, the experiment results are given. The conclusion and future works are discussed in Section 6.