A Novel Method for Missing Data Estimation in Intelligent Internet of Vehicles: Postprint

Authors: Zhang De-gan, Zhang Ting, Gao Jinxin

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Abstract

Intelligent vehicle networking obtains information regarding traffic conditions through data collected from extensive ground sensors. The collected data typically exhibits irregular spatial and temporal resolution, and data loss constitutes a common challenge in intelligent vehicle networking. In view of this, the missing data problem in large-scale and diverse vehicle networks is addressed. By extracting public traffic patterns from intelligent vehicle networking and comparing the merits of methods such as function estimation and tensor decomposition for estimating these missing values, a novel tensor low-rank approximation estimation method is proposed. This method acquires traffic patterns under missing data conditions, yielding a low-rank representation of large-scale vehicular road networks. Experimental testing across diverse road vehicle networks demonstrates that the proposed method achieves favorable performance in terms of estimation accuracy and dataset bias.

Full Text

Preamble

A Novel Approach for Missing Data Estimation in Intelligent Internet of Vehicles

Zhang Degang[1,2], *Zhang Ting*[1,2]†, *Gao Jinxin*[1,2]

[1]Key Laboratory of Computer Vision & System, Ministry of Education
[2]Tianjin Key Laboratory of Intelligent Computing & Novel Software Technology
School of Computer Science & Engineering, Tianjin University of Technology, Tianjin 300384, China

Abstract: Intelligent Internet of Vehicles (IIOV) gathers traffic information through extensive ground-based sensor networks, yet the collected data often exhibit irregular spatial and temporal resolutions, making data loss a pervasive challenge. This paper addresses the missing data problem in large-scale and heterogeneous vehicular networks. By extracting common traffic patterns from intelligent IIOV systems and comparing the effectiveness of functional estimation and tensor decomposition approaches, we propose a novel tensor low-rank approximation method (VBPCA) that captures traffic patterns under missing data conditions and obtains low-rank representations of large-scale road networks. Experimental tests across diverse road networks demonstrate that the proposed method achieves superior performance in estimation accuracy and dataset bias reduction.

Keywords: Internet of Vehicles (IOV); intelligent; data loss; estimation; bias

0 Introduction

Missing data percentages in traffic datasets can reach as high as 90% [13], posing a critical challenge for traffic management systems [14-16]. With advances in sensor technology, intelligent IIOV can now collect traffic data from a wide range of fixed and mobile sensors [1-3]. Fixed sensors such as loop detectors and roadside cameras have limited spatial coverage, while mobile sensors like GPS probes produce data with highly unstable spatial and temporal resolutions. These issues inevitably lead to data loss in traffic datasets. Furthermore, failures such as detector malfunctions and lossy communication systems can result in incomplete traffic information [4-8], potentially causing high proportions of missing data. Consequently, missing data represents a common problem in traffic datasets [9-12], with various studies reporting loss rates of up to 90%.

Existing approaches for addressing missing data fall into two categories: functional estimation and matrix/tensor completion. Functional estimation methods typically assume the missing data problem is localized to certain known links and time intervals, enabling the use of historical data to derive relationship functions between target roads and their neighbors or historical counterparts. For instance, studies [17,18] utilized historical data to model relationships between adjacent loop detectors, using these functions to impute missing values from faulty detectors. References [19,20] trained neural networks leveraging temporal features for missing value estimation, while [21-23] employed similar approaches using least squares support vector machines. However, functional estimation techniques require complete historical data to build relationship models, rendering them ineffective when historical data itself contains missing values —a common scenario in practice.

In contrast, matrix and tensor completion methods do not require training data for imputation, making them increasingly popular in transportation research. These methods exploit the observation that traffic states on adjacent roads tend to be strongly correlated [24-26], implying that road networks can be represented using low-dimensional models. Matrix and tensor completion approaches leverage these patterns to estimate missing values by obtaining appropriate low-rank approximations of incomplete tensors or matrices. Nevertheless, previous studies on matrix/tensor completion for traffic data have primarily focused on data from a few roads or intersections. For example, [24-26] applied Bayesian Principal Component Analysis (BPCA) to impute traffic flow data, analyzing a small network of 100 roads. Similarly, [8-13] used tensor decomposition for missing data imputation, constructing 3D tensors from four road segments and their representative data.

Urban-scale networks also exhibit certain common global traffic patterns. While limited in scope, some studies [21-26] have addressed missing data in large networks, though they did not analyze algorithm performance across different road types (highways, arterials, roads) or different days within a week or half-month. Moreover, they did not examine the bias and variance of imputed traffic data. In summary, functional estimation methods are limited in large networks due to their reliance on uncorrupted historical data, while previous matrix/tensor completion studies have typically considered only one or a few intersections. These studies generally do not analyze performance across different road types and days of the week, nor do they consider the effects of variance, bias, and the rank of low-dimensional models on imputation performance.

To overcome these limitations, this paper extends missing data imputation to large-scale road networks encompassing highways, arterial roads, secondary arterials, and branch roads. We propose a novel tensor low-rank approximation method (VBPCA) that extracts global traffic patterns from incomplete data. The performance of VBPCA is compared against weighted least squares (LS) and fixed-point continuation approximate singular value decomposition (FPCA). We analyze the performance of these methods across different road categories and days of the week, as well as their variance and bias in estimating speed data. Experimental results across various road networks demonstrate that the proposed method achieves favorable performance in estimation accuracy and dataset bias.

The main contributions are as follows: (1) For the missing data problem in large-scale intelligent IIOV systems, we propose a tensor low-rank approximation method (VBPCA) that extracts traffic patterns under missing data conditions to obtain low-rank representations of large-scale road networks, after comparing functional estimation and tensor decomposition approaches. (2) Results show the algorithm’ s performance is insensitive to daily variations in traffic data, and the method demonstrates superior performance in weighted relative error (WE), mean square error (MSE), variance (V), and bias (B).

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1 Vehicle Network Dataset and Performance Metrics

For the vehicle network dataset, we represent a test road network of size p using a set of road segments $\{s_i\}_{i=1}^{p} = \mathcal{E}$. In this study, we consider average speed data, where $\bar{s}_i(t)$ denotes the average speed on link s_i during interval t. The sampling interval Δt is 3 minutes. For each link s_i, we create a speed profile $\mathbf{s}_i = [\bar{s}_i(t_1), \bar{s}_i(t_2), ..., \bar{s}_i(t_n)]^T \in \mathbb{R}^n$, which contains daily speed data for each link. From these speed profiles, we obtain the network configuration matrix $\mathbf{A} \in \mathbb{R}^{p\times n}$, where $\mathbf{D} \in \mathbb{R}^{p\times n}$ is the corresponding incomplete observation data matrix. The set $\Omega \subseteq [p] \times [n]$ indexes positions where speed data is available, while set $\Theta \subseteq [p] \times [n]$ indexes positions with missing speed values.

For tensor-based approaches, we create a network configuration tensor $\mathcal{A} \in \mathbb{R}^{p\times n\times q}$ by stacking network configuration matrices $\{\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_q\}$ from different days to form a 3D tensor. Here, q represents the number of days, with $7 \leq q \leq 14$ in our analysis. The corresponding incomplete data tensor is $\mathcal{D} \in \mathbb{R}^{p\times n\times q}$.

Performance Evaluation Metrics

For matrices, we define the Weighted Relative Error (WE) between actual $\mathbf{A}$ and estimated $\hat{\mathbf{A}}$ across the network distribution:

$$\text{WE} = \frac{\|\mathbf{W} \circ (\mathbf{A} - \hat{\mathbf{A}})\|_F}{\|\mathbf{W} \circ \mathbf{A}\|_F}$$

where $\circ$ denotes element-wise multiplication between matrices. The weight matrix $\mathbf{W} \in \mathbb{R}^{p\times n}$ is defined as:

$$w_{ij} = \begin{cases} 1 & \text{if } (i,j) \in \Omega \\ 0 & \text{if } (i,j) \in \Theta \end{cases}$$

The Frobenius norm $\|\mathbf{A}\|_F$ is defined as $\|\mathbf{A}\|_F = \sqrt{\sum_{i=1}^{p} \sum_{j=1}^{n} a_{ij}^2}$. Similarly, WE for tensors is defined as:

$$\text{WE} = \frac{\|\mathcal{W} \circ (\mathcal{A} - \hat{\mathcal{A}})\|_F}{\|\mathcal{W} \circ \mathcal{A}\|_F}$$

where $\mathcal{W} \in \mathbb{R}^{p\times n\times q}$ is the weight tensor:

$$w_{ijk} = \begin{cases} 1 & \text{if } (i,j,k) \in \Omega \\ 0 & \text{if } (i,j,k) \in \Theta \end{cases}$$

The Frobenius norm for tensors is $\|\mathcal{A}\|_F = \sqrt{\sum_{i=1}^{p} \sum_{j=1}^{n} \sum_{k=1}^{q} a_{ijk}^2}$.

Weighted relative error is commonly used to evaluate matrix and tensor completion algorithms. We also calculate the Mean Square Error (MSE) of estimation algorithms:

$$\mathrm{MSE}_{\mathrm{mat}} = \frac{1}{|\Theta|} \sum_{(i,j)\in\Theta} (a_{ij} - \hat{a}_{ij})^2$$

$$\mathrm{MSE}_{\mathrm{ten}} = \frac{1}{|\Theta|} \sum_{(i,j,k)\in\Theta} (a_{ijk} - \hat{a}_{ijk})^2$$

where $|\Theta|$ represents the size of set Θ.

The bias in estimated speed data is calculated as:

$$\mathrm{Bias}_{\mathrm{mat}} = \frac{1}{|\Theta|} \sum_{(i,j)\in\Theta} (a_{ij} - \hat{a}_{ij})$$

$$\mathrm{Bias}_{\mathrm{ten}} = \frac{1}{|\Theta|} \sum_{(i,j,k)\in\Theta} (a_{ijk} - \hat{a}_{ijk})$$

Additionally, the variance of estimates is computed as:

$$\mathrm{Var}_{\mathrm{mat}} = \frac{1}{|\Theta|} \sum_{(i,j)\in\Theta} (a_{ij} - \hat{a}_{ij} - \mathrm{Bias}_{\mathrm{mat}})^2$$

$$\mathrm{Var}_{\mathrm{ten}} = \frac{1}{|\Theta|} \sum_{(i,j,k)\in\Theta} (a_{ijk} - \hat{a}_{ijk} - \mathrm{Bias}_{\mathrm{ten}})^2$$

where $\hat{a}_{ij}$ and $\hat{a}_{ijk}$ represent the averages defined in equations (11) and (12) respectively.

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2 New Method for Missing Data Estimation

This section discusses the least squares (LS) and fixed-point continuation approximate singular value decomposition (FPCA) methods for recovering missing speed information from incomplete matrices, then designs a novel missing data estimation approach called VBPCA.

2.1 Least Squares Method (LS)

In an interconnected network, traffic parameters such as speed tend to exhibit similar patterns. We leverage these underlying patterns to recover missing speed information in incomplete matrix **D**. To complete the network configuration matrix **A**, we apply Principal Component Analysis (PCA) to obtain a low-rank approximation (rank r) from **A**:

$$\mathbf{A} \approx \hat{\mathbf{A}} = \mathbf{M} + \mathbf{W}\mathbf{X}$$

where $\mathbf{M} \in \mathbb{R}^{p \times n}$ and $\mathbf{W} \in \mathbb{R}^{p \times r}$, $\mathbf{X} \in \mathbb{R}^{r \times n}$ are low-rank matrices, and $\mathbf{m} \in \mathbb{R}^{n}$ contains the row means of $\mathbf{A}$. This decomposition is obtained by solving the following least squares optimization problem:

$$\min_{\mathbf{W},\mathbf{X}} \sum_{i=1}^{p} \sum_{j=1}^{n} (a_{ij} - \hat{a}_{ij})^2 \quad \text{subject to} \quad \mathbf{w}_i^T \mathbf{w}_i = 1$$

where vectors $\mathbf{w}_i$ are constrained to remain orthogonal. For incomplete matrix $\mathbf{D}$, the problem can be reformulated to minimize reconstruction error using only observed speed data a_{ij} for $(i,j) \in \Omega$:

$$\min_{\mathbf{W},\mathbf{X}} \sum_{(i,j)\in\Omega} (a_{ij} - \hat{a}_{ij})^2 \quad \text{subject to} \quad \mathbf{w}_i^T \mathbf{w}_i = 1$$

where $\hat{a}_{ij} = \mathbf{m}_j + \mathbf{w}_i^T \mathbf{x}_j$ represents the speed value at road segment i and time j.

2.2 Fixed-Point Continuation Approximate SVD (FPCA)

This section discusses an alternative approach for estimating missing traffic information. Our objective is to exploit common traffic behaviors across different roads to recover missing speed values in incomplete data matrix $\mathbf{D}$. We seek a suitable low-rank matrix $\hat{\mathbf{A}}$ that approximates the incomplete speed data while preserving speed information available in $\mathbf{D}$ within a certain tolerance limit ϵ, such that $|d_{ij} - \hat{a}_{ij}| < \epsilon$ for $(i,j) \in \Omega$. This leads to the following optimization problem:

$$\min_{\hat{\mathbf{A}}} \operatorname{rank}(\hat{\mathbf{A}}) \quad \text{subject to} \quad |d_{ij} - \hat{a}_{ij}| < \epsilon, \forall (i,j) \in \Omega$$

However, this is a non-convex NP-hard problem. To make it tractable, we replace $\operatorname{rank}(\hat{\mathbf{A}})$ with its convex envelope, which is the nuclear norm $\|\hat{\mathbf{A}}\|_*$ for matrix estimation. The problem in (15) can thus be rewritten as:

$$\min_{\hat{\mathbf{A}}} \|\hat{\mathbf{A}}\|_* \quad \text{subject to} \quad |d_{ij} - \hat{a}_{ij}| < \epsilon, \forall (i,j) \in \Omega$$

where the nuclear norm of a rank-r matrix $\hat{\mathbf{A}}$ is defined as $\|\hat{\mathbf{A}}\|_* = \sum_{i=1}^{r} \sigma_i$, with σ_i being the i-th singular value. We employ the Fixed-Point Continuation Approximate SVD (FPCA) to solve this optimization problem defined in (16).

2.3 Novel Missing Data Estimation Method (VBPCA)

Building upon the discussion of LS and FPCA methods for completing missing speed information, this section designs a novel missing data estimation approach called VBPCA (Tensor Low-Rank Approximation Estimation Method). While matrix completion methods can extract underlying traffic patterns, they cannot effectively exploit multi-way dependencies in traffic datasets. For instance, consider traffic behavior across different times of the week—traffic parameters like speed tend to follow similar daily patterns. We can more effectively extract these temporal relationships by creating a multi-way structure of traffic data.

We represent speed data as a 3D tensor $\mathcal{A} \in \mathbb{R}^{p\times n\times q}$, formed by stacking network configuration matrices $\{\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_q\}$ obtained from different days. The CANDECOMP/PARAFAC (CP) decomposition is commonly used to obtain a low-rank approximation of tensors. For incomplete tensor configuration $\mathcal{D}$, we can minimize the reconstruction error of observed speed data to obtain a suitable low-rank approximation $\hat{\mathcal{A}}$:

$$\min_{\hat{\mathcal{A}}} \|\mathcal{W} \circ (\mathcal{D} - \hat{\mathcal{A}})\|_F^2$$

where $\hat{\mathcal{A}} = \sum_{i=1}^{r} \mathbf{b}_i^{(1)} \circ \mathbf{b}_i^{(2)} \circ \mathbf{b}_i^{(3)}$, with $\mathbf{b}_i^{(m)}$ being the i-th column vector of the factor matrix $\mathbf{B}^{(m)}$. In equation (17), $\circ$ denotes vector outer product, while $\circ$ represents element-wise multiplication between tensors. The factor matrices $\mathbf{B}^{(1)}$, $\mathbf{B}^{(2)}$, and $\mathbf{B}^{(3)}$ contain common traffic patterns across different modes of the tensor, including public traffic behaviors across different days and roads.

We apply CP-weighted optimization (CP-OPT) to obtain a suitable estimate $\hat{\mathcal{A}}$ from incomplete network configuration tensor $\mathcal{D}$. To study the multi-way characterization effects on imputation performance, we create another network configuration matrix $\mathbf{U} \in \mathbb{R}^{pq\times n}$ by unfolding the tensor. This network configuration matrix $\mathbf{U}$ is essentially the unfolded representation of tensor $\mathcal{A}$. The corresponding incomplete data matrix $\mathbf{D}_u$ is represented similarly. By minimizing the reconstruction error of observed speed data, we obtain a low-rank approximation $\hat{\mathbf{U}}$ of the incomplete speed data $\mathbf{D}_u$:

$$\min_{\hat{\mathbf{U}}} \|\mathbf{W}_u \circ (\mathbf{D}_u - \hat{\mathbf{U}})\|_F^2$$

Thus, using CP-OPT to obtain the estimated network distribution matrix $\hat{\mathbf{U}}$, this method is called the Tensor Low-Rank Approximation Estimation Method (VBPCA).

Based on the above analysis, the steps of the VBPCA algorithm can be described as follows:

a) **Initialize parameters**: Represent the test road network of size p using a fixed set of road segments $\{s_i\}_{i=1}^{p} = \mathcal{E}$. Let $\bar{s}_i(t)$ denote the average speed on link s_i during interval t. Set sampling interval $\Delta t = 5$ minutes. For each link s_i, create a speed profile $\mathbf{s}_i$ containing daily speed data.

b) **Calculate relevant vectors** from the speed profiles.

c) **Collect data**: Gather relevant parameter data (speed, time, road, vehicle count, etc.) from different road types (highways, arterials, secondary roads, etc.) on different dates via vehicular sensor networks to obtain dataset $\mathcal{D}$. Extract network configuration matrix $\mathbf{A}$ from the dataset, where $\mathbf{D}$ represents the corresponding incomplete observation data matrix.

d) **Process tensors and norms**: Use equations (1)-(6) to process tensors and norms, equations (7)-(8) to compute root mean square error, and equations (9)-(12) to compute variance of estimates.

e) **Reconstruct and optimize**: Based on equation (17), process reconstruction error of observed speed data to obtain a suitable low-rank approximation $\hat{\mathcal{A}}$. Apply CP-OPT to obtain appropriate estimate $\hat{\mathcal{A}}$ from incomplete network configuration tensor $\mathcal{D}$.

f) **Obtain low-rank approximation**: Using equation (18), obtain low-rank approximation $\hat{\mathbf{U}}$ of incomplete speed data $\mathbf{D}_u$ to derive the estimated network distribution matrix $\hat{\mathbf{U}}$.

g) **Evaluate and iterate**: Based on the test dataset, evaluate the weighted relative error of missing data considering different numbers of latent factors (rank) and different road networks across various days. If the missing data estimation accuracy error is within the predetermined tolerance range, terminate the estimation process; otherwise, return to step b) for another iteration until requirements are met.

The algorithm steps can be described in pseudocode as:

1. Set $\Delta t = 300$s
2. Extract $\mathbf{A}$ from $\mathcal{D}$
3. Calculate WE, $\|\mathbf{A}\|_F$, MSE, Bias, Variance using equations (1)-(12)
4. Obtain $\hat{\mathcal{A}}$ via CP-OPT
5. Obtain $\hat{\mathbf{U}}$ using equation (18)
6. If error $E < \delta$ then exit; else go to step 2.

3 Testing and Discussion

For large amounts of missing data, reconstruction errors of these algorithms can vary significantly based on the choice of rank. Moreover, performance fluctuations are more pronounced on arterial roads compared to highways (see Figures 1 and 2). The colors and numerical values in the right-side graphs of Figures 1 and 2 represent weighted relative error (with the same meaning as the vertical axis in Figure 3). More frequent color changes or darker colors indicate more significant performance fluctuations and larger relative errors. On the other hand, reconstruction errors for FPCA and VBPCA do not change substantially at different rank values.

The results show that the proposed VBPCA method can automatically select the optimal number of factors and estimate missing values in incomplete data matrices **D**. Figures 1(c) and 2(c) illustrate that VBPCA' s rank value represents the upper limit on the maximum number of factors that can be used to reconstruct the estimated network distribution matrix. Given this, we conclude that even when appropriate critical rank values are unavailable, VBPCA does not overfit.

This section discusses how the selection of rank (number of latent factors) affects algorithm performance. Figure 1 [Figure 1: see original paper] shows the variation in reconstruction performance caused by different rank selections for speed data obtained from the Beijing-Tianjin Expressway. Figure 2 [Figure 2: see original paper] displays these variations for speed data from the Beijing-Tianjin arterial road. We discuss the performance of three algorithms—LS, FPCA, and VBPCA—in attempting to extract common patterns from observed speed information through MSE minimization.

The analysis reveals that for large missing data percentages, reconstruction errors vary significantly with rank selection. The performance fluctuation is more notable on arterial roads than highways. The VBPCA method automatically selects optimal factor numbers and estimates missing values without overfitting, even when critical rank thresholds are unavailable.

Figure 3 [Figure 3: see original paper] shows the imputation errors of LS, FPCA, and VBPCA at different times during a week. The results present speed data for different road categories with 70% missing data. For highways, VBPCA achieves lower weighted relative error compared to other methods during most time periods. As expected, VBPCA yields the lowest overall estimation error for highway speed data. For arterial roads, all three methods show similar performance during most periods, though FPCA and LS exhibit larger estimation errors at certain times. VBPCA' s estimation performance varies insignificantly from day to day. Similar trends are observed for expressways. For primary and secondary local roads, all three methods produce larger imputation errors, though VBPCA' s errors are the smallest.

The phenomenon where VBPCA is not always optimal on certain dates occurs because reconstructed data contains noise or redundancy, causing some perturbation in imputation performance during noise/redundancy removal. This is normal and within acceptable error tolerance. We conclude that VBPCA' s imputation performance demonstrates stronger robustness compared to LS and FPCA under conditions of daily traffic variation.

Table 1 shows the bias introduced by various methods in recovering speed data, with bias units in km/hr. Results indicate that in all test cases, when bias values are less than 1, the proposed algorithms do not add significant bias to estimated data. However, FPCA and LS produce slightly higher bias (0.5 km/hr) compared to other methods. Values in parentheses represent percentage changes of estimated speed data relative to actual speed data. The table also shows actual speed data variance. As expected, imputation algorithms underestimate the variance of estimated data. For example, actual variance of highway speed data is approximately 149 $(km/hr)^2$, while variance from different imputation methods ranges from 90-120 $(km/hr)^2$. Furthermore, as the missing data percentage increases, the difference between actual and expected speed data variance becomes larger. For highways, VBPCA provides the best variance estimation. For other road types like arterials, expressways, secondary roads, and alleys, VBPCA' s estimated data variance is closest to actual speed data variance.

These results can be analyzed as follows: LS, FPCA, and VBPCA all attempt to reduce the sum of squared reconstruction errors of observed speed data to fill missing values. Among least squares-based methods, multi-way representation (tensor methods) tend to achieve optimal performance. Moreover, for arterials and interchanges, multi-way representation achieves better imputation accuracy than other methods like FPCA and VBPCA. However, for highways, the advantages of multi-way representation are less pronounced. Tensor representation appears more useful for local roads where traffic behavior is more volatile. In such cases, the multi-way representation of speed data serves as an effective means to extract underlying traffic patterns.

We analyzed the performance of relevant methods across various road networks, first examining different imputation methods' performance over a week. Figure 3 shows the imputation accuracy for different road types. In highway scenarios, VBPCA achieves the lowest weighted relative error, followed by FPCA. Highway imputation errors are lower than all other road categories across algorithms. For primary and secondary arterials, VBPCA provides better performance than other methods. For branch roads, VBPCA also achieves superior performance. In urban alley scenarios, all relevant algorithms exhibit larger imputation errors, but VBPCA' s errors are minimal.

The results demonstrate that VBPCA' s performance is highly sensitive to rank selection compared to LS and FPCA. However, because VBPCA' s performance is least sensitive to daily variations, it is particularly useful for imputing traffic datasets. Additionally, it provides better performance than other algorithms across different road categories.

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Note: Figure translations are in progress. See original paper for figures.