doi:10.3788/gzxb20144307.0706014

基于网络层析成像的光网络流量矩阵估计方法

蒋定德,秦文达,唐庆怡,聂来森,张健
(东北大学 信息科学与工程学院,沈阳 110819)

摘　要:提出一种面向光传输网络的流量矩阵估计方法.采用压缩感知理论研究光传输网络中的流量矩阵估计,根据信号稀疏表示将流量矩阵稀疏化,基于矩阵变换理论提出新的面向光传输网络的网络层析成像模型.该模型克服了已有网络层析成像模型的病态特性,并通过凸优化来获得流量矩阵的估计等式.提出了具体的估计算法,获得关于光传输网络流量矩阵的精确估计.真实网络的数据仿真表明所提出的方法是有效和可行的.

关键词:流量矩阵;光网络;凸优化;网络层析成像;压缩感知

中图分类号:TP393　　**文献标识码**:A　　**文章编号**:1004-4213(2014)07-0706014-5

An Estimation Approach to Traffic Matrix in Optical Networks Based on Network Tomography

JIANG Ding-de, QIN Wen-da, TANG Qing-yi, NIE Lai-sen, ZHANG Jian
(*College of Information Science and Engineering, Northeastern University, Shenyang* 110819, *China*)

Abstract: A traffic matrix estimation approach for optical transportation networks was proposed. Compressive sensing theory was used to study traffic matrix estimation in optical transportation networks. According to the sparse representation of signals, traffic matrix was processed in the sparse way. Matrix transform theory was exploited to present a new network tomography model for optical transportation networks. This model can overcome the ill-posed nature of the existing network tomography. Conex optimization was used to attain the estimation equation about traffic matrix. The detailed estimation algorithm is presented. The accurate estimation about traffic matrix for optical transportation networks was obtained. The data from the real network was used to perform the simulation. Simulation results show that the proposed method is effective and feasible.

Key words: Traffic matrix; Optical network; Convex optimization; Network tomography; Compressive sensing

OCIS Codes: 060.4256; 060.4251; 060.4258; 060.1155

0 Introduction

For an optical transportation network, its traffic matrix represents the amounts of traffic that flows between origin nodes to destination nodes (i. e. OD pairs)[1-5]. As an input parameter for network managements, it is really crucial for network operators, e. g. network operators can design their backbone network according to traffic matrix. In addition, optical layer traffic engineering remains the networks without congestion based on traffic matrix[6-9]. But achieving traffic matrix is significantly difficult. One of the most popular ways to estimate traffic matrix is network tomography. It estimates traffic matrix in terms of the

Foundation item: The National Natural Science Foundation of China (Nos. 61071124, 61172051), the Specialized Research Fund for the Doctoral Program of Higher Education (No. 20100042120035), the Program for New Century Excellent Talents in University (No. NCET-11-0075), the Fundamental Research Funds for the Central Universities (Nos. N120804004, N110404001)

First author: JIANG Ding-de (1974—), male, associate professor, Ph. D. degree, mainly focuses on network measurement and energy-efficient networks. Email: jiangdingde@ise.neu.edu.cn

Received: Oct. 22, 2013; **Accepted**: Jan. 27, 2014

linear relationship between link counts, routing matrix and traffic matrix[10-15]. Nevertheless, due to the ill-posed nature of this problem, traffic matrix estimation still has to face the several challenges.

Some researchers studied this problem and provided some methods to solve it. J. Cao et al.[12] presented an algorithm to estimate traffic matrix in a high speed network, which held the better estimation accuracy and used smaller memory and per packet update overhead. A compact probabilistic traffic digest at each network node was built and the traffic digests received at a central location was used to perform the quasi maximum likelihood estimation of traffic matrix. And this algorithm did not require prior knowledge of the packet size distributions. A. Soule et al.[14] evaluated the existing estimation methods about traffic matrix, studied the structure of traffic matrix in a network, used principal component analysis and pseudo-inverse to infer network tomography model. Y. Ohsita et al.[4] proposed a traffic matrix estimation method that exploited the cooperation with the virtual network topology reconfiguration to decrease estimation errors of traffic matrix. They divided the virtual network topology reconfiguration into multiple stages, and achieved the calibration of estimation errors in each stage by using information monitored in prior stages. These methods can solve network problem by different additional information.

This paper estimates traffic matrix in optical networks by solving a convex optimization problem based on network tomography. Firstly, we discuss the traffic matrix and network tomography model for optical networks. Then the idea of compressive sensing is exploited to modified network tomography method in order to attain the accurate estimation results of traffic matrix in optical networks. We focus on the assumptions in which the convex optimization has a single and optimal solution, and put forward a modified network tomography. Thirdly, an estimation method is proposed and its detailed steps are given. Finally, we use the real data from a backbone network to validate our approach. Simulation results show that our method is feasible and promising.

1 Problem statement

1.1 Traffic matrix

An optical network consists of IP routers and optical cross-connects (OXCs) (Fig. 1). Traffic matrices reveal the volume of traffic between edge routers in optical networks. If a backbone network consists of q nodes, and the number of OD pairs is $N=q^2$. In a traffic matrix, each row is a description of an OD pair. In this paper, we denote a traffic matrix by $\boldsymbol{M}$. It is a N by T matrix. In other words, it reports the traffic volume with T time slots. In practice, each entry of traffic matrix denotes the size of traffic during a specific time interval in the optical network.

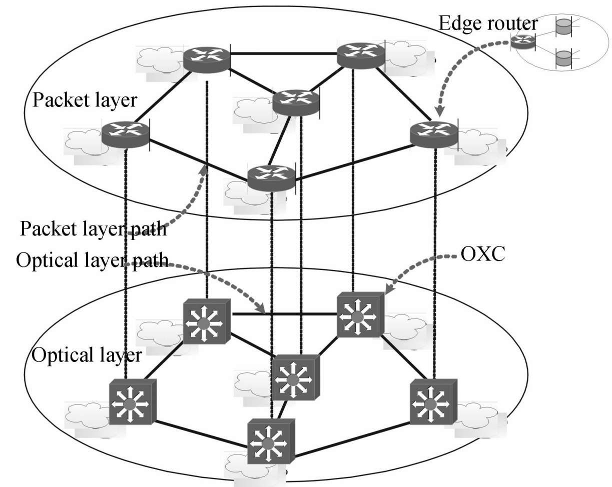

Fig. 1 Network tomography for optical networks

1.2 Network tomography model

Network tomography was used to find traffic matrix estimation[3-4]. It estimates traffic matrix by the following linear equation.

$$\boldsymbol{L}=\boldsymbol{A}\boldsymbol{M} \tag{1}$$

where $\boldsymbol{M}$ is traffic matrix, $\boldsymbol{L}$ represents link counts of packet layer paths in the optical network[4,6], $\boldsymbol{A}$ is routing matrix whose entries are 1 or 0. In this paper, assume that matrices $\boldsymbol{L}$ (where there exist H links in the network), $\boldsymbol{A}$ and $\boldsymbol{M}$ are $H\times T$, $H\times N$ and $N\times T$, respectively.

The link counts of an optical layer path can be obtained easily. Likewise, we can gain routing matrix through the status information and configuration files of the network. Generally speaking, the number of optical links is less than that of OD pairs, i. e. $H<N$[12]. It causes the ill-posed nature of the above linear system. Therefore how to overcome this ill-posed nature is the main challenge of network traffic estimation in optical networks. The general methods to solve this problem are to add some prior information about traffic matrix in the optical network. In our approach, we are to deal with it by means of the convex optimization.

2 Convex optimization and sparsity reconstruction

Currently, compressive sensing has received the extensive attention. This technology can sample original data with smaller sampling frequency. Meanwhile, the decoding algorithms can recover original data by solving convex optimization. Compressive sensing is modeled as[15]

$$\boldsymbol{y}=\boldsymbol{\Phi s} \tag{2}$$

where $\boldsymbol{s}$ is original data, $\boldsymbol{\Phi}$ is measurement matrix, and $\boldsymbol{y}$ is referred to as observed data. Without loss of generality, we assume that s is a N-dimensional vector in C^N, and in the meantime $\boldsymbol{y}$ and $\boldsymbol{\Phi}$ are $H\times 1$ and $H\times N$. For the encoding procedure, one needs to recover $\boldsymbol{s}$ when $\boldsymbol{y}$ and $\boldsymbol{\Phi}$ are already known. Obviously, the system denoted in Eq. (2) is also highly ill-posed and under-constrained as same as network tomography model in Eq. (1). The inference problem in Eq. (2) can be solved by ℓ_1 minimization represented in [15]

$$\hat{\boldsymbol{s}}=\operatorname{argmin}\|\boldsymbol{s}\|_1 \ s.t. \quad \boldsymbol{y}=\boldsymbol{\Phi s} \tag{3}$$

where $\|\cdot\|_1$ denotes ℓ_1-norm. Eq. (3) denotes a convex optimization. For the general reconstruction algorithms, there are two necessary assumptions in order to ensure overall reconstruction [16-18].

Assumption 1: Original data $\boldsymbol{s}$ should be sparse. It means that most of entries in $\boldsymbol{s}$ are zero. Specially, if the number of non-zero entries is K with $K\ll N$, $\boldsymbol{s}$ is called K-sparse.

Assumption 2: Measurement matrix $\boldsymbol{\Phi}$ needs to meet the following inequalities for any $3k$-sparse vector $\boldsymbol{v}$.

$$(1-\delta_{3k})\|\boldsymbol{v}\|_2\leqslant\|\boldsymbol{\Phi v}\|_2\leqslant(1+\delta_{3k})\|\boldsymbol{v}\|_2 \tag{4}$$

where $\delta_{3k}\in(0,\frac{1}{3})$ and notation $\|\cdot\|_2$ denotes ℓ_2-norm.

Assumption 2 is so-called Restricted Isometry Property (RIP). According to the above inequalities, it is significantly difficult to determine whether $\boldsymbol{\Phi}$ has RIP nature or not. Baraniuk et al. gave another way to prove the RIP nature of measurement matrices[18]. They used the concentration inequality to prove the RIP nature. Besides, it is useful to observe that the concentration inequality has unitary invariant property[16]. In other words, if assume $\boldsymbol{s}$ is not sparse and $\boldsymbol{s}=\boldsymbol{\Psi c}$, where $\boldsymbol{\Psi}$ is a data dictionary and $\boldsymbol{c}$ is coefficient vector with respect to this dictionary. Under this scenario, one can overall recover $\boldsymbol{s}$ when $\boldsymbol{c}$ is sparse, though $\boldsymbol{s}$ is not sparse. From previous work, the popular measurement matrices that obey RIP are Gaussian and Bernoulli matrices [16]. In this paper, we take advantage of Bernoulli matrix to produce our model.

3 Proposed estimation method

In our approach, we produce a novel network tomography model via Bernoulli random matrix denoted by

$$\boldsymbol{Y}=\boldsymbol{BC}(\gamma)\boldsymbol{AM}=\boldsymbol{\Theta M} \tag{5}$$

where $\boldsymbol{Y}=\boldsymbol{BC}(\gamma)\boldsymbol{L}$, $\boldsymbol{\Theta}=\boldsymbol{BC}(\gamma)\boldsymbol{A}$ and $\boldsymbol{B}$ is a $H\times H$ Bernoulli random matrix whose entries are independent and identically distributed (i. i. d). $\boldsymbol{C}(\gamma)$ is a $H\times H$ diagonal matrix whose diagonal entries are 1 or 0. Considering the properties of routing matrix $\boldsymbol{A}$, it is a deterministic matrix. Hence it is hard to construct a measurement matrix whose entries are i. i. d. In that case, $\boldsymbol{C}(\gamma)$ is used to decrease the coherence of matrix $\boldsymbol{\Theta}$. The goal of matrix $\boldsymbol{C}(\gamma)$ is to delete partial rows of routing matrix $\boldsymbol{A}$, since the coherence between the entries of $\boldsymbol{\Theta}$ dependents on ℓ_1-norm of the rows of routing matrix $\boldsymbol{A}$. So we delete γ rows of routing matrix with γ-largest ℓ_1-norms. And then measurement matrix $\boldsymbol{\Theta}$ is an random matrix with small correlation.

So far, we still can' t solve Eq. (5) by ℓ_1 minimization since each column of traffic matrix is not totally sparse at all. However, in general, traffic matrices in optical networks have a dimensional nature, thus we can find a data dictionary and a transform matrix with sparsity to describe the traffic matrix. We denote above procedure by

$$\boldsymbol{M}=\boldsymbol{DX} \tag{6}$$

where $\boldsymbol{D}$ and $\boldsymbol{X}$ are data dictionary and transform coefficient matrix. In our method, we utilize partial history traffic data as training set. KSVD[19] is used to obtain a dictionary denoted by $\boldsymbol{D}'$. According to Eqs. (5) and (6), the following equation holds

$$\boldsymbol{Y}=\boldsymbol{\Theta DX} \tag{7}$$

And then we take advantage of $\boldsymbol{D}'$ to replace $\boldsymbol{D}$, and the following equation can be attained

$$\boldsymbol{Y}=\boldsymbol{\Theta D}'\boldsymbol{X} \tag{8}$$

For a moment, the following equation is deduced:

$$\boldsymbol{y}_t=\boldsymbol{\Theta D}'\boldsymbol{x}_t, t=1,2,\ldots,T \tag{9}$$

where $\boldsymbol{y}_t$ and $\boldsymbol{x}_t$ are columns of matrices $\boldsymbol{Y}$ and $\boldsymbol{X}$, respectively. Due to the low-dimensional nature of traffic matrix of optical network, $\boldsymbol{x}_t$ is sparse. Then the system showed in Eq. (9) obeys the assumptions 1 and 2. We can calculate $\boldsymbol{x}_t$ by tackling the ℓ_1 minimization

$$\hat{\boldsymbol{x}}_t=\operatorname{argmin}\|\boldsymbol{x}_t\|_1 \quad s.t. \quad \boldsymbol{y}_t=\boldsymbol{\Theta D}'\boldsymbol{x}_t \tag{10}$$

Up to now, we have formulated our method in detail. As described above, the following is to give the detailed steps of our method:

Step 1: Initiate γ and the training set;

Step 2: Cut history traffic as training set;

Step 3: Enable KSVD algorithm to produce $\boldsymbol{D}'$;

Step 4: Generate Bernoulli random matrix;

Step 5: Build $\boldsymbol{C}(\gamma)$ according to routing matrix;

Step 6: Calculate measurements $\boldsymbol{Y}=\boldsymbol{BC}(\gamma)\boldsymbol{L}$;

Step 7: Compute $\boldsymbol{\Theta}=\boldsymbol{BC}(\gamma)\boldsymbol{A}$;

Step 8: Achieve estimates $\hat{\boldsymbol{x}}_t$ by CS recovery algorithm;

Step 9: Perform T iterations, and obtain coefficient matrix $\hat{\boldsymbol{X}}$;

Step 10: Calculate the final estimations about traffic matrix $\hat{\boldsymbol{M}}=\boldsymbol{D}'\hat{\boldsymbol{X}}$.

4 Simulation results and analysis

In this section, we will discuss the properties of our method. We use real traffic matrix from a real backbone network collected by NetFlow with 5-min interval. We collect 1364-point data for our simulations. First 500-point data will be used as training set to construct data dictionary. Then we estimate the other 864-point data. That is, this traffic matrix reports 3-day traffic volume in a network. In our simulation process, the number of rows of Bernoulli matrix is 54, and all its entries are equal probability.

In our approach, we use orthogonal matching pursuit algorithm[20] in compressive sensing reconstruction process to estimate traffic matrix. Hence, two important parameters should be discussed. One is the iteration times of orthogonal matching pursuit algorithm, and the other is γ. We use Normalized Mean Absolute Errors (NMAE) to evaluate the algorithm performance. NMAE is defined as

$$\mathrm{NMAE}=\frac{\sum_{i,j}|\hat{m}_{i,j}-m_{i,j}|}{\sum_{i,j}|m_{i,j}|} \tag{11}$$

where $m_{i,j}$ and $\hat{m}_{i,j}$ are real traffic data and its estimation results.

As plotted in Fig. 2, the trend of NMAE is stable and NMAE has no dramatic fluctuation. This indicates that our method is not sensitive to the iteration times and the parameter γ, and thus it holds the better robustness . This is because ℓ_1 - norm of each row of routing matrix is small. Hence, $\boldsymbol{C}(\gamma)$ have no noticeable effect on NMAE. Similarly, the range of the iteration times is equal to the rank of traffic matrix. In this case, it influences NMAE weakly. This show that our method can more accurately estimate and reconstruct the traffic matrix at the different moment in the optical network.

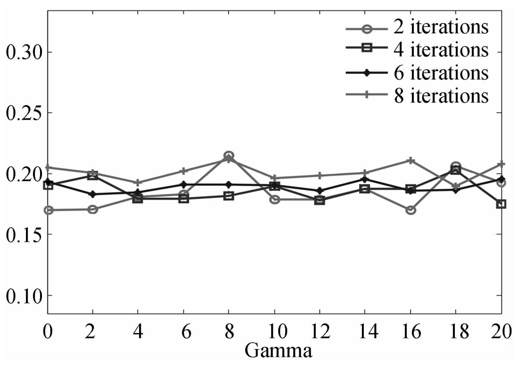

Fig. 2 Normalized mean absolute errors

Now we discuss and analyze the estimation performance of our method. Due to Tomogravity method[21] was brought forward by Y. Zhang et al and reported as a better estimation method about traffic matrix. We are to compare it with our method to validate further the estimation capacity of our method. In Fig. 3(a), we find that two methods can estimate OD 63 with small estimation errors. But our method has large estimation errors between time slots 750-800, and the same phenomenon occurs for Tomogravity method during time slot 1000-1100. Fig. 3(b) states that our method and Tomogravity emerge over-estimation or under-estimation, though they can capture the trend of OD 96. Likewise, Fig. 4 (a) shows that Tomogravity performs the under-estimation for OD 48 in the different moment, while our method can yield the better estimation results. Fig. 4 (b) shows that Tomogravity performs the over-estimation for OD 125 in the different moment, while our method can yield the better estimation results. Although our method can obtain the fairly accurate estimations, Fig. 4 indicates that it also holds the larger estimation errors.

In order to assess this property, we are here to use the bias and standard deviation of estimates to verify them. The bias of estimations is defined as follows

$$\mathrm{bias}(i)=\frac{1}{T}\sum_{t=1}^{T}(\hat{m}_{i,t}-m_{i,t}) \tag{12}$$

where $m_{i,j}$ and $\hat{m}_{i,j}$ are real traffic data and its estimation results.

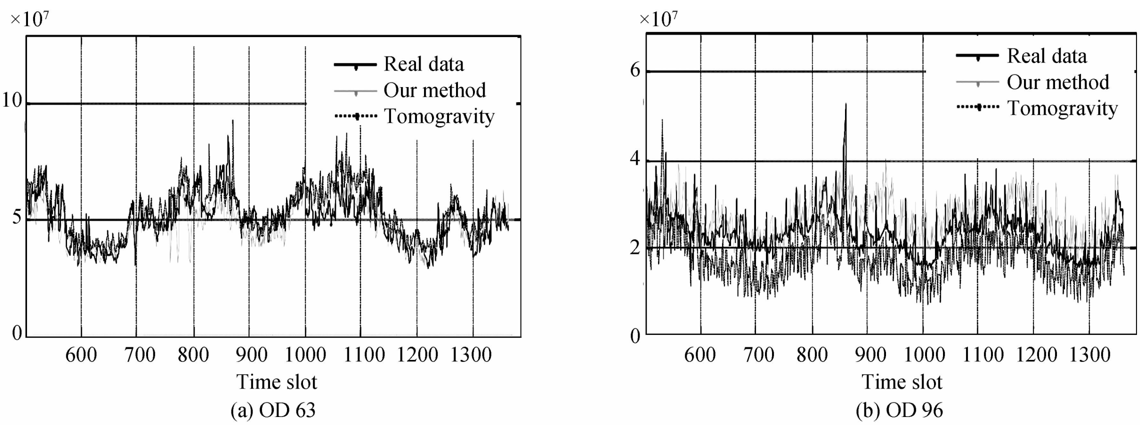

Fig. 3 Estimation results of ODs 63 and 96

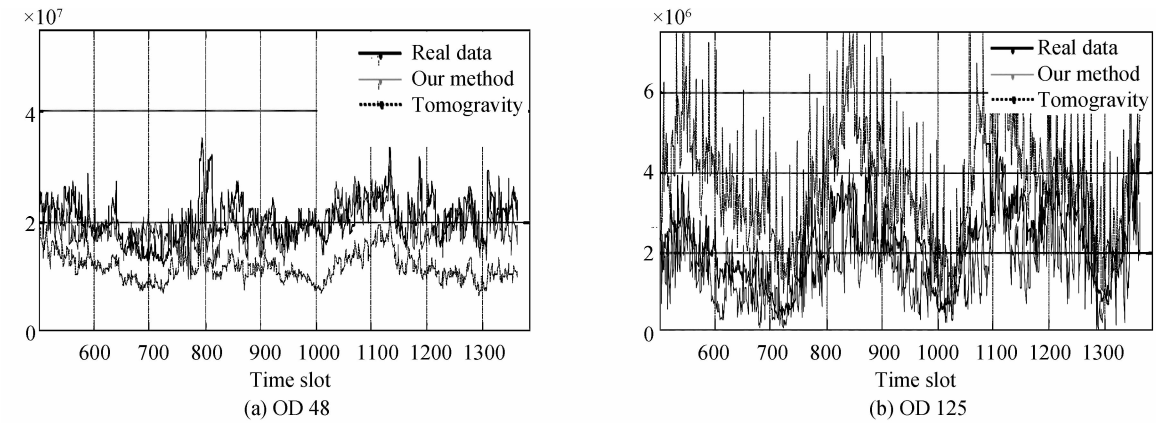

Fig. 4 Estimation results of ODs 48 and 125

And the standard deviation is denoted as

$$\mathrm{sd}(i)=\sqrt{\frac{1}{T-1}\sum_{t=1}^{T}((\hat{m}_{i,t}-m_{i,t})-\mathrm{bias}(i))^2} \tag{13}$$

Fig. 5 reveals that Tomogravity method has large bias and yields large over-estimation and under-estimation. Fig. 6 depicts the bias for each OD flow against their standard deviations errors of two algorithms. The standard deviation error of our method is lower than that of Tomogravity method. It implies that our method tends to estimate the flows′ mean values well over long time intervals.

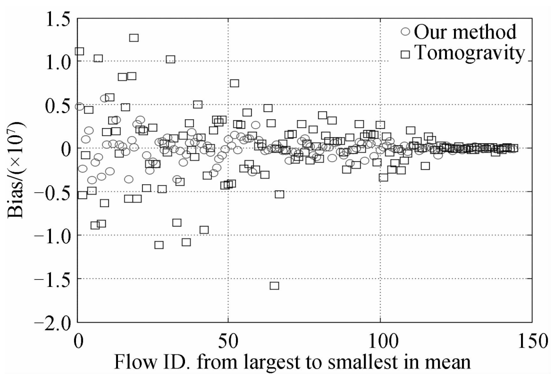

Fig. 5 Estimation bias about traffic matrix

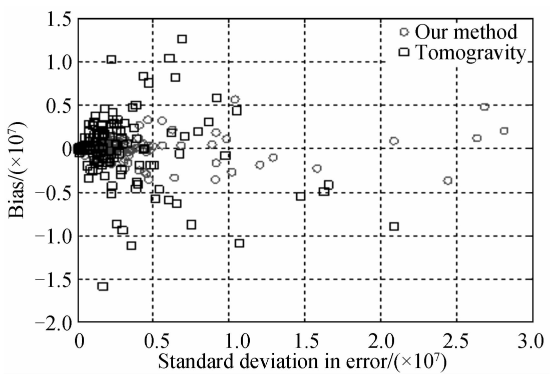

Fig. 6 Bias versus standard deviation error

5 Conclusions

Focusing on the problem of traffic matrix estimation for optical networks, we propose an efficient algorithm to find the single solution of network tomography. We present a modified network tomography model and estimate traffic matrix by solving a convex optimization. Simulation results shows that our method obtains exact estimations of traffic matrix.

Reference

[1] TARUTANI Y, OHSITA Y, ARAKAWA S, *et al*. Optical-layer traffic engineering with link load estimation for large-scale optical networks [J]. *IEEE Journal of Optical Communications and Networking*, 2012, **4**(1): 38-52.

[2] GUO Lei, LI Le-min. A novel survivable routing algorithm with partial shared-risk link groups (SRLG)-disjoint protection based on differentiated reliability constraints in WDM optical mesh networks[J]. *Journal of Lightwave Technology*, 2007, **25**(6): 1410-1415.

[3] JIANG Ding-de, XU Zheng-zheng, NIE Lai-sen, *et al*. An approximate approach to end-to-end traffic in communication networks[J]. *Chinese Journal of Electronics*, 2012, **21**(4): 705-710.

[4] OHSITA Y, MIYAMURA T, ARAKAWA S, *et al*. Gradually reconfiguring virtual network topologies based on estimated traffic matrices[J]. *IEEE Transaction on Networking*, 2010, **18**(1): 177-189.

[5] CHEN Ai-you, CAO Jin, BU Tian. Network tomogrpahy: identifiability and Fourier domain estimation [J]. *IEEE Transactions on Signal Processing*, 2010, **58**(12): 6029-6039.

[6] JIANG Ding-de, XU Zheng-zheng, CHEN Zhen-hua, *et al*. Joint time-frequency sparse estimation of large-scale network traffic [J]. *Computer Networks*, 2011, **55**(10): 3533-3547.

[7] GUO Lei. LSSP: A novel local segment-shared protection for multi-domain optical mesh networks [J]. *Computer Communications*, 2007, **30**(8): 1794-1801.

[8] JIANG Ding-de, WANG Xing-wei, GUO Lei, *et al*. Accurate estimation of large-scale IP traffic matrix [J]. *AEU-International Journal of Electronics and Communications*, 2011, **65**(1): 75-86.

[9] CAI Ting, HUANG Shan-guo, LI Xin, *et al*. Dynamic survivable mapping algorithm based on ant colony optimization in IP over WDM networks[J]. *Acta Photonica Sinica*, 2012, **41**(12): 1400-1404.

[10] GUAN Ai-hong, WANG Bo-yun, FU Hong-liang, *et al*. A Deflection routing mechanism based on priority and burst segmentation in optical burst switching networks[J]. *Acta Photonica Sinica*, 2012, **41**(2): 127-132.

[11] JIANG Ding-de, XU Zheng-zheng, XU Hong-wei, *et al*. An approximation method of origin-destination flow traffic from link load counts[J]. *Computers and Electrical Engineering*, 2011, **37**(6): 1106-1121.

[12] CAO Jin, CHEN Ai-you, BU Tian. A quasi likelihood approach for accurate traffic matrix estimation in a high speed network[C]. INFOCOM 2008, 2008. 4.

[13] CHEN Cun-kang, QIAO Yao-jun, JI Yue-feng, *et al*. Dynamic bandwidth allocation algorithm for orthogonal frequency division multiplexing access-passive optical network[J]. *Acta Photonica Sinica*, 2011, **40**(5): 684-689.

[14] SOULE A, LAKHINA A, TAFT N, *et al*. Traffic matrices: balancing measurements, inference and modeling [C]. SIGMETRICS 2005, 2005.

[15] DONOHO D. Compressive sensing[J]. *IEEE Transactions on Information Theory*, 2006, **52**(4): 1289-1306.

[16] FORNASIER M, RAUHUT H. Compressive sensing [C]. Handbook of Mathematical Methods in Imaging, 2011.

[17] CARVAJALINO J D, YU G, CARIN L, *et al*. Task-driven adaptive statistical compressive sensing of Gaussian mixture models[J]. *IEEE Transactions on Singal Processing*, 2013, **61**(3): 585-600.

[18] BARANIUK R, DAVENPORT M, DEVORE R, *et al*. A simple proof of the restricted isometry property for random matrices[J]. *Constr Approx*, 2008, **28**(3): 253-263.

[19] AHARON M, ELAD M, BRUCKSTEIN A. K-SVD: an algorithm for designing overcomplete dictionaries for sparse representation[J]. *IEEE Transactions on Signal Processing*, 2006, **54**(11): 4311-4322.

[20] TROPP J A, GILBERT A C. Signal recovery from random measurements via orthogonal matching pursuit [J]. *IEEE Transactions on Information Theory*, 2007, **53**(12): 4655-4666.

[21] ZHANG Ying, ROUGHAN M, DUFFIELD N, *et al*. Fast accurate computation of large-scale IP traffic matrices from link loads[C]. ACM SIGMETRICS, 2003, **31**(1): 206-217.