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Compressed sensing based loss tomography using weighted ℓ_1 minimization

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ABSTRACT

Network tomography allows the measurements of end-to-end to infer network internal links characteristics such as packet loss rates and delay. In this paper, we focus on the problem of estimating links loss rates, especially locating the congested links in network. Applying concepts of compressed sensing and Maximum A-Posteriori (MAP) estimation, we propose a new loss tomography scheme. Contrary to existing works that use ℓ_1 minimization, the proposed scheme adopts *weighted* ℓ_1 minimization as the implementation of compressed sensing, whose weights can be set wisely in order to improve tomography result. We exploit the temporal correlations of link losses and determine weights using the links prior congestion probabilities. The probabilities can be uniquely identified from multiple measurements by solving boolean algebra equations. We conduct a simulation performance analysis of loss tomography, demonstrating that higher estimation accuracy can be obtained through the proposed scheme.

1. Introduction

Network management tasks such as fault and congestion detection or traffic management often require performance parameter estimation of internal links. *Network tomography* [1–13] allows the measurement of end-to-end to infer network internal links performance characteristics such as link packet loss rates and delay. Roughly speaking, packets are sent from source nodes and processed at receivers to get path performance measurements, then link characteristics are obtained by exploiting the dependence between links and corresponding paths. There are two schemes to collect measurements on measurement paths in network tomography: *passive measurement* and *active measurement*, where the former collects end-to-end measurements by exploiting existing packets in network and the latter collects them by injecting probe packets. Active measurement always can get a more accurate result while needs additional traffic, which increases network burden. However, the additional traffic is small if the measurement paths are well designed. In this paper, we use active measurement scheme in which we also call measurement path *probe path*.

We focus on the problem of estimating links loss rates from paths loss rates, which is also known as *loss tomography*, especially the identification of congested links in network. We consider a link is congested if the number of dropped packets has exceeded a certain percentage of all packets, i.e. the link loss rate is much large. Determining link loss rates is not trivial since the end-to-end path measurements do not provide enough information. In fact, the inference of loss tomography can be represented as a linear model [8], where link loss rates are represented by variables to be solved, that is, we can formulate loss tomography as a linear inverse problem. However, in practice network monitor system, the probe paths often unable to determine loss rates uniquely, which makes the inverse problem *ill-posed*.

Many schemes have been proposed to handle the ill-posed problem in loss tomography [4–6,8–11]. Generally speaking, these methods make different assumptions and bring in additional information. In [4,6], loss rate is estimated based on multicast transmission assumption by exploiting temporal correlation between packets. As multicast is not widely deployed in actual network, unicast is used to imitate the packets behavior of multicast in [5]. Some methods [8–10] do not utilize the correlation of packets but take advantage of correlation between paths, which make it much easier for them to implement. There are also some works combine loss tomography with network coding theory to reveal correlation between probe paths [11]. In this paper, different from the methods above, we adopt the *compressed sensing* theory and apply the *weighted* ℓ_1 *minimization* method to loss tomography.

The concept of "*compressed sensing*" [14], which is an emerging theory in signal/image processing, has been proposed for network tomography recently. Compressed sensing can solve the ill-posed linear inverse problem with a prior information that the solution is *sparse*. The terminology sparse towards a vector means that only a few non-zero values exist in the vector. One advantage of utilizing compressed sensing to tomography problem is that it only needs a few probe paths. According to the compressed sensing theory, if a vector is k-sparse, then we can precisely recover it with only $O(k\log(n/k))$ measurements

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[15,16]. That means when we apply compressed sensing to loss tomography, it can significantly reduce traffic burden induced by probe paths.

Many network tomography problems can benefit from compressed sensing due to their naturally sparse characteristics, that is, the links with high loss rates or large delay are always sparse. For loss tomography, it means that the congested links with high link loss rates are only a mall fraction of all links. Several works have been done related to this domain. Xu et al. [12] illuminates compressed sensing under graph constraint. Firooz and Roy [13] prove the condition measurement matrix should be satisfied to identify the k largest value of link delay. T. Matsuda et al. [17] roughly classifies network links according to their packets loss rate using $\ell_1 - \ell_2$ optimization, and recently, a tomography method using sparse Bayesian learning has been proposed in [18]. These works generally try to answer the two questions:

- How many probe paths should be established and how to establish probe paths between measurement nodes under graph constraint.
- How to implement compressed sensing so as to get link-level performance parameters.

Our work here focuses on the latter problem. Most works in the literature adopt ℓ_1 minimization to estimate link characteristics, and a sparse approximation of link loss rates is obtained by solving ℓ_1 minimization. Therefore, it is reasonable to use a *prior* information to improve the accuracy of sparse approximation. The weighted ℓ_1 minimization has been used to enhance sparsity in compressed sensing [19]. The technology of using weights to attach prior information to improve the performance of ℓ_1 minimization have been studied in [20,21]. As far as we know, this is the first time applying it to network tomography.

In this paper, we propose a new loss tomography scheme using weighted ℓ_1 minimization. In the proposed scheme, we employ active measurements, where probe packets are transmitted on measurement paths in order to obtain paths loss rates. Then links loss rates are estimated by weighted ℓ_1 minimization, whose weights are determined by links recent "behavior"—frequent congested links with small weights. Finally, links are classified into *normal* or *congested* classes according to their loss rates. With the proposed scheme, we can efficiently implement loss tomography.

Our contributions in this paper are as follows:

- We propose a loss tomography scheme using weighted ℓ_1 minimization. The scheme enhances the power of traditional compressed sensing applied to network tomography, especially when the number of congested links is so large that beyond the ability of ℓ_1 or $\ell_1 - \ell_2$ minimization.
- We determine the weights using Maximum A-Posteriori (MAP) estimation based on the prior probability of congestion, and thus connect compressed sensing theory with Bayesian theory.

The remainder of this paper is organized as follows. In Section 2, we formulate the loss tomography and congested links location problem. In Section 3, we explain compressed sensing and use it on loss tomography. In Section 4, we describe the proposed scheme, including the determination of the weights and computation of prior probability. In Section 5, we evaluate the performance of the proposed scheme with simulation experiments. Finally, we conclude the paper with reflections on future work in Section 6.

2. Loss tomography model

As is customary, we model the network topology as an undirected graph $G = (V, E)$. The nodes V represents the hosts/routers of the network and E denotes the links. In order to get end-to-end measurements, some nodes in the network are chosen as *measurement nodes*, which usually located at the boundary of a network. Then probe paths are established between the measurement nodes and packets are sent on these paths to get end-to-end performance.

Given the network topology with n links and r probe paths, we can easily establish relationships between the link loss rates and the path loss rates. We employ two loss tomography models in this work: linear model and boolean model. The linear model establishs linear relationships between links and paths while boolean model keeps boolean relationships (the former is known as *analog tomography* while the latter represents *boolean tomography* [22]). In this paper, we use linear model to implement loss tomography and boolean model to calculate the prior probabilities.

2.1. Linear model

Because the overall transmission rate of a path is the product of the transmission rate of all links belonging to the path, take the logarithm and we have the linear model [8]:

$$-\log(\phi_i) = -\sum_{k=1}^{n} r_{ik}\log(\phi_{e_k}) \tag{1}$$

where ϕ_i is the transmission rate (i.e., one minus the loss rate) of path m_i and ϕ_{e_k} is the transmission rate of link e_k, the value of r_{ik} is 1 if measurement path m_i pass link e_k and 0 otherwise. If there are r end-to-end paths, then (1) can be rewrited as the matrix form,

$$\boldsymbol{y} = R\boldsymbol{x} \tag{2}$$

where $\boldsymbol{y} = (y_1, y_2, \cdots, y_r)^{\mathrm{T}}$ with $y_i = -\log(\phi_i)$, and $\boldsymbol{x} = (x_1, x_2, \cdots, x_n)^{\mathrm{T}}$ with $x_i = -\log(\phi_{e_i})$. The R is an $r \times n$ *routing matrix* that consists of r_{ik}. In this paper, we use a bold letter to represent a vector and T denote the transposition of a vector or matrix.

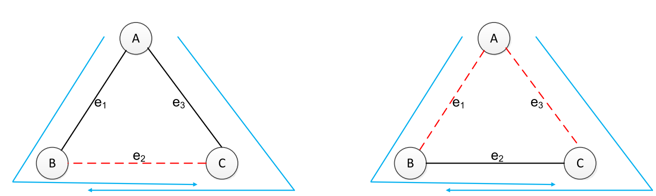
For the simple example in Fig. 1, if we have two measurement paths $\{e_1e_2, e_3e_2\}$, then the equivalent routing matrix is

$$R = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}. \tag{3}$$

Obviously, we can get $\boldsymbol{x} = R_L^{-1}\boldsymbol{y}$ from (2) if the rank $r(R) = n$, where R_L^{-1} is the left-inverse of R. However, in practical loss tomography, $r(R) < n$ is always desirable in order to reduce additional traffic burden, which means the equation has many candidates of the solution. In this paper, we utilize the sparsity of the congested links to deal with the problem. We call link e_k is *congested* if $\phi_{e_k} < \phi_{th}$, and call e_k is *normal* if $\phi_{e_k} \geq \phi_{th}$. We denote E_c the set of congested links and E_n the set of normal links. The threshold ϕ_{th} is specified by user and can be changed by the applications depending on their performance requirements.

2.2. Boolean model

The boolean model is adopted to calculate the prior probabilities. Let p_k denote the probability that link e_k is congested and $\boldsymbol{p} = (p_1, p_2, \cdots p_n)^{\mathrm{T}}$ the vector of link state probabilities. One possible way to obtain $\boldsymbol{p}$ has been studied in [10]. In the paper, they first show theoretically that it is possible to learn $\boldsymbol{p}$ from end-to-end measurements



(a) ℓ_1 minimization (b) weighted ℓ_1 minimization

Fig. 1. ℓ_1 minimization and weighted ℓ_1 minimization for 3-node ring network. The true congested links are e_1, e_3 and the dotted links are the results identified by the algorithms.

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