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Article

Algorithm Based on Heuristic Strategy to Infer Lossy Links in Wireless Sensor Networks

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Abstract: With the maturing of the actual application of wireless sensor networks, network fault management is eagerly demanded. Severe link packet loss affects the performance of wireless sensor networks, so it must be found and repaired. Subject to the constraints on limited resources, lossy link is inferred using end to end measurement and network tomography. The algorithm based on heuristic strategy is proposed. This maps the problem of lossy links inferences to minimal set-cover problems. The performance of inference algorithms is evaluated by simulation, and the simulation results indicate feasibility and efficiency of the method.

Keywords: lossy link inference; network tomography; minimal set-cover problem; heuristic strategy

1. Introduction

Lossy link refers to the link which frequently loses packets. With the maturing of wireless sensor network technology, the practical application system of wireless sensor networks gradually appears in many fields, such as environmental monitoring, data collection, *etc.* Network congestion, too low energy of nodes or wireless communication interferences in wireless sensor networks will result in the loss of severe packets upon linking. Lossy link seriously affects the performance of wireless sensor networks, so it must be found and repaired.

The detecting technology of lossy links is divided into two types: measurement based on collaborative internal nodes and that based on end-to-end nodes. The measurement based on collaborative internal nodes requires each internal node to monitor the packets loss rate of its adjacency link and report it to the sink node. It is straightforward but results in a huge traffic burden, so it is not suitable for wireless sensor networks of limited resources. Each deployed sensor network faces one or some certain applications, in which the node sends application data to the sink node regularly. The technology to infer the performance of links using end-to-end measurement data is called Network Tomography (NT) technology [1]. The advantage of end-to-end measurement is that it does not generate extra monitoring traffic, and this passive measurement does not need extra consumption energy of nodes. Packets loss of application data onto sensor nodes to sink nodes is measured passively using the measurement, and lossy link is inferred using Network Tomography.

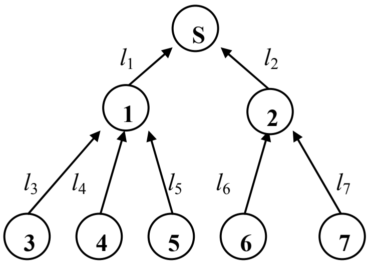
Network Tomography currently used to infer lossy links is divided into two types: probing correlations between data packets and scanning single fault. The method of probing correlations between data packets needs to make sure that there are strict correlations between probe packets. Hartl and Li [2] propose that a data collection framework based on data fusion is used to make sure there are correlations between data packets. The method can infer the specific packets loss rate of each link. The method is highly accurate but is difficult to deploy, so the scope of its application is restricted. The method of scanning single faults is mainly used to infer the nature of networks which have a Boolean characteristic, such as network connectivity, lossy link, *etc.* It assumes there are a few link failures of networks, which lead to packets loss, and do not need correlations between data packets, so it is simple [3]. Padmanabhan *et al.* [4] propose a Linear Programming (LP) algorithm and Bayesian inference algorithm based on Gibbs sampling. Duffield [5,6] proposes a SCFS inference algorithm based on a greedy strategy. Gibbs' sampling algorithms have the highest accuracy, but are difficult to apply in inference computation in large-scale network because of high computational cost. SCFS algorithm is simple and its computing speed is very fast, but it tends to give priority to select the links closed to root nodes as lossy links, so it has a big error and can only be used for tree topology. Based on the above research, this paper proposes a heuristic algorithm to infer lossy links, mapping the problem of lossy link inferences to minimal set-cover problems.

2. Network Model

2.1. Topology Model

The network logical topology formed into data collection of wireless sensor networks is modeled on reverse trees, $T = (V,L)$, shown in Figure 1. In which, V represents a collection of nodes, L represents a collection of links which connect the nodes. Root nodes of T, named s, represent sink nodes. n_v represents the number of nodes, $n_v = |V|$. n_e Represents the number of logic links, $n_e = |L|$. Orderly nodes pair (i,j) represents the link between the node i and the node j, $(i,j) \in V \times V$, that means the node i is the next hop node of the node j, i is the child node of j in topology T. Link $(i,j) \in L$ is shorthanded for l_i. Any node i has the only father node $f(i)$, except root node s, $(i,j) \in L$, that is $j = f(i)$. Assume that there is a positive integer, n, which establishes the formula $k = f^n(i)$, then node k is called the ancestor node of node i, node i is the descendant node of node k. A collection, $d(i) = \{k \in V | \exists\, n > 0, i = f^n(k)\}$, represents a descendant nodes collection of the node i. In $T = (V,L)$, the path form the node i to the node s is p_i. Set p represents all paths to sink nodes, $n_p = |P|$ is the number of paths. M_i represents a set of all links which compose path p_i.

Figure 1. Schematic diagram of reverse tree network topology.



Setting $T = (V,L)$ and P, the routing matrix, $A=(a_{ij})_{n_p \times n_e}$ can be calculated: line i of A corresponds to path p_i, row j corresponds to link l_j, in which, $a_{ij} = 1$, represents that path p_i includes link l_j, that is, $l_j \in M_i$. This paper assumes that any link is covered by at least one path.

If the routing between the internal node i and the gather node s in wireless sensor networks has not changed into the data collection periods, topological relations are considered to be stable between the sensor node i and the gather node s. When inferring lossy links, we assume that network topology is known. Network topology can be inferred using end-to-end measurement data if it is not known.

2.2. Performance Model

The performance model used in this paper is described as follows. It puts forward some hypothesis. Suppose that logical topology in sensor networks can keep relatively stable in data collection period T_R and that it makes enough data to be collected. Each sensor node in networks sends or forwards sensor data to a sink node. On a sink node it can be perceived that the data of a sensor node reach a sink node. According to sampling frequency of sensor nodes, the number of sending data packets and of loss data packets in transmission path can be known in T_R. Suppose that packets loss among the links is independent, following the Bernoulli distribution. The data flow flowing through T, can be described as a random process, $Z = (z_{i,j})$, $i \in d(j), j \in V$. In which, $z_{i,j} \in \{0,1\}$. $z_{i,j} = 1$, represents that data sent successfully from the node i arrive the node j, otherwise, data is lost on the link. Suppose ϕ_k represents average arrival rates of packets of link l_k, then the packets loss rate is $1 - \phi_k$. If path p_i consists of m links, that is, $M_i = \{l_1, \ldots, l_m\}$, suppose φ_i represents average arrival rates of routing packets, then $\varphi_i = \prod_{k=1}^{m} \phi_k$.

Duffield [7] describes the reason why ϕ_k has no statistical identification, that is, the packets loss rate of each link can not be calculated using packets loss rate of a path alone, so the link is classified using the threshold value of link packets arrival rate t_l as: when $\phi_k < t_l$, the link is a lossy link or bad link, otherwise it is not a lossy link. The value of t_l can be determined according to specific application requirements or historical data. Ferrari [8] and Kumar [9] show that the link in wireless sensor networks can be clearly distinguished as a good link or bad link. Distinguishability is defined that good paths all consist of good links, and a bad path contains at least one lossy link. Under the assumption that lossy links are relatively rare, the most likely understanding of using end-to-end measurement data to infer the lossy link should be the solution to the minimum number of lossy links.

3. Inference Algorithm

$D = \{D_1, \ldots, D_n\}$ represents a set of end-to-end measurement data. In which, $D_i = (r_i, f_i)$, r_i is the number of packets arrived of path p_i during measurement, f_i is the number of loss packets. Arrival rate of packets of path p_i is $\varphi_i = r_i/(r_i + f_i)$. Threshold value of packets arrival rates of path p_i is set as t_p, which can be used to distinguish good or bad path: if $\varphi_i \geq t_p$, path p_i is good, otherwise it is bad. The path set P is divided into good path set p_G and bad path set p_B according to t_p.

t_p is set artificially, two kinds of judgment errors are introduced inevitably. False positive error means that good paths are judged on bad paths, and false negative error means that a path is considered to be good but in fact it is bad. When $t_p = t_l$ is chosen, if a bad link l_k ($\forall l_k \in M_i$, $\phi_{l_k} < t_l$) exits *in* path p_i, transfer arrival rate of the path is lower than t_p ($\varphi_i = \prod_{l_k \in M_i} \phi_{l_k} \leq t_l = t_p$), at this time there is not exit false positive error. When $t_p = t_l^m$ is chosen ($m = |M_i|$ is the number of links contained in P_i), if the transfer arrival rate of the path is lower than t_l^m, then there is at least a link whose delivery success rate is less than link t_l, so there is no false negative error. When specific distribution of link packets loss rates is not known, the optimal choice of t_p cannot be acquired by analysis. This paper chooses t_p as $(t_l + t_l^m)/2$.

3.1. Problem Description

Definition 1: the link control field refers to a path set which contains specified links, that is,

$$Domain(l_k)=\{p_i | \, p_i \in P \text{ and } l_k \in M_i\} \; Domain(l_k)=\{p_i | \, p_i \in P \text{ and } l_k \in M_i\}$$

Suppose the most likely solution to lossy links is $X \subseteq L$, x is a mark vector whose length is n_e, when $l_k \in X$, $x_k = 1$, otherwise, $x_k = 0$. The problem of lossy link inferences can be described as:

$$\begin{cases} minminze \;\; 1_{n_e} \, x^T \\ s.t. \; P_R = \cup_{x=1} Domain(l_i) \end{cases} \tag{1}$$

In Formula (1), $1_{n_e} = \{1, 1, \ldots 1\}$ is n_e dimensional row vector, so the problems of lossy links inferences can be mapped to minimum set-cover problems. Lossy links can be inferred by solving Formula (1).

3.2. Algorithm Description

The minimal set-cover problem is a typical NP hard problem. SCFS algorithms proposed by Duffield [6] can be seen as a greedy method of solving of set-cover problems. This paper uses the heuristic algorithms to solve it.

Definition 2: path frequency $k(i)$ is the occurrence number of path p_i in link control domains sets formed into all links to P_B. Suppose $p_i \in P_B$, if and only if p_i appears in link control domain k, its path frequency is $k(i)$.

Definition 3: link coverage $C(i)$ is the minimum of all paths frequency included in link control domains, $Domain(l_i)$. That is, $C(i) = \min\{k(j) | P_j \in Domain(l_i)\}$.

Definition 4: required links are the links that the coverage is 1.

Definition 5: if the link l_i is not selected, R required links will appear in alternative links set based on m, required degree of the link l_i is called R, that is $R(i)$.

Heuristic strategies are proposed using the above definitions, as follows.

Strategy 1: if there is the link l_i which makes $Domain(l_i) = P_B$, l_i is selected as the only lossy link.

Strategy 2: required links must be selected as lossy links.

Strategy 3: if $Domain(li) \subseteq Domain(lj)$, the link li should be excluded.

Strategy 4: if $R(i) > R(j)$, the priority that link l_i is selected is higher than link l_j.

If l_i is not selected, the number of links which must be selected next is more than the number of links when l_j is excluded. The more the required links are, the harder optimization is; it is reasonable to select l_i. It is a strategy to prevent the algorithm being too greedy.

Strategy 5: the required degree of two links is same, the link selected to control the domain bases should be the higher one. This is a generalization of the simple greedy idea.

Heuristic Lossy Link Inference (HLLI) is described as follows.

Input: Network Topology $T(V,L)$, measurement data set D, threshold value of arrival rate of link packets t_i.

(1) Initialization: suppose X is a set of lossy links. $X = \phi$, $P_G = \phi$, $P_B = \phi$, initialization of mask vectors is zero, that is $x = [0,0,\cdots 0]_{n_e}$.

(2) Calculate t_p and arrival rate of link packets for each path in networks, $\forall p_i \in P$, $\varphi_i = r_i/(r_i + f_i)$. If $\varphi_i = t_p$, $P_G \Leftarrow P_G \cup \{p_i\}$, otherwise, $P_B \Leftarrow P_B \cup \{p_i\}$.

(3) Sets corresponding flag bits to l for constituent links between each path of P_B, $x_i = 1$, if $l_i \in M_i$, $p_i \in P_B$.

(4) Calculate path frequency, link coverage and required degree.

(5) While $P_B \neq \phi$.

① If the link l_i exists which make $Domain(l_i) = P_B$, the link l_i is added into X, $X: = X \cup \{l_i\}$; break;

② If required links exists, the link is added into X: if $\exists\, C(j) = 1$ then $X: = X \cup \{l_j\}$, $P_B \Leftarrow P_B\text{-}Domain(l_i)$, continue; otherwise return to ③;

③ $\exists\, l_i, l_j$, meet $Domain(l_i) \subseteq Domain(l_j)$, $P_B \Leftarrow P_B\text{-}Domain\{l_i\}$, continue; otherwise return to ④;

④ Choose the link that required degree is the highest and add it to X: if $\forall x_j = 1$, $\exists\, l_i$, max $R(i)$, then $X: = X \cup \{l_j\}$, $P_B \Leftarrow P_B\text{-}Domain(j_i)$, continue; otherwise return to ⑤;

⑤ Select the links that control the biggest domain bases, add it into X.

(6) Output: X.

4. Simulation and Evaluation

Two indicators are used to evaluate the performance of algorithms: Detection Rate (DR) and False Positive Rate (FPD). Set F as a set of actual lossy links in networks, X represents a set of lossy links inferred by algorithms, so the definitions of DR and FPD are:

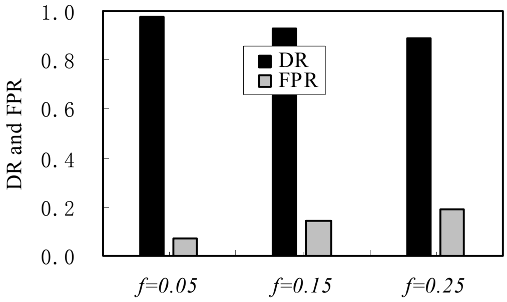
$$DR = \frac{|F \cap X|}{|F|}; FPR = \frac{|X \setminus F|}{|F|}$$

Simulation experiment uses the NS2 network simulation version and uses it to simulate a data gathering algorithm by expanding NS2 in a wireless sensor network. During each round of gathering data, it is determined by random if nodes can successfully get sensor data which is sent from the child nodes. A packets loss rate is set on each link. Emulation and actual packets loss rate tends to presuppose packets loss rate when the round of gathering data gradually increases. The actual number of packets loss on each link is counted to calculate actual packets loss rates of each link with simulation. The accuracy and effectiveness of the algorithm are evaluated by the comparison with the results of inference.

The simulation process constructs tree network using Transit-Stub graphics module generated by GT-ITM Topology Generator. The number of nodes, *v*, changes in the range of 100~1000. Setting *f* as the proportion of lossy links in networks, *f* changes in the range of 0.05~0.25. The definition of packet loss model LM is that the packet loss rate of good links obeys the uniform distribution of the interval [0, 0.01] and the packet loss rate of lossy links obeys uniform distribution of the interval [0.05, 1]. Once a packet loss rate of each link is assigned, the actual process of packets being lost on the link uses the Bernoulli process. The probability of each data packets loss during transmission is determined by the packets loss rate for this link. Each experiment collects data onto 200 rounds, and infers lossy links by measurement data, and calculates *DR* and *FPR* of each experiment. The experiment is performed 100 times under each configuration condition, and the advantages and disadvantages of algorithm performance are evaluated by calculating the average value of *DR* and *FPR*.

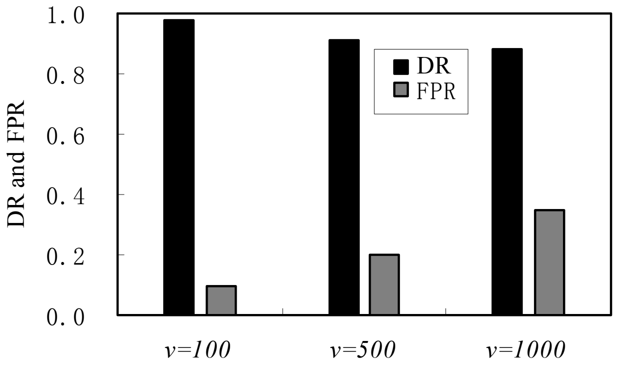
(1) The factor of bad link ratios. The changing trend of algorithm performance is shown as Figure 2 when Network Topology is fixed, the number of nodes *v* is equal to 500, and the proportion of lossy links, *f*, changes in the range of [0.05~0.25]. *DR* decrease, *FPR* increases, and the algorithm performance reduces as *f* increases. This trend appears and inference algorithms are built on the assumption that the numbers of lossy links are relatively rare. The assumptions are weakening which leads to a reduction in algorithm performance as the proportion of bad links increases [10,11].

Figure 2. Comparison of performance when f changes, nodes number *v* = 500.



(2) The affect factors of Network Topology. The changing trend of algorithm performance is shown as Figure 3, the proportion of bad links, *f*, is equal to 0.2, network scales are changed, the number of nodes, *v*, changes in the range of [100~1000]. As network scales increase, the performance decreases, but the extent of the decrease is much smaller. This means that the algorithm has strong robustness for a change of network scales.

Figure 3. Comparison of performance when the number of nodes changes and *f* = 0.2.



(3) Comparison of SCFS algorithm. The results of comparing HLLI algorithm against SCFS algorithm are shown in Table 1. The coverage of HLLI algorithm is slightly higher than SCFS, but misjudgment rate of HLLI is significantly better than SCFS algorithm. SCFS algorithm uses a greedy strategy based on link control domain bases, and selects the links closed to root nodes as loosy links in the first place. However, the HLLI algorithm can select lossy links more accurately using heuristics strategy.

Table 1. Comparison of performance between Heuristic Lossy Link Inference (HLLI) and Smallest Consistent Failure Set (SCFS).

Performance	***f* = 0.05**	***v* = 100**	***f* = 0.15**	***v* = 500**	***f* = 0.25**	***v* = 1000**
	HLLI	**SCFS**	**HLLI**	**SCFS**	**HLLI**	**SCFS**
DR/(%)	98	98	93	91	89	88
FPR/(%)	0.7	2.0	1.4	4.0	1.9	6.9

5. Conclusions

Detecting lossy links is an important part of wireless sensor networks management. This method measures application data packets of wireless sensor networks passively, and infers lossy links using the technology of network tomography. This paper proposes a heuristic algorithm of inferring lossy links by mapping the problem of lossy link inferences to minimal set-cover problems, and proves the validity of this algorithm using a simulation experiment.

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Author Contributions

All the authors contributed to the content of this paper. The idea for this research work was proposed by Jing Zhang, the writing of this paper and the design of the algorithm were achieved by Wen-Qing Ma. Both authors discussed the results of the paper before publishing them.

Conflicts of Interest

The authors declare no conflict of interest.

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