Fault Diagnosis Based on Evidences Screening in Virtual Network

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***Abstract*—Network virtualization has been regarded as a core attribute of Future Internet. To improve the quality of virtual network, it is important to diagnose the faulty components quickly and accurately. Recently more and more researches focus on end-user fault diagnosis, which can fit incomplete knowledge and dynamic challenges. In this paper, we present a fault diagnosis system called DiaEO in virtual network. It improves the present end-user fault diagnosis methods by screening evidences before analyzing to reduce the time-consuming. Besides that, DiaEO also improves the anti-noise ability of the system. The simulation results show that the proposed method can keep high accuracy and ameliorate time performance.**

Keywords—Fault diagnosis; Virtual network; Dempster-Shafer theory

I. Introduction

A Network Virtualization Environment (NVE) allows coexistence of multiple virtual networks on the same physical substrate. Each virtual network (VN) in NVE is a collection of virtual nodes and virtual links. Fundamentally, a VN is a subset of the underlying physical network components. Network virtualization proposes decoupling of functionalities in a network environment by separating the role of the traditional Internet Service Providers (ISPs) into two: infrastructure providers (InPs), who manage the physical infrastructure, and service providers (SPs), who create virtual networks by aggregating resources from multiple InPs and offer end-to-end network services.

Fault diagnosis of NVE is quite different from the traditional ones. Because a virtual network is a typically large-scale distributed network. And it involves a large number of virtual nodes and links which can be changed dynamically as required. What's more, virtualization services are provisioned and operated by SPs over impervious substrate networks. It is unwilling for InPs to share the network statistics information with SPs. Besides, it is infeasible to monitor the whole virtual networks. So the knowledge of virtual network is incomplete. They are the major challenges to fault diagnosis in VN.

There are some diagnostic approaches in the field of virtual network. The fault diagnosis methods based on the passive monitoring or the methods based on active probes is not applicable for the scalable or dynamic virtual network [1]. And the approaches based on the end-user observation such as [2] still has space for upgrading in the field of time performance. This paper focuses on the fault diagnosis based on the end-user observation. However, it boosts a way of evidences screening to have better time performance and adds some coefficients to avoid the influence of noisy observation maximally. Besides these, using the end-user observation with Dempster-Shafer theory to locate the faulty components, our system DiaEO can adjust incomplete knowledge and have good scalability.

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II. Related Work

There are an amount of significant works in the area of fault diagnosis for both Internet and virtual network. Generally speaking, the corresponding solutions can be classified into Administrator fault diagnosis and End-user fault diagnosis.

A. Administrator Fault Diagnosis

Administrative fault diagnosis is used to infer the root faults based on the observation which is gained by the passive monitoring or active probing. The classical approach is using passive monitoring. It usually depends on monitoring agents to detect and report network faults by alarms or symptom events. Steinder and Sethi present a survey of such approach [3]. [4] gives a practical definition of diagnosability, and develops an overlay assignment method which aims to optimize the placement of overlay probes for the quickness of fault diagnosis. However, such approaches need the knowledge of the whole network to make clear the dependency between the network components. As mentioned in Section I, it is impossible for virtual network. What's more, Bayesian needs to meet the stringent using conditions which is difficult to be satisfied. Active probing is an effective method for fault diagnosis, especially in the network with noisy observation. A probe station which is a particular node sends out a probe to the network. And by measuring the responses of the probe, the faulty components could be located actively. [5] [6] offer a probe station selection algorithm to minimize the number of the probe stations and an adaptive probing algorithm to locate the faults in the network with the probe set. [7] describes a useful model to formalize comprehensive action selection for computing utility profit maximization problems. In [8], by exploiting the conditionally independent property in Bayesian networks, Cheng etc. prove a theorem on the information provided by a set of probes. However, in such approaches, it is necessary to know the initial topology of the network. In addition, most of these approaches need a mass of probes even though they do a lot of works to find the minimum number of the probes.

B. *End-user Fault Diagnosis*

More and more researches have focused on end-user fault diagnosis which is based on the end-user observation. In this method, there is no need to know the whole knowledge of the virtual network. And it is able to adapt to the dynamic scalability of the virtual network. Moreover it eliminates the overhead cost of the probes. In [2], Tang develops an evidential overlay fault diagnosis framework called DigOver to tackle the challenges. In DigOver, each potential faulty component is evaluated to quantify its fault likelihood and the corresponding evaluation uncertainty by Dempster-Shafer theory. Although it has high accuracy, the cost time of calculating fault likelihood is long, particularly when the evidences focus on few faulty components. Thus in this paper, we propose a fault diagnosis system called DiaEO to minimize the cost of time and improve diagnostic accuracy. It can reduce the impact of network structure caused by uncertainty and keep the time of cost from increasing.

III. Problem Formulation

We model a virtual network which comprising a set of virtual nodes N joined by a set of virtual links L. A link is a network path between two adjacent nodes, and a virtual network path may consist of many links. An end-user observed symptom is called an evidence which could be a negative symptom or a positive symptom. A negative symptom indicates that the path observed is faulty, and a positive one indicates it is not faulty.

We assume the virtual network has a set of evidences E, make a matrix M= <C+1, E>. Each row of the matrix denotes an evidence, and each column denotes a component (If the evidence e_i is negative, m_{i0}= 1; else m_{i0}= 0). So the matrix M of the virtual network with 5 evidences {{c1, c3, c4, c5}, {c1, c2, c5}, {c3, c5}, {c2}, {c3, c4}} can be that as follow:

$$\mathrm{M} = \begin{bmatrix} x & 1 & 0 & 1 & 1 & 1 \\ x & 1 & 1 & 0 & 0 & 1 \\ x & 0 & 0 & 1 & 0 & 1 \\ x & 0 & 1 & 0 & 0 & 0 \\ x & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

After observing the results, x will be assigned as 1 or 0, it depends on that the symptom is negative or positive.

IV. Evidences Reasoning

The fault diagnosis system DiaEO process includes three functional modules: Evidences Screening, Evidences Analysis & Combination and Possibility Selection. We will present them in this section.

A. *Evidences Screening*

The time for finding fault is an important metrics in fault diagnosis system. However, there is a potential explosive situation of calculation amount in Dempster-Shafer theory. For n evidences, the maximum time complexity is O (n^3). When the negative evidences are more focused on a certain faulty component, it will spend more time to locate the fault. And the Locality-Principle in computer science and the Power-Law distribution of network both may create this situation easily. To some extent, screening the evidences can deal with the negative time performance. Because the time of evidences combination is short relatively, after evidences screening, the maximum time complexity of n evidences shrinks down to half of O (n^3) theoretically. And in practice DiaEO improves the efficiency from 20% to 30% averagely.

For minimizing the effect from the two factors we mentioned above, we make the set of evidence E_c into subsets by multiple interlaced method. Taking the Evidence matrix M as an instance, it could be screened into two parts evidence matrixes M_1 {{n_3, n_4, n_5}, {n_3, n_5}, {n_3, n_4}} and M_2 {{n_1, n_2, n_5}, {n_2}} shown as follows:

$$M_1 = \begin{bmatrix} x & 0 & 0 & 1 & 1 & 1 \\ x & 0 & 0 & 1 & 0 & 1 \\ x & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

$$M_2 = \begin{bmatrix} x & 1 & 1 & 0 & 0 & 1 \\ x & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

And then, we could analyze the evidences in the new matrixes.

B. *Evidences Analysis and Combination*

The faulty components in virtual network can cause a mass of negative symptoms. And it is unnecessary and impossible to record all of them by the end-user observing. However, whether the component is faulty is judged by likelihood and the probability of simultaneous fault in a virtual network is low. With the Basic Probability Assignment (BPA), the faulty components could be found by Dempster-Shafer theory breezily and almost completely.

For each component, it could be faulty or not. Let P_i be the prior probability that component C_i is bad. The value of P_i depends on the knowledge or the history logs. And Q_i is the posterior probability that component C_i is good. Based on the evidence matrix, component C_i has a set of relate components denoted as $Relate_i$= {C_j, where C_j and C_i in the same evidence from negative symptom}. Q_i is evaluated by the prior probability of the components in $Relate_i$ with Algorithm1.

Taking the Evidence matrix M_1 as an example:

$$Q_3 = P_4 * \left(P_5 + \mathcal{F}(P_5)\right) + \mathcal{F}(P_4) * \left(P_5 + \mathcal{F}(P_5) * G\right) \quad (1)$$

Where F(x) = (1- x)* G and G is the probability of the probe being broken. Sometimes the researches consider that probe is right acquiescently. DiaEO takes into account that the probe may have problems, although the probability of it is much lower than the one of other components.

A component C_i is probably faulty if $P_i > Q_i$, otherwise C_i is possibly working normally. In order to facilitate the calculation of fault diagnosis, the determinant factor of component C_i is denoted as D_i, Di= log (P_i\ Q_i).

The result of the end-user observed system is based on the evidences. Here, the frame of discernment of the component C_i is denoted as Θ_i, which is the set of possible condition.

$$\Theta_i = \{N_i, A_i\} \quad (2)$$

Algorithm 1. Get Posterior Probability Q

Input: negative evidence matrix M, $Relate_k$, count(initially count = 1 and Q_k= 1)
Output: Q_k
Procedure:

```
If Relate_k = Ø
{
   Q_k = Q_k * FaultRate;
   return Q_k;
}
Else
{
   Delete all the evidences e_i where Relate_k[count] ∈ e_i;
   Then get the new evidence matrix M1;
   Put away the component Relate_k[count] from the
         quondam evidence matrix M;
   Then get the new evidence matrix M2;
   Count ++;
   retrun p_relatek[count] * loop (count, relate_k, M_1)+
         (1- p_relatek[count])* loop (count, relate_k, M_2);
}
```

Here, N_i stands for that component C_i is working normally, and A_i stands for that component C_i is faulty. And $N_i \cap A_i= \emptyset$ means N_i and A_i are mutually exclusive. Define the Basic Belief Assignments function m_i: $p(\{N_i, A_i\})\rightarrow[0,1]$, $m(\emptyset)= 0$, $m(\{N_i, A_i\})+ m(N_i)+ m(A_i)= 1$. m ($N_i$) represents the belief of that the component C_i is working normally, m (A_i) represents the belief of that the component C_i is faulty. And the m ($\{N_i, A_i\}$) represents the belief of that something uncertain, the component C_i is faulty or not. When Di> 0, m(Ni)= min(1, Di\r), m({Ni, Ai})= 1- m(Ni), m(Ai)= 0; when Di⩽ 0, m(Ai)= min(1, -Di\r), m({Ni, Ai})= 1- m(Ni), m(Ni)= 0. Where r= log ((1- pi)\pi), as the threshold limit variable. For each evidence matrix M, a set of function-m of all the components could be gotten after evidences analysis. And for one component, different function-m getting from different evidence matrix can show a combination function-m with Dempster-Shafer's rule of combination.

C. Possibility Selection

Denoting the ultimate function-m of the component C_i as □$_i$, if □$_i$ > □$_j$, it represents that C_i is more likely to be faulty component. However, with the end-user observation, it is unable to notarize the actual number of the faulty components. This problem can be solved by Algorithm 2. *F* is a set of faulty components, *C* is the set of all the components, *E* is the set of the evidences. Without the coefficient k, the algorithm may enter an infinite loop, when there is some mistakes in the evidence matrix by noisy observation. The probability that recording or transmitting of the evidence matrix with mistakes is low, but the infinite loop will make the fault diagnosis system paralytic.

V. SIMULATION RESULTS

In this section, the advantages of the proposed method in this paper will be evaluated through simulations. DiaEO has a better time performance and also keeps high accuracy.

Algorithm 2. Get Function-m

Input: m of each component C,
Output: the reckoned faulty components
Procedure:

1: $F\leftarrow\emptyset$;
2: Find the C_i with max m , where $C_i \in C$;
3: $F= F\cap C_i$, $C= C- C_i$;
4: $E= E- Ec_i$, Ec_i means the set of evidences which have C_i;
5: Go to 2, until the number of evidence in E<k* the number of evidence in initial E;

A. Evaluation Metrics

The rate of spending-time exhibits the capability of saving time by the method in this paper, denoted as R_{time}. The time spent by DiaEO method in this paper is T_{es}, and the one spent by the evidences un-screening method (denoted as Tra) is T_{te}.

$$R_{time} = \frac{T_{es}}{T_{te}} \tag{3}$$

Accuracy and False-positive are two evaluation metrics to measure the performance of the fault diagnosis algorithm. Let the set of true faults as TF and the set of reckoned faults as RF.

$$Accuracy = \frac{RF\cap TF}{TF} \tag{4}$$

$$False - positive = \frac{RF-TF}{TF} \tag{5}$$

B. Simulation Methodology

We consider the following measurement for simulation and define the case where faults and noise happen.

Virtual Network Topology: Inet is a current mainstream topology generator. The topology model in this paper is based on it. And vary network size from 1000 to 20000. We choose 10-20% nodes with the least degree as virtual components.

Fault Rate: The rate is the independent failure probabilities to components as shown in the topology model and vary it from 0. 5% to 1.5%. With the fault rate, we pick the faulty components randomly.

Evidence Observation: The number of evidence is range from 1000 to 20000. Because the evidences are obtained randomly, most of the evidences are positive. However the time complexity of these algorithms is mainly depended on the negative ones.

Noise Rate: The element in the evidence matrix may be abnormal by noise. Because it is infrequent, the rate of noise is low, let it be 0.01% in the model.

C. Simulation Results

The simulation results are shown in the following graphs, it will be analyzed from three aspects.

1) The impact of network size on time performance

In order to study the impact of network size in these algorithms, the fault rate is increased in the range from 0.5%

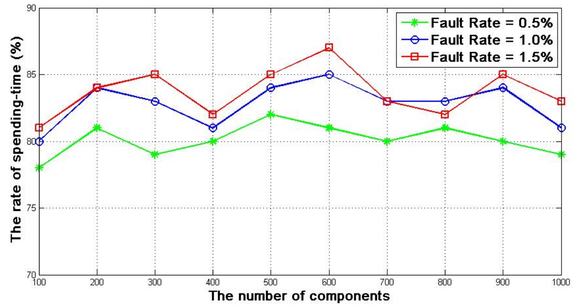

Fig. 1 The impact of network size

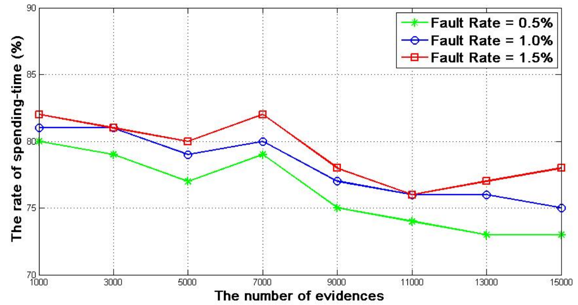

Fig. 2 The impact of evidence number

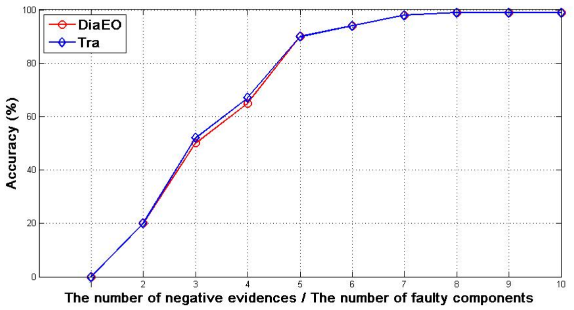

Fig. 3 The accuracy with Fault Rate= 0.4%

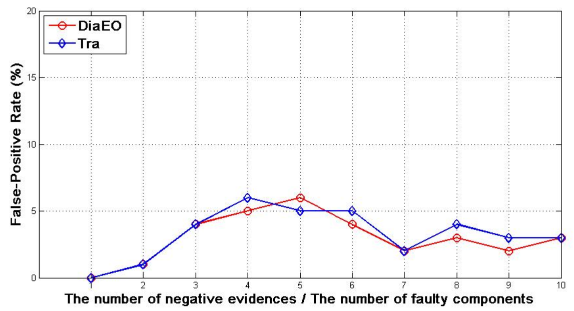

Fig. 4 The False-Positive Rate with Fault Rate= 0.4%

to 1.5%. And we let the number of evidences: the number of components = 1: 20 and the number of component is increased from 100 to 1000. As shown in Fig. 1, R_{time} is fluctuated from 77% to 85% with the growth of the network size, and it represents that the evidence screening method in this paper can save more time than the un-screening method, the impact of network size is slight.

2) The impact of evidence number on time performance

In the Fig. 2, the fault rate is increased in the range from 0.5% to 1.5% and the number of component is 500 fixedly. When the number of evidence rises, R_{time} falls off gradually. It confirms the statement that the more evidences focus on one component, the more time the evidences screening method can save.

3) The impact of fault rate on time performance

As displayed in Fig. 1 and Fig. 2, when the fault rate is growing that means there is more faulty components, R_{time} is slightly growing too. It demonstrates that when the faulty components are scattered with evidences equably, the superiority of DiaEO is inconspicuous.

4) The impact on accuracy

As in the previous diagrams, DiaEO can lead to greater efficiency. In Fig. 3 and Fig. 4, it indicates that DiaEO has high accuracy and low false-positive rate respectively. No matter when the fault rate is 0.4%(lack of space forbids more rates, however, they have the same trend.), only if the number of negative evidences is from twice to five times the number of faulty components, the accuracy of DiaEO is slighter than the one of the un-screening evidences fault reasoning. And the false-positive rate DiaEO is near balance with the un-screening one. Therefore DiaEO is more efficient with high accuracy.

VI. Conclusion and Future Work

In this paper, we present a fault diagnosis system called DiaEO in virtual network. In DiaEO, the evidences obtained by end-user observation have been screened before analyzed. This could save considerable time, though it sacrifices very little accuracy performance. In addition, DiaEO also improves the anti-noise ability of the system to ensure the accuracy. The simulation shows our algorithms can keep high accuracy and improve time performance in virtual network fault diagnosis. In the future, we would like to investigate the automatic evidence screening based on the dynamic virtual network and let the fault diagnosis become more efficient.

References

[1] Y. Tang, E. Hab S. Al-Shaer, and R. Boutaba. "Active Integrated Fault Localization in Communication Networks," IEEE/IFIP Integrated Management (IM'2005), May, 2005.

[2] Y. Tang, E. Al-Shaer, and K. Joshi, "Reasoning under uncertainty for overlay fault diagnosis," Network and Service Management, IEEE Transactions, Vol. 9, No. 1, pp. 34-47, 2012.

[3] M. Steinder, and A.S. Sethi, "A survey of fault localization techniques in computer networks," Science of Computer Programming, Vol. 53, pp.165–194, 2004.

[4] M. Demirci, F. Gillani, M. Ammar, *et al*. "Overlay network placement for diagnosability," in Proc. IEEE GLOBECOM, pp. 2236-2242, 2013.

[5] M. Natu and A. S. Sethi, "Probe Station Placement for Fault Diagnosis," in Proc. IEEE GLOBECOM, 2007.

[6] M. Natu and A. S. Sethi, "Probabilistic Fault Diagnosis Using Adaptive Probing," in Proc. DSOM, LNCS 4785, pp. 38–49, 2007.

[7] J. HELLERSTEIN, K. KATIRCIOGLU, and M. SURENDRA. "A Framework for Applying Inventory Control to Capacity Management for Utility Computing," IEEE/IFIP Integrated Management (IM'2005), May, 2005.

[8] L. Cheng, *et al*. "Efficient Active Probing for Fault Diagnosis in Large Scale and Noisy Networks." IEEE INFOCOM, pp. 1-9, 2010.