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# Wireless multimedia network feasible path routing algorithm

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**Abstract.** The congestion routing algorithm based on the minimal set covering theory is adopted to carry out inference only on the shared bottleneck path. When there are multiple path congestions in the congested path, the inference performance of the algorithm decreases drastically. Aiming at this problem, an improved Moore Relaxation Sub-gradient algorithm based on KMP (hereinafter referred to as MRSKMP for short) on the basis of Kalman Maximum Posterior (hereinafter referred to as KMP for short) is put forward. In view of the influence of the path coverage in the algorithm on the inference performance of the algorithm, the cost problem is taken into consideration on the basis of the guaranteed path coverage, so as to ensure the inference performance of the algorithm. The experiment has verified the accuracy and robustness of the proposed algorithm.

**Key words.** Congestion path inference, tomography, Kalman network model, Moore relaxation, Kalman maximum posteriori (KMP) criterion.

## 1. Introduction

With the increasing scale of the wireless multimedia network and the rapid growth in the number of network terminal accesses, the number of routers/switches is increasing, in addition to the network congestion caused by the physical path cut-off, complex network structure and unreasonable routing principles will all lead to the occurrence of network feasible path congestion, causing the sharp decline in the overall network performance and quality of service. The high network latency and high packet loss rate of the wireless multimedia network caused by the feasible path congestion may also be caused by the violation of the related service level agreements (SLAs) such as Service Level Agreement (hereinafter referred to as SLA for short) [1–2]. Therefore, the network manager needs to locate and handle the congestion in the network in timely and accurate manner.

At present, domestic and foreign wireless multimedia network internal path performance inference is mainly through two methods including the active detection and

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passive detection. In this paper, the active detection of path performance based on a small number of end-to-end (E2E) path detection methods [3–5] is proposed, as it has the advantages of not involving user privacy, real-time performance, small cost, and little impact on the network performance and other advantages, it is preferred by network operators and research scholars at home and abroad. At present, by the application of Boolean algebra, the method of congestion path inference based on the Smallest Consistent Failure Set (SCFS) theory [6] is adopted. When the proportion of the congested path of wireless multimedia network is increasing, in particular, when there are other congestion paths in addition to shared bottleneck paths in a certain congestion path, the performance of algorithmic inference will degrade due to the defects of algorithm theory. In addition, there are some literatures on the active detection method in the probe deployment point [7–8] and E2E contract path optimization [9–10] and other aspects, on the basis of the minimization of cost, to cover as much path range in the wireless multimedia network to be measured as possible. But it does not study the influence of path coverage changes on the performance of algorithm inference. In addition, Boolean tomography makes use of the priori probability of path congestion and CLINK algorithm of congestion path inference based on Kalman theory, which can effectively avoid the dependency of single time slot E2E path detection on time strong correlation. However, in the case of large-scale wireless multimedia networks, it is difficult to solve the problem due to the sparseness of the system matrix coefficient matrix to be solved by the path prior probabilities, it tends to lead to the failure of the solution, and no good solution has been proposed in the literature so far.

In view of the aforementioned problems, based on the practicality of Boolean tomography, this paper proposes an improved Moore Relaxation Sub-gradient algorithm based on KMP (MRSKMP) based on Kalman Maximum A-Posterior (KMP) for large-scale wireless multi-media network feasible path congestion scenario is proposed. Considering the degree of network user and manager's tolerance to the wireless multimedia network congestion, the Path Congestion Time (PCT) parameter is introduced in the process of path prior probabilistic learning, and the E2E path with number of congestion less than PCT in the process of $N$ times of E2E performance detection is regarded as the normal path. By removing the normal path and the transit path, the congested routing matrix and the congestion Kalman network model in the wireless multimedia network to be measured are constructed during the learning process of path congestion priori probabilities. In the process of congestion path inference, firstly, the normal path and transit path are removed from the congestion Kalman network model which is constructed during the learning process of path congestion priori probabilities, and the remnant congestion routing in the process of congestion path inference is obtained. Finally, based on the KMP criterion, the wireless multimedia network congestion path inference problem is transformed into the Set Cover Problem (SCP), and the MRSKMP algorithm proposed in this paper is used to solve the SCP iterative solution within the polynomial time.

## 2. MRSKMP algorithm

In this paper, a feasible routing algorithm MRSKMP for the large-scale wireless multimedia network is proposed, which mainly consists of three parts:

(1) E2E path and probe deployment optimization. Based on the guaranteed path coverage, according to the wireless multimedia network topology to be measured, the E2E contract detection path and contract routing probe deployment location optimization is conducted.

(2) Path congestion priori learning. According to the result of N times of E2E path performance measurement, the learning algorithm covered congestion priori probabilities of each path are obtained.

(3) Current time congestion path inference. According to the congestion status of each E2E path at the current inference time, the set of path where congestion is most likely to occur in the current wireless multimedia network is deduced based on the KMP criterion. And the algorithm block diagram is shown in Fig. 1.

## 3. Congestion Kalman network model and congestion routing matrix construction

The Kalman network model is a directed acyclic graph (hereinafter referred to as DAG for short), which can be expressed by the equation

$$G = (v, \varepsilon) \ , \tag{1}$$

where $v$ represents the node, and $\varepsilon$ represents the directed edge of the connected node. In the Kalman network, each node stores a conditional probability table. When the node is a known evidence node, the condition probability table is the priori probability distribution of the node. According to the causality in the graph and the consistent conditional probability and prior probability, the unknown hidden node state can be inferred through the evidence node. When constructing the Kalman network model for the wireless multimedia network, the set of state variables $Y = \left(y_1, \ldots, y_i, \ldots, y_{n_p}\right)$ of each E2E path is the observation nodes in the Kalman network. The state variables $X = (x_1, \ldots, x_j, \ldots, x_{n_c})$ of each E2E path's transit path are hidden nodes. In order to carry out the congestion path inference, it is necessary to construct the congestion Kalman network model of the wireless multimedia network to be measured at the time of inference.

*Definition 1.* E2E path $\mathrm{P}_i$ congestion, its state variable$y_i = 1$; normally, $y_i = 0$. Similarly, in path congestion, its state variable $x_j = 1$; normally, $x_j = 0$

The Kalman network inference model constructed by the wireless multimedia network is shown is Fig. 2.

When the congested path inference is carried out in the wireless multimedia network, as the path where the congestion path is located must be the congested path, in order to simplify the inference process, the normal path and the transit path in the wireless multimedia network can be omitted in the consideration.

*Definition 2.* Remove each of the E2E probed normal paths (observation nodes)

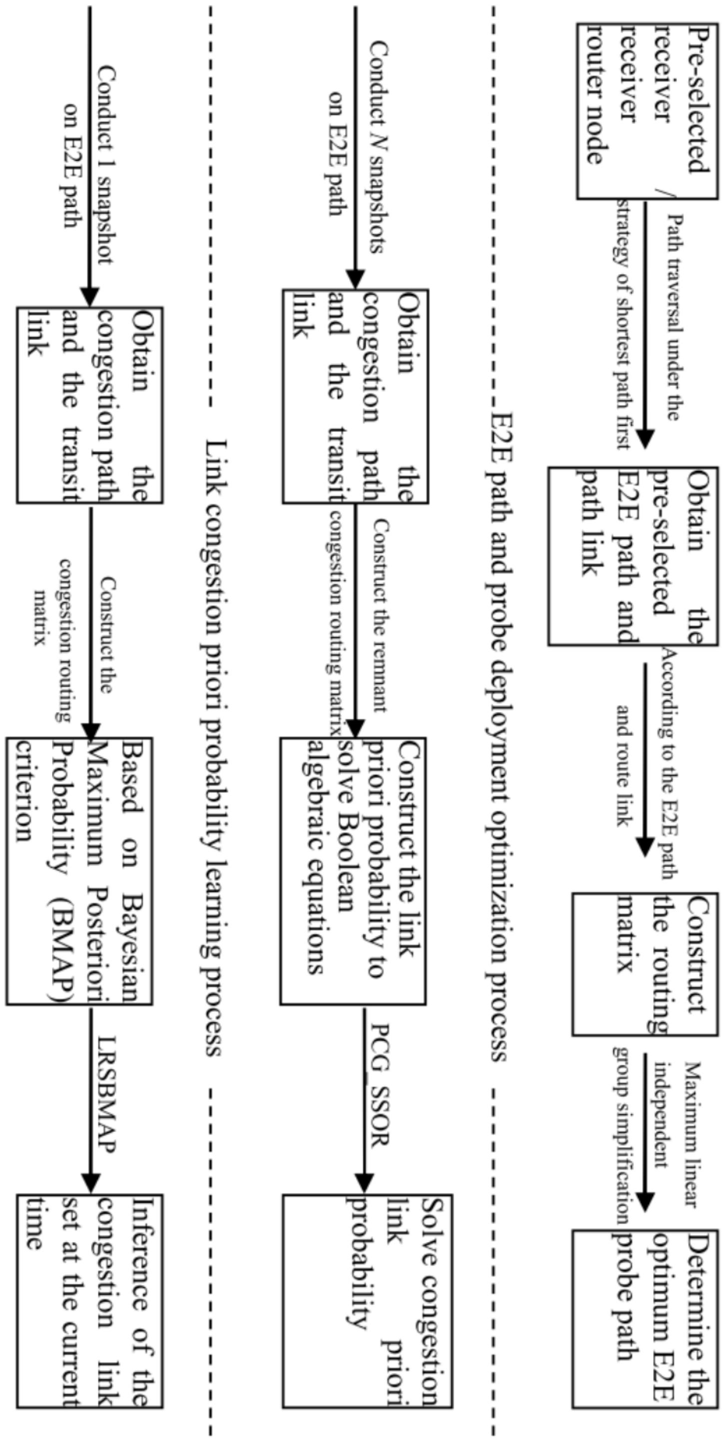


Fig. 1. MRSKMP algorithm block diagram

and the transit paths (hidden nodes) and connect the directed edges in the Kalman network model constructed in the wireless multimedia network to be measured, then the congestion Kalman network model of the wireless multimedia network to be measured is obtained.

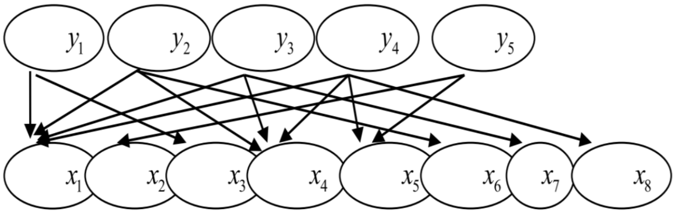


Fig. 2. Kalman network inference model of wireless multimedia network

The process of congestion path inference in this paper includes the construction process of two congestion Kalman network models, which are divided into the construction of the congestion Kalman network model in the wireless multimedia network path congestion priori probabilities learning process and the construction of the congestion Kalman network model in the congestion path inference process.

### *3.1. Construction of congestion routing matrix in the learning process*

In the path congestion priori probability learning process, the congestion routing matrix is used as the coefficient matrix in the system of linear equations. Therefore, it is necessary to construct the Kalman network model and the congestion routing matrix in the learning process. $N$ times of snapshots are performed for each E2E path of the wireless multimedia network to be measured. When the path congestion number does not exceed the set threshold PCT (Path Congestion Time), the path is normal and the transit path is also normal. On the contrary, the path is congested. The size of the parameter PCT can also be set according to the degree of congestion tolerance of the wireless multimedia network to be measured according to the network user or manager. If the network performance requirement is high, PCT $= 0$ can be set. That is, in $N$ times snapshot, as long as there is path congestion in one time of detection, then the path is congested. Remove the normal path and transit path from the Kalman network model of the wireless multimedia network as shown in Fig. 3, then the congestion Kalman network model in the learning process of the path congestion priori probabilities can be obtained.

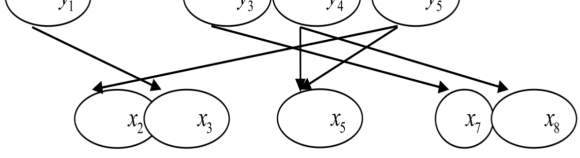


Fig. 3. Congestion Kalman network model of wireless multimedia network

Remove the normal path and the transit route path corresponding matrix rows and columns in $N$ times of E2E path snapshots from the linearly independent simplified path matrix $D'$, and linearly independent simplification is performed again to obtain the path congestion routing matrix $D''$ of the wireless multimedia network to be measured in the path congestion priori probability learning process. $N = 30$ times of E2E path detection is performed for the wireless multimedia network as shown in Fig. 2, and the path $P_2$ remains normal all the time, then the path $P_2$ and the state variables $x_1$, $x_4$, $\mathrm{X}_6$ corresponding to the transit path $L_1$, $L_4$ and $L_6$ as well as the connected directed edges can be removed from the wireless multimedia network Kalman model as shown in Fig. 3, and the congestion Kalman network model in the solving process of the priori probabilities can be obtained after the removal.

Similarly, remove the matrix rows and columns corresponding to the congestion path in the decorrelation reduced matrix $D'$, and the matrix after the removal is $\mathrm{D}_1'$ in the form

$$D_1' = \begin{array}{c} \begin{array}{cccccccc} L_1 & L_2 & L_3 & L_4 & L_5 & L_6 & L_7 & L_8 \end{array} \\ \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{c} \\ P_1 \\ P_2 \\ P_3 \\ P_4 \\ P_5 \end{array} \Rightarrow D_1' =$$

$$= \begin{array}{c} \begin{array}{ccccc} L_2 & L_3 & L_5 & L_7 & L_8 \end{array} \\ \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{c} \\ P_1 \\ P_3 \\ P_4 \\ P_5 \end{array} . \tag{2}$$

For the matrix $\mathrm{D}_1'$: after de-correlation and simplification $D''$can be obtained, where $D'' = D_1'$, as shown in the equation

$$D'' = \begin{array}{c} \begin{array}{ccccc} L_2 & L_3 & L_5 & L_7 & L_8 \end{array} \\ \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{c} \\ P_1 \\ P_3 \\ P_4 \\ P_5 \end{array} . \tag{3}$$

In the inference of the congestion path, such as path $P_1$ congestion, it is caused by the congestion path $L_3$, similarly, path $L_3$ congestion is caused by the path $L_7$. The construction of the congestion Kalman network model can effectively reduce the complexity of the congestion path inference.

### 3.2. Construction of the congestion routing matrix in the inference process

In the process of the congestion path inference, it is necessary to construct the remnant congestion routing matrix $\mathrm{D}_d$ to perform one time of E2E performance detection snapshot for the corresponding congestion path in the congestion Kalman network model during the learning process of path congestion prior probabilities, to obtain the performance results of each E2E path, and the remnant congested Kalman-net model of the current congestion chain inference can be obtained by removing the normal path in the detection results and the corresponding node as well as the directed edge of the transit path in the learning process. In the same way, the normal path at the time of inference and the transit path corresponding matrix lines and matrix columns are removed from the congestion routing matrix D$''$ constructed during the learning process of path congestion priori probabilities. After the linearity-independent simplification, the remnant congestion matrix D$_d$ of the wireless multimedia network to be measured in the congestion path inference can be obtained. As shown in Fig. 2, for the wireless multimedia network, in the inference process, if the measured path P4 is a normal path, the remnant congestion routing matrix is shown in the following equation

$$D_d = \begin{array}{c} \begin{array}{ccccc} L_2 & L_3 & L_5 & L_7 & L_8 \end{array} \\ \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{c} P_1 \\ P_3 \\ P_4 \\ P_5 \end{array} \Rightarrow D_d = \begin{array}{c} \begin{array}{ccc} L_2 & L_3 & L_7 \end{array} \\ \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{pmatrix} \end{array} \begin{array}{c} P_1 \\ P_3 \\ P_5 \end{array} . \quad (4)$$

## 4. Experimental verification

In order to validate the effectiveness and accuracy of the routing algorithm, three different types and scales of Waxman, BA and GLP are generated respectively by Brite topology generator. Among them, the Waxman model is the representative based on the random graph model, and the node degree value in the model increases with the number of nodes, but the random graph model cannot generate a network with many nodes but the one with small node average value. As the scale of the wireless multimedia network continues to expand, new router nodes tend to connect to the "Big nodes" with high values, when they join the Internet. Based on these two features, the scale-free network model BA and GLP with the power distribution of degree distribution are constructed so as to better verify the performance of the proposed algorithm in different Internet environments, and experiment is conducted to compare the algorithm performance under the three kinds of topological network models.

The topology model is introduced to complete the construction of the network to be measured through the Eclipse platform, and all the routing algorithms are used to verify the congestion path inference experimental verification. In the experiment of congestion path inference, the shortest path first principle of the wireless multimedia network routing algorithm is simulated, and the ICMP protocol is used to perform the snapshots (including Traceroute and Ping) respectively, and E2E path and route path and E2E path performance measurement values are obtained. The RNM (Random Number Model) in this paper is applied to simulate the congestion events generated by the path covered by the algorithm in each snapshots of the wireless multimedia network to be measured.

In this paper, the parameters of the proposed algorithm mainly include:

When DTV-router degree $\leq$ DTV, the router is taken as the pre-selected transceiver router, and automatically optimized according to the value of $\rho$ for DTV;

In the PCT-N times E2E path detection, the path with number of congestion less than $\leq$ PCT is normal. The algorithm defaults to set $N = 30$ and PCT $= 0$;

LCR (Link Congestion Ratio) - parameters set in the MRSKMP algorithm simulation experiment. That is: the ratio of the congestion path to the path covered by the algorithm, with the value taking range of [0, 1]. By selecting the path random number assigned from large to small according to LCR to obtain the congestion path of each snapshots. The detection rate DR and the false positive rate (FPR) is used to evaluate the congestion path inference result of the MRSKMP algorithm proposed in this paper. In order to reduce the effect of the random number model on the inference performance of the algorithm, the DR and FPR in each experiment are the results obtained after averaging the 10 experimental results under the same parameters.

The calculation formula of DR and FPR is shown in equation

$$DR = \frac{F \cap X}{F} FPR = \frac{X \backslash F}{X}, \tag{5}$$

where $F$ is the actual congestion path and $X$ is the congestion path deduced by the algorithm. The simulation experiment process is shown in Fig. 4 as the following.

In order to verify the effectiveness and accuracy of the proposed MRSKMP algorithm in congestion path inference, Brite topology generator is adopted to simulate wireless multimedia network models Waxman, BA and GLP with different types and sizes by the default parameters, and compared with the CLINK algorithm on the inference performance.

For the wireless multimedia network model with the scale of 150 nodes, CLR changes from 0.05$\sim$0.6, and DR and FPR of the two algorithms under optimal DTV are shown in Fig. 5.

In different types of wireless multimedia network model, MRSKMP algorithm inference performance is superior to CLINK algorithm. With the increase of CLR, DR shows a decreasing trend. The DR of the two algorithms is the highest under the GLP model, followed by the BA and Waxman models. As Waxman is a stochastic model, the path is relatively long, while BA and GLP are power-rate models, in which some routers have larger values and share more paths than Waxman's model in the wireless multimedia network model topology. Therefore, in the Waxman model, DR has decreased significantly compared with GLP and BA model. When CLR $< 0.2$, the inference performance of MRSKMP and CLINK algorithm in GLP and BA model is not very different. However, when CLR $> 0.2$, the inference performance of MRSKMP algorithm is better than CLINK algorithm in Waxman, BA and GLP models, and when CLR increases, the inference performance advantage is more significant, demonstrating the performance advantage of MRSKMP algorithm under feasible path congestion. As the CLR increases, the performance degradation of the MRSKMP algorithm is slower than that of the CLINK algorithm. CLRR is

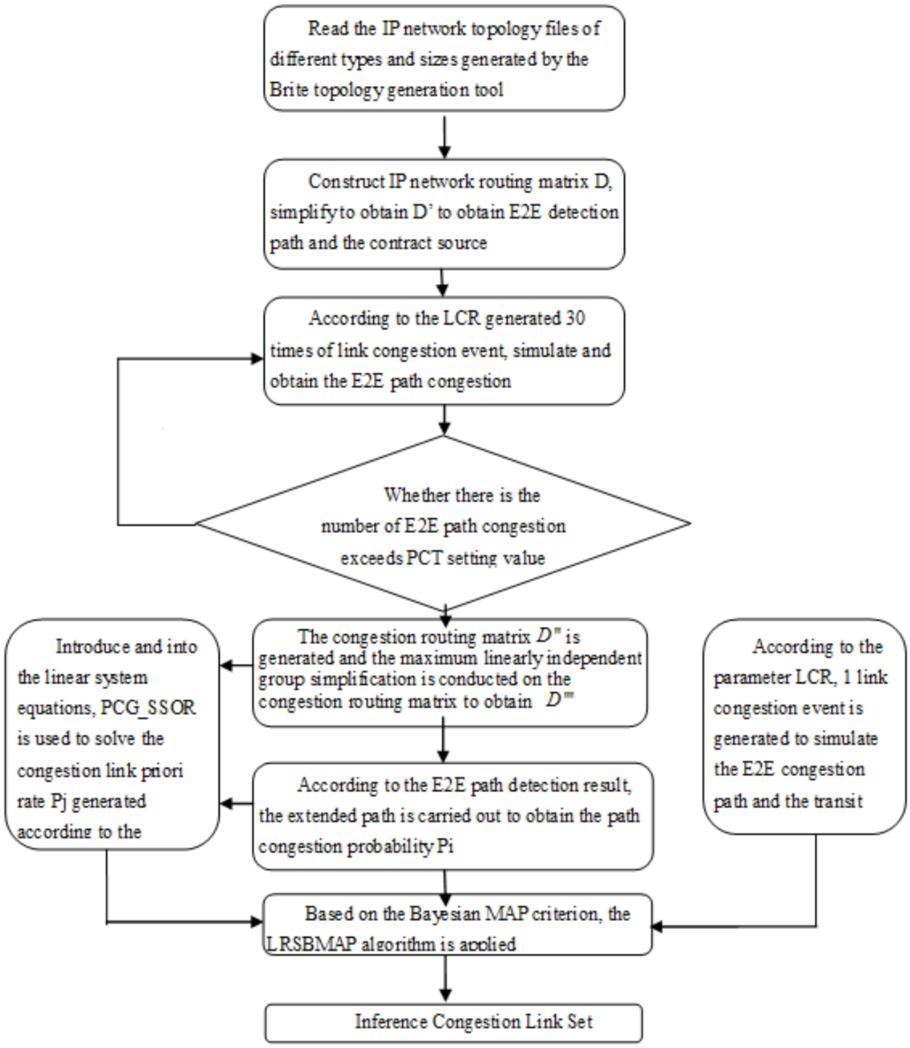


Fig. 4. Simulation experiment process

less than 55 % in GLP and BA model, and only 40 % in Waxman model; and DR still remains about 75 in DRP model, and is 65 % and 55 % and above in the BA and Waxman model respectively. Both algorithms have the lowest FPR in the GLP model, followed by the BA and Waxman models. With the increase of CLR, FPR first shows a slowly rising trend, and when CLR reaches a certain percentage, FPR shows a downward trend.

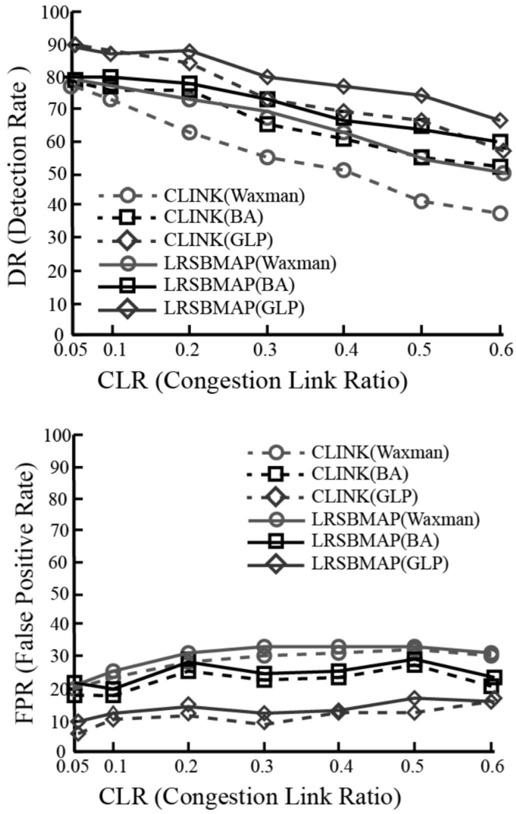


Fig. 5. Comparison of the inference performance of two algorithms under different CLR (number of nodes = 150)

### *4.1. Influence of different network scale on the algorithm*

In order to verify the inference performance of the algorithm in different wireless multimedia network types and scales, the Waxman, BA and GLP network topological model with the node number 50∼500 generated by Brite is adopted. Set the feasible path congestion scenario, CLR = 0.5. DR and FPR of MRSKMP algorithm and CLINK algorithm are shown in Fig. 6.

From Fig. 6, the inference performance of the two algorithms in different types and scales of wireless multimedia network models decreases slowly with the increase of network scale. Among them, MRSKMP algorithm is superior to CLINK algorithm in the reference performance for the Waxman, BA and GLP model, and DR is highest in the GLP model, followed by BA and Waxman model. In the GLP model, FPR is the lowest, followed by the BA and Waxman model. The inference FPR of the two algorithms in the Waxman, BA and GLP models remain basically stable with the increase of the wireless multimedia network scale. And FPR in the GLP model is lower than that in the BA and Waxman models. Under the three different network models, the difference of the congestion path inference FPR between the MRSKMP and the CLINK algorithm is small. When CLR = 0.5, the average FPR of the MRSKMP algorithm is slightly higher than that of the CLINK algorithm.

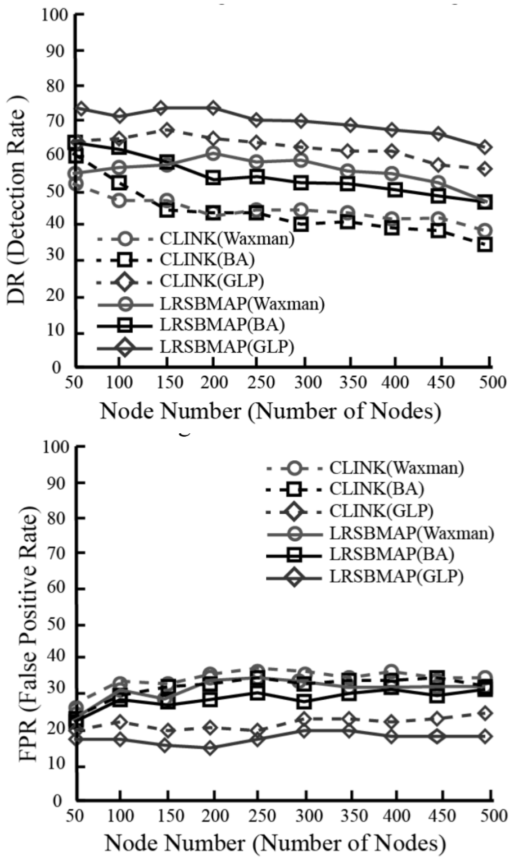


Fig. 6. Comparison of the inference performance of two algorithms CLR = 0.5 under different network scale

## 5. Conclusion

This paper proposes a congestion path routing algorithm MRSKMP in the scenario of a large scale wireless multimedia network with feasible path congestion. The path coverage and the number of E2E probe paths and the probe deployment overhead are taken into account through degree threshold optimization, so as to cover as many paths to be measured as possible; based on the remnant congestion routing matrix and KMP criterion at the time of inference, the improved Moore relaxation sub-gradient algorithm is adopted to infer the set of paths where congestion is most likely to occur. And the experiment has verified the accuracy and robustness of the algorithm proposed in the paper.

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