Master's Thesis

Title

Measuring packet loss ratio on overlay networks based on spatial composition

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Abstract

In overlay networks, it is important to know the performance of underlying IP networks because the performance of the overlay network strongly depends on that. Therefore, measuring the performance characteristics of overlay paths is an important task to obtain real-time and precise condition of overlay paths constructing the overlay network. Most of existing measurement mechanisms for overlay networks employ the full-mesh measurement, meaning that the overlay paths between all possible node pairs would be measured. Those methods are effective for small-scale overlay networks in terms of reducing the time required for obtaining enough information of overlay paths. For large-scale overlay networks, however, the increase in the measurement overhead and the degradation of the measurement accuracy due to path overlapping become a serious problem. Some measurement mechanisms that reduce the measurement overhead have been proposed, but they loss integrity, which means measuring all paths, or measure latency only.

Due to overcome these problems, spatial composition, which reduces the measurement while keeping integrity, is attracted much attention. It avoids lengthy measurements of an overlapping path and the path is divided into some sub-paths when multiple overlay paths share the underlay network route. The performance of the overall path is estimated by spatially composing measurement results of the sub-paths. However, such estimation methods based on spatial composition may include the additional errors caused by the measurement inaccuracy of sub-paths. Therefore, we need to assess the estimation accuracy of the spatial composition-based method and introduce statistical processing to suppress the estimation errors.

In this thesis, we propose statistical processing methods of measurement results to improve estimation accuracy of spatial composition-based measurement method for packet loss ratio. We introduce a statistical test for measurement results to exclude outliers from spatial composition.

We also propose some statistical indexes for determining whether we should discard the measurement results and reconduct the measurement.

We evaluate the performance of the proposed method by using measurement results obtained on PlanetLab environment. From the evaluation results we find that proposed two methods can decrease the estimation error of the spatial composition of packet loss ratio by 36% and 23%, respectively.

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1 Introduction

Overlay network [1] is defined in this thesis as an upper-layer logical network constructed upon the under-layer IP network as shown in Figure 1. Overlay networks are now considered as an effective means to apply networked application services quickly. Typical examples are VoIP applications (e.g. Viber [2]), file sharing applications (e.g. μtorrent [3]), real-time communication (e.g. Real Time Media Flow Protocol (RTMFP) [4]), and Grid [5] (e.g. Data Grid Environment and Tools (DGET) [6], Grido [7] and P-Grid [8]). Some of the overlay networks select an overlay-level route for data transmission according to network conditions such as link speed, delay, packet loss ratio, hop count, and TCP throughput between overlay nodes. For instance, content delivery network (CDN) such as NetLightning [9] and Akamai [10] distributes overlay nodes (content servers) over the entire Internet and select appropriate source and destination hosts according to the network condition when the contents would be moved, duplicated, or cached.

Due to its fundamental nature of overlay networks, the characteristics of the overlay path between overlay nodes, such as IP-level route, latency, bandwidth-related information, packet loss ratio, and so on, is not known explicitly in advance. Therefore, for improving the performance of overlay networks, measuring overlay paths is an important task to obtain real-time and precise condition of overlay paths constructing the overlay network. Although some measurement mechanisms for overlay networks have been proposed in the previous works [11], most of them employ the full-mesh measurement, meaning that all of overlay paths between all possible node pairs would be monitored. Those methods are effective for small-scale overlay networks by reducing the time required for obtaining enough information of overlay paths. For large-scale overlay networks, however, the increase of the measurement overhead and the decrease of the measurement accuracy due to path overlapping become a serious problem. For example, in RON, the measurement overhead become $O(n^2)$, where n is the number of overlay nodes, therefore, the number of participant overlay nodes is limited to around 50 [12]. To accommodate large-scale overlay networks, we need effective and scalable method for decreasing the measurement overhead.

One possible method to overcome these problems is spatial composition [13–15], which reduces the measurement while keeping integrity, is attracted much attention. It avoids lengthy measurements of an overlapping path by dividing the path into some sub-paths when multiple overlay paths share the underlay network route. The performance of the overall path is estimated by com-
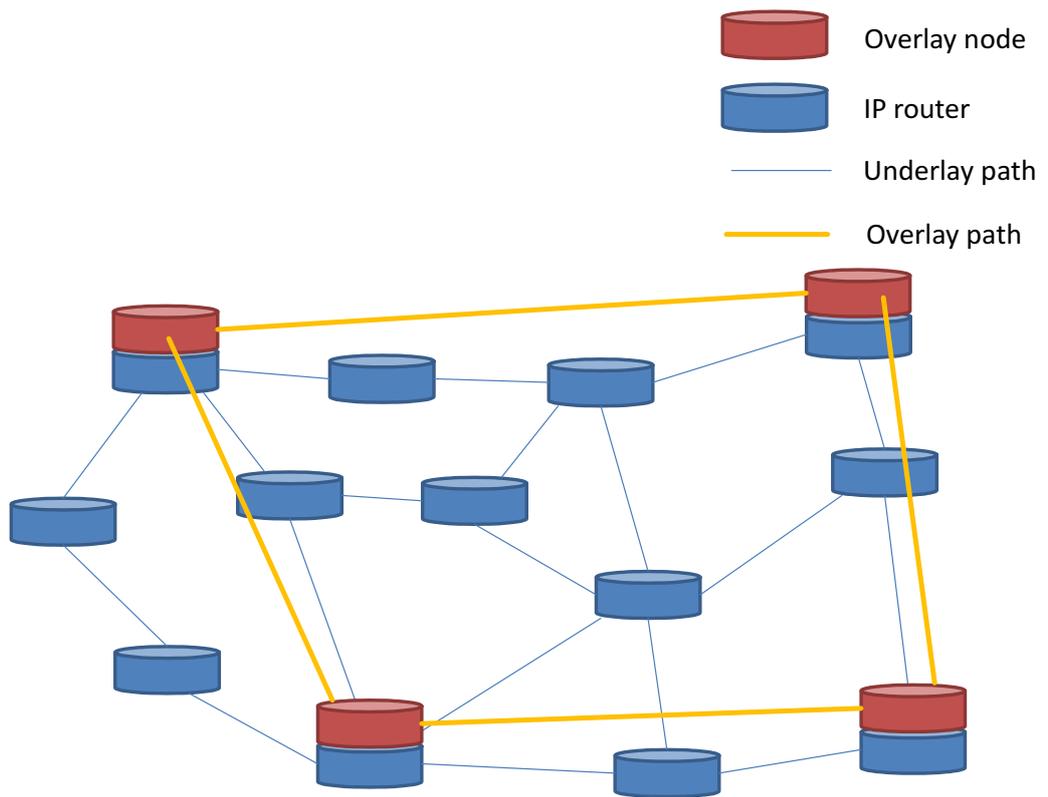
Figure 1: Overlay network

posing measurement results of the sub-paths. Generally, if overlay nodes increase in a network, other overlay nodes tend to exist on the overlay paths. Therefore, by increasing of overlapping path, the measuring cost becomes decrease. The authors in [14] reported that the measuring cost becomes 1/4000 at best. However, such estimation methods based on spatial composition may include the additional errors caused by the measurement inaccuracy of sub-paths. Therefore, we need to assess the estimation accuracy of the spatial composition-based method and introduce statistical processing to reduce the estimation errors.

In our research group, we proposed the statistical processing method of measurement results to improve estimation accuracy of spatial composition-based measurement method for end-to-end latency. It dramatically reduces error of estimation, from 88% to 0.6% [16]. However, we have not assessed the performance of the proposed method for packet loss ratio measurement, although the characteristics of the end-to-end latency and packet loss ratio is quite different.

In this thesis, we propose statistical processing methods of measurement results to improve estimation accuracy of spatial composition-based measurement method for packet loss ratio. We introduce a statistical test for measurement results to exclude outliers from spatial composition. We detect outliers from measurement results of sub-path by using Smirnov-Grubbs' test. We also propose some statistical indexes for determining whether we should discard the measurement results and reconduct the measurement. We evaluate the effectiveness of the proposed method by using the actual measurement results obtained on PlanetLab [17] environment.

The rest of this thesis is organized as follows. In Section 2, we explain the spatial composition method for packet loss ratio measurement. In Section 3, we propose the statistical processing methods for the spatial composition of packet loss ratio. In Section 4, we evaluate the performance of the proposed method by using measurement results obtained on PlanetLab environment. Finally, in Section 5, we present the conclusions of this thesis and areas for future works.

2   Spatial composition of measurement results on overlay networks

Spatial composition method [13–15] avoids the lengthy measurement of an overlay path and estimates the measurement result from measurement results of other overlay paths related to the original path. In detail, when we can divide the original path into sub-paths at intermediate overlay node(s), we spatially compose the measurement result of the original path from the measurement results of the sub-paths. This method can greatly decrease the number of measurement tasks on the overlay network especially when the density of the overlay node is high.

We show an example of the spatial composition for packet loss ratio by using Figure 2. In this figure we focus on the path AC between the overlay nodes A and C, which passes through the overlay node B. In the normal full-mesh measurement scenario, we should measure all paths of AC, AB, and BC. On the other hand, with spatial composition method, we only measure the paths AB and BC, and estimate the performance of the path AC by using the measurement results of the paths AB and BC.

We denote the actual value of the packet loss ratio on the overlay path AC as P_{AC}. Similarly, we denote the packet loss ratios that are measured on the overlay paths AB and BC as P_{AB} and P_{BC}, respectively. Then, the spatial composition method estimates the packet loss ratio of the overlay path AC, which is denoted as P'_{AC}, by using the following equation.

$$P'_{AC} = 1 - (1 - P_{AB})(1 - P_{BC}) \tag{1}$$

For maintaining the measurement accuracy of the spatial composition method, which is evaluated by the estimation error defined by the difference between P_{AC} and P'_{AC}, we need enough accurate measurement results for sub-paths, P_{AB} and P_{BC} in the above case. One possible way to keep the estimation accuracy is that when we find that the measurement results of sub-paths are not enough accurate we discard those measurement results from spatial composition. Furthermore, reconducting the measurement of sub-paths may be necessary. In the following section, we propose the statistical processing methods of measurement results to improve the estimation accuracy of spatial composition-based measurement method for packet loss ratio.
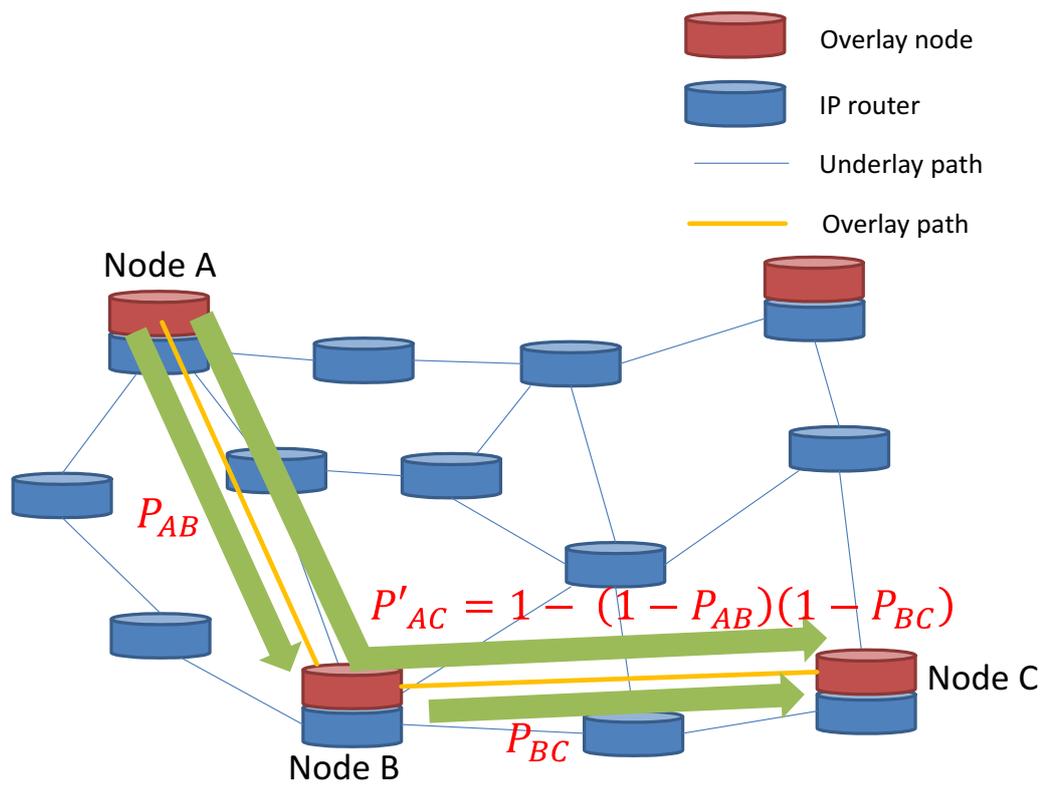
Figure 2: Spatial composition

3 Measurement data processing for spatial composition method

We define the packet loss ratio of an overlay path as the ratio of the number of the lost packets to the total number of sent packets from the source overlay node to the destination overlay node. Here, we consider the following two reasons why the estimation accuracy of the packet loss ratio by the spatial composition method degrades. One is due to the processing overhead at intermediate overlay nodes on the overlay path between source and destination overlay nodes. In general, overlay nodes on the network routers are implemented by software technologies such as virtual machines on server computers [18]. Therefore, the intermediate overlay node may not be able to process packets passing through itself due to the temporal increase in the server machine load. Such packet losses may degrade the estimation results of the spatial composition method since they are not related to the changes in the congestion level of the network. Therefore, we should discard the measurement results in such situations and reconduct the measurement to obtain the accurate estimation results.

The other reason is the abrupt changes in the packet loss ratio itself in the network. Since the objective of the packet loss ratio measurement in this thesis is to obtain the information of the network condition at steady state, such large and short-term changes should be removed for spatial composition. Note that such abrupt changes in the network condition can be utilized for detecting network failures, that is out of scope of this thesis.

In what follows we introduce two methods for measurement data processing. The first method is to exclude outliers by statistical test and the second method is to determine which measurement results are discarded and obtained again based on the statistical indexes.

3.1 Statistical test to exclude outliers

We propose a statistical test for measurement results to exclude outliers from spatial composition. We assume that a measurement result X for a certain overlay path can be divided into multiple results $X_1, X_2, \ldots, X_n$. For example, when the packet loss ratio is measured by sending 10,000 probe packets, we divide it into ten measurement results, each of which has 1,000 probe packets. We detect outliers from measurement results by using Smirnov-Grubbs' test [19]. For the statistical test, we set up the following null hypothesis and alternative hypothesis as H_0 and H_1, and conduct one-tailed test with the significance level of α.

Null hypothesis H_0: There are no outlier in the measurement results.

Alternative hypothesis H_1: The largest value in the measurement results is an outlier.

The detailed algorithm is as follows;

1. Prepare the measurement results of the packet loss ratio as $X_1, X_2, \ldots, X_n$.

2. Calculate the mean value $\bar{X}$ and the unbiased variance U of $X_1, X_2, \ldots, X_n$.

3. For the largest value X_i in $X_1, X_2, \ldots, X_n$, calculate T_i as follows.

$$T_i = \frac{|X_i - \overline{X}|}{\sqrt{U}} \tag{2}$$

4. From the number of data n and the significance level α, calculate the critical value t as follows.

$$t = (n-1)\sqrt{\frac{t'^2}{n(n-2) + nt'}} \tag{3}$$

In addition, t' is the $(1 - 100\alpha/n)$th percentile of the t-distribution with $n - 2$ degrees of freedom.

5. Determine whether H_0 is rejected or not as follows.

   - When $T_i < t$, H_0 is not rejected. That is, we determine that X_i is not an outlier and terminate the procedure algorithm.

   - When $T_i \geq t$, H_0 is rejected. That is, we determine that X_i is an outlier and remove X_i from data set. Furthermore, for testing additional outliers, go back to the step 2.

3.2 Statistical indexes for finding inaccurate measurement results

We also introduce some statistical indexes for determining whether we should discard the whole measurement results of a certain overlay path and reconduct the measurement. We have investigated many candidates for the statistical index for this purpose and selected the following indexes appropriate for the spatial composition method of packet loss ratio. Here, we denote the mean value and the standard deviation of the measurement results $X_1, X_2, \ldots, X_n$ as $\bar{X}$ and σ, respectively. We also denote the maximum and minimum values in $X_1, X_2, \ldots, X_n$ by X_{max} and X_{min}, respectively.

- $I_1 = \frac{\sigma}{X}$

- $I_2 = \frac{X_{max} - X_{min}}{X}$

- $I_3 = \frac{X_{max}}{X}$

Note that the first index, I_1, means the coefficient of variation of $X_1, X_2, \ldots, X_n$. For each measurement result of the overlay path, when one and more of the above indexes are large, we determine that the estimation accuracy would degrade when using the measurement results for spatial composition. So, we discard the measurement results and reconduct the measurement, or the measure the original path itself.

4 Performance evaluation

4.1 Methodology

For evaluating the performance of our proposed method explained in Section 3, we utilized measurement results of packet loss ratio between nodes on the PlanetLab [17]. For measuring the packet loss ratio we used a UDP-based probing software. The detailed steps for measuring packet loss ratio for a certain path is as follows.

1. Choose three PlanetLab nodes as the node A, B and C.

2. Send 2,500 UDP packets from node A to node C via node B at 1.0 second intervals.

3. Send 2,500 UDP packets from node A to node B at 1.0 second intervals.

4. Send 2,500 UDP packets from node B to node C at 1.0 second intervals.

5. Repeat steps 2, 3, and 4 20 times.

Note that we control the path between nodes A and C at the application layer so that it traverses node B. In each step, the sending node sends 2,500 UDP packets to the receiving node and the receiving node echo the UDP packet back to the sending node just for the confirmation of receipt of the packet. Then the sending node calculates the packet loss ratio based on the number of sent packets and that of received echo packets. The total number of probe packets is 50,000, which is divided into twenty sub-results, each of which has 2,500 probe packets. Here, we define one *data set* as the measurement results of paths AC, AB, and BC from three PlanetLab nodes A, B, and C. We utilize 3,348 data sets with different combinations of three PlanetLab nodes. The measurements were conducted from 21st January to 30th May in 2012.

We denote the actual value of the packet loss ratio on the overlay path AC as P_{AC}, and the estimated value of the packet loss ratio on the overlay path AC by the spatial composition method as P'_{AC}. Then, we define the estimation error E as the following equation.

$$E = |\log_{10} P'_{AC} - \log_{10} P_{AC}| \tag{4}$$

For the evaluation of the statistical indexes explained in Subsection 3.2, we do not reconduct the measurement even when the measurement results are determined to be inaccurate. Instead, we

just discard the measurement results and evaluate the average estimation error of the remaining measurement results.

4.2 Estimation error distribution

We first investigate the estimation error when the data processing methods explained in Subsections 3.1 and 3.2 are not utilized. Figure 3 shows the distribution of the estimation error of the spatial composition method for all paths. From this figure we can observe that most results of the estimation error is less than 1.0, but there are some results with very large estimation error ($>$ 2.0). We assessed such results in detail and found the following two major reasons for the large estimation error.

- One or two measurement results out of the twenty measurement results of 2,500 probe packets has large packet loss ratio compared with others.

- The actual packet loss ratio of the path AC, P_{AC}, is quite larger than the estimated value, P'_{AC}.

In what follows, we show the results of introducing the data processing methods in Subsections 3.1 and 3.2 to decrease the estimation error.

4.3 Evaluation of the statistical indexes for discarding the measurement results

We first evaluate the performance of the statistical indexes for discarding the measurement results proposed in Subsection 3.2. Here, for each index I_1, I_2, and I_3, we first sort the measured paths in the order of the index value. We then remove the measurement results of the paths one-by-one according to the order oand evaluate the estimation error for remaining measurement results.

Figures 4, 5, and 6 show the evaluation results for the index I_1, I_2, and I_3, respectively. In each figure we have three graphs plotting the changes in the mean value, 90th percentile value, and the worst value of the estimation errors. In these figures we plot the results when we remove the measurement data based on the measurement results of the receiver-side sub-path (path BC in Figure 2). We can see from these figures that for the removal of around 100 data sets, the estimation error distribution remain almost unchanged. This is because some paths have extremely large estimation errors. In detail, in such paths, 19 out of 20 measurement results has zero packet
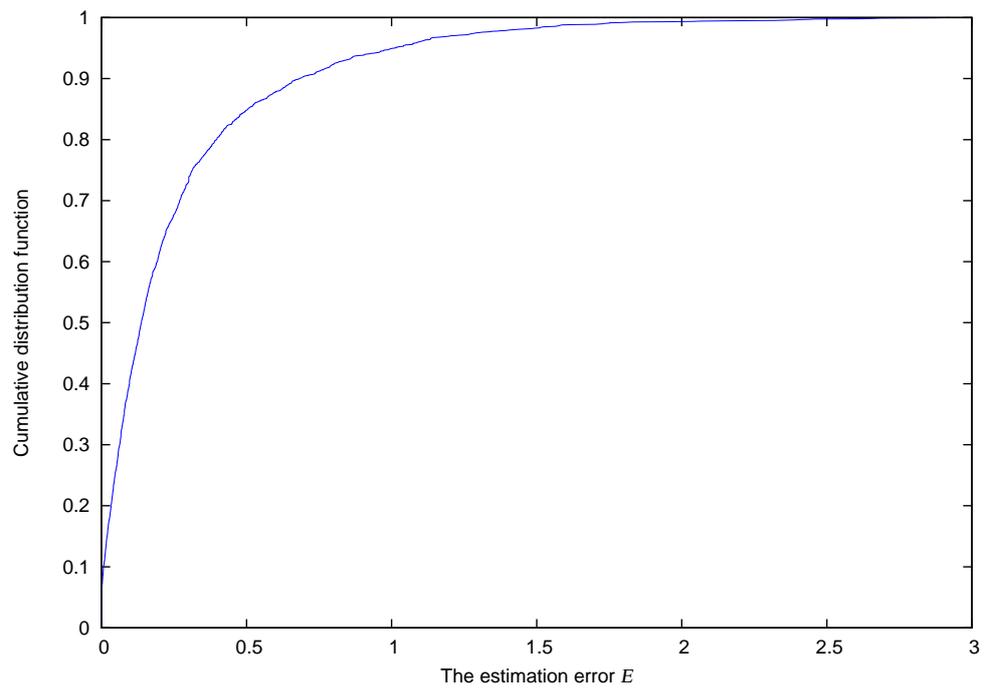
Figure 3: Estimation error distribution

loss ratio, and the remaining one measurement has only one packet loss in 2,500 probe packets. Such extreme case has large effect on the overall estimation error distribution.

However, when the number of removed data sets increases, the mean and 90th percentile values of the estimation error decrease significantly. This means that the proposed method has positive effect on decreasing the estimation error in the spatial composition of packet loss ratio. On the other hand, for the worst value of the estimation error, the proposed method has almost no effect. We believe that such worst values should be detected by other methods. One possible way is to utilize other metrics than packet loss ratio itself, such as the latency. This is one of our important future work.

4.4   Evaluation the effect of the statistical test

We next evaluate the effect of the statistical test proposed in Subsection 3.1. Figure 7 plots the distribution of the estimation error with various values of α, that represents the significance level. In the figure we show the overall distribution In Figure 7(a) and the magnified distribution when in Figure 7(b) to observe the effect of α clearly. We also plot the case when we do not apply the statistical test. Also, in Figure 8, we plot the mean value and 90th percentile value of the estimation errors as a function of α. From these figures we can observe that the statistical test can improve the estimation error significantly. In detail, we can decrease the mean estimation error by 25.8% and 90th percentile value by 36.1% when we set α to 0.064.

We also confirm that we should set the value of α carefully since too large or too small value of α degrades the performance of the proposed method. This is because when we utilize too large value of α we remove the measurement data which is considered not to be an outlier. On the other hand, with too small value of α we can not remove the outliers that should actually be removed.

We also investigate the effect of the statistical test on the performance of the statistical indexes for discarding the measurement results. Figure 9 shows the changes in the mean estimation errors as a function of the number of removed data sets after applying the statistical test with various values of α. Figures 10 and 11 shows the similar results for 90th percentile value and worst values, respectively. From these figures we can see that the statistical test largely affects the performance of the statistical indexes for discarding the measurement results and decreases the estimation error largely, especially for the mean and 90th percentile values. On the other hand, the worst value of the estimation error can not be decreased even with the statistical test. This again shows the
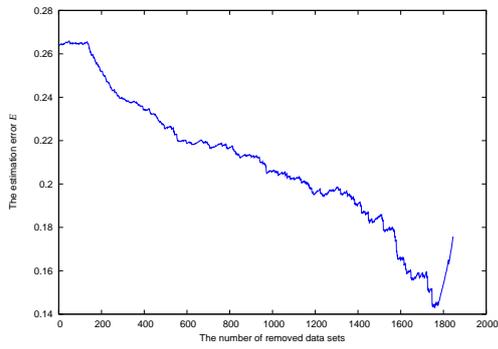
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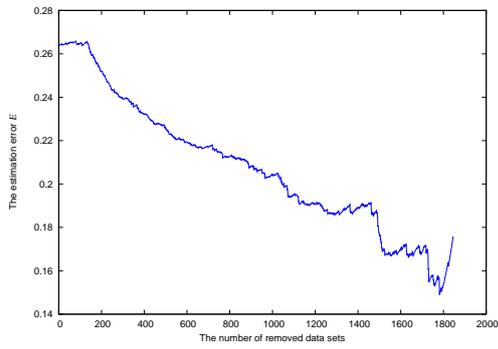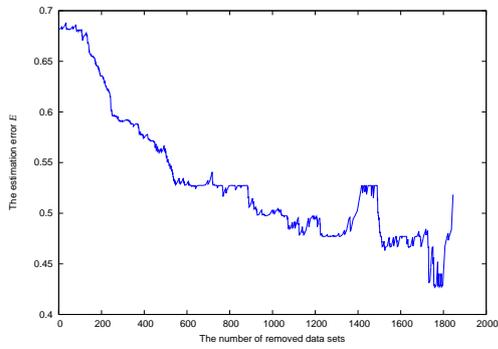
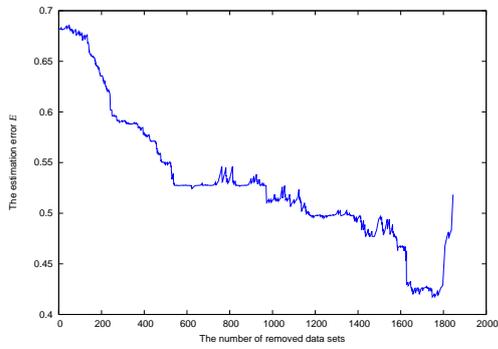(a) The mean value

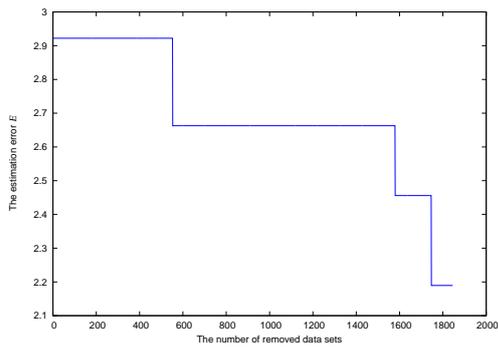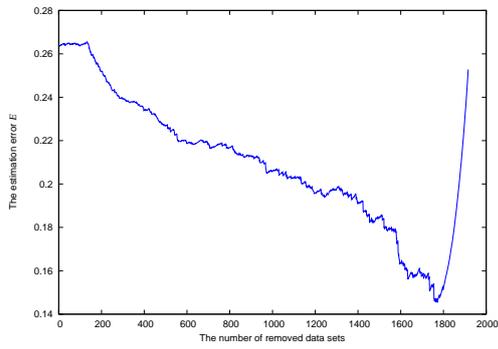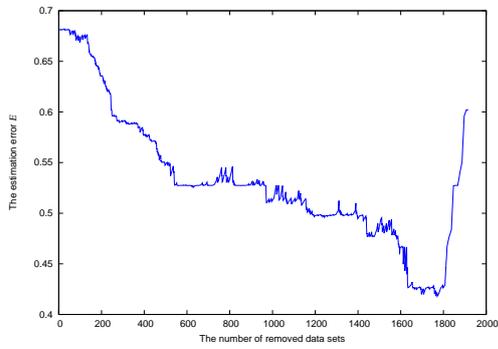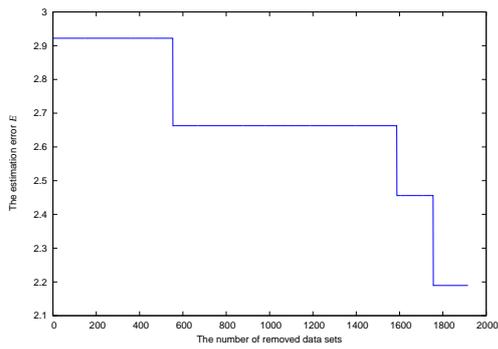(b) The 90th percentile value
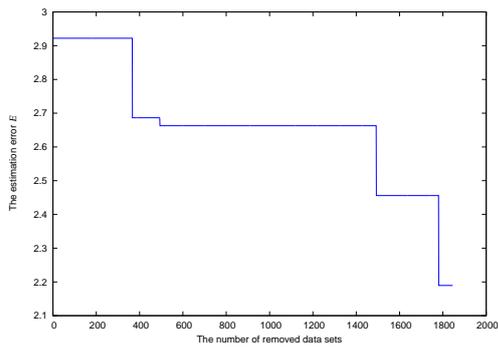
(c) The worst value

Figure 4: Effect of the measurement data removal based on the index I_1

(a) The mean value

(b) The 90th percentile value

(c) The worst value

Figure 5: Effect of the measurement data removal based on the index I_2
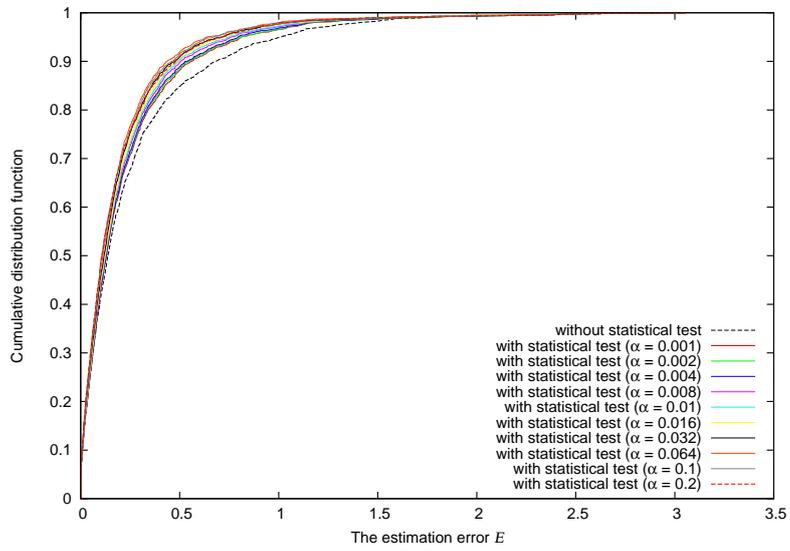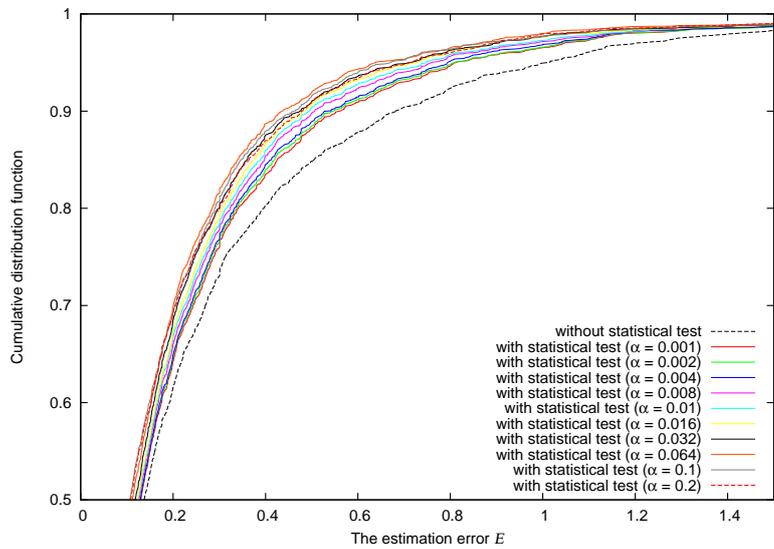
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(a) The mean value

(b) The 90th percentile value

(c) The worst value

Figure 6: Effect of the measurement data removal based on the index I_3

(a) Overall distribution

(b) Magnified distribution

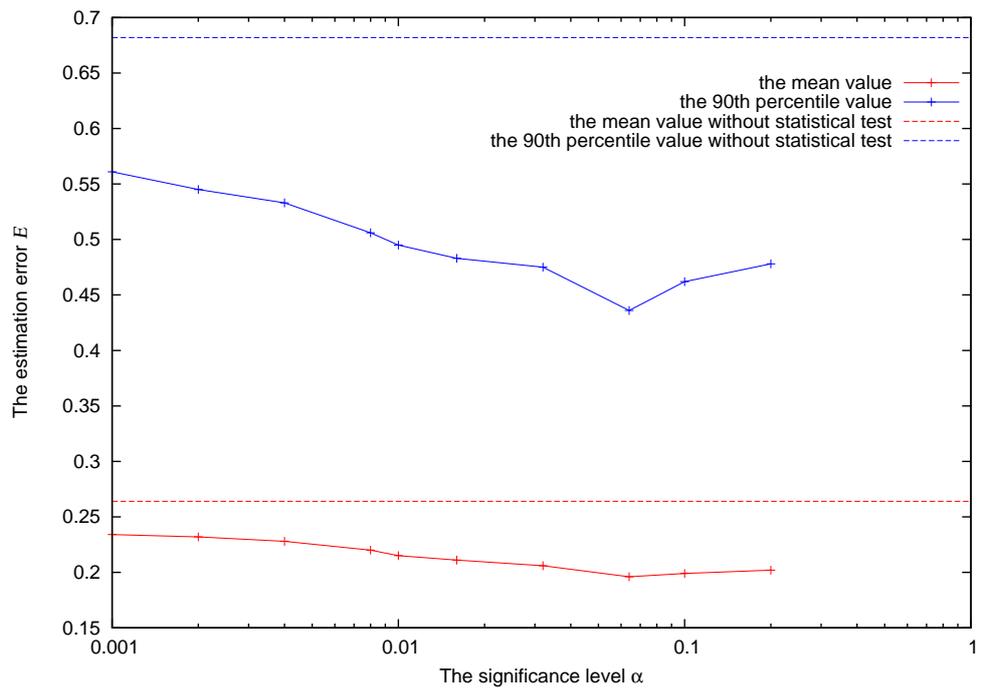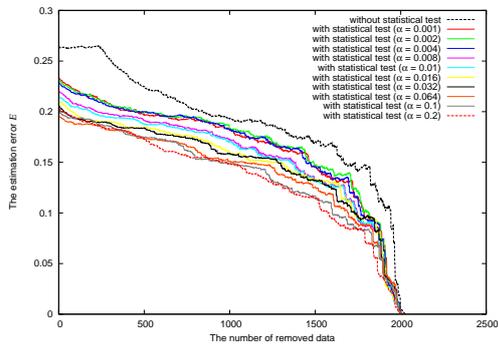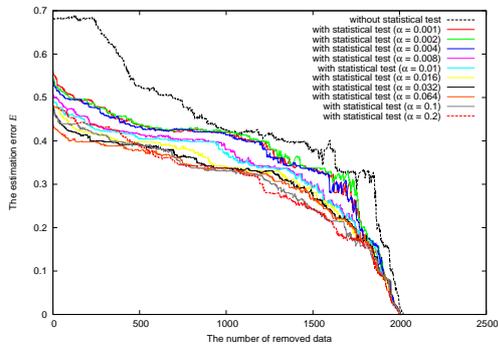Figure 7: Estimation error distribution with various values of α

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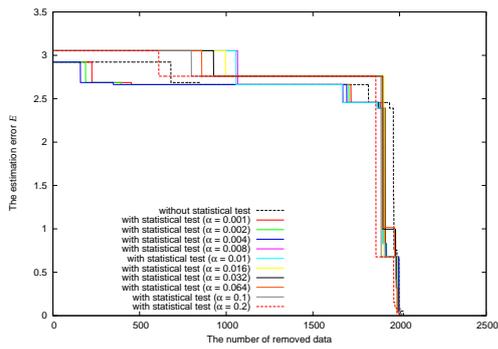Figure 8: The estimation errors with various values of α

limitation of the proposed methods in this thesis. We also see that the best setting of α is around 0.064, which is identical to the results in the estimation error distribution shown in Figure 7.
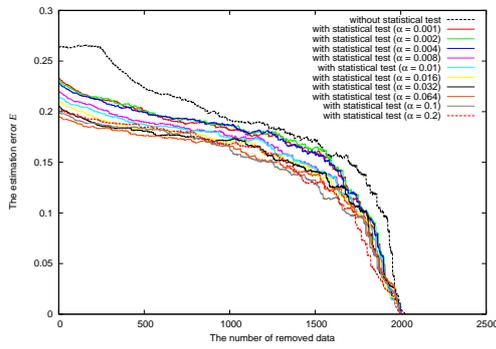
(a) The mean value

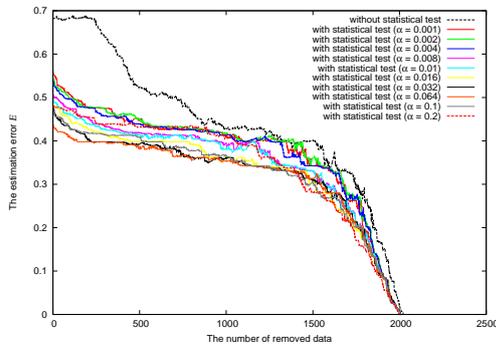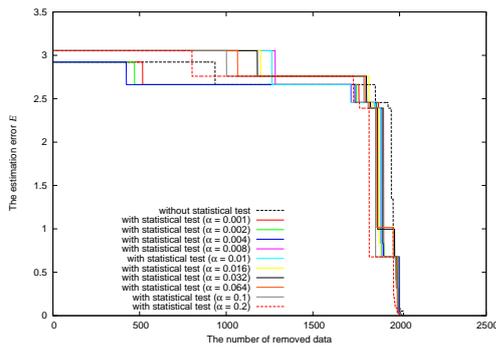
(b) The 90th percentile value

(c) The worst value

Figure 9: Effect of the measurement data removal based on index I_1 after statistical test
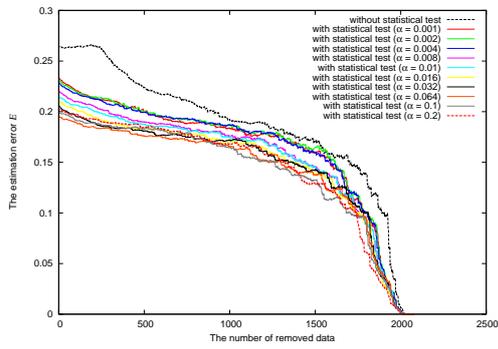
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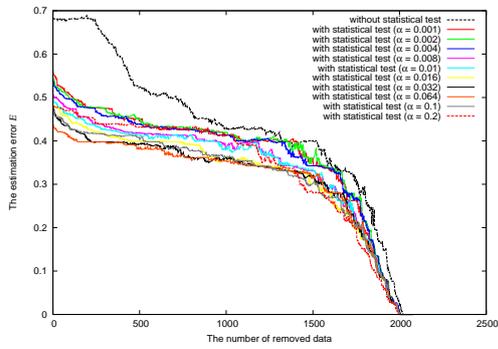(a) The mean value

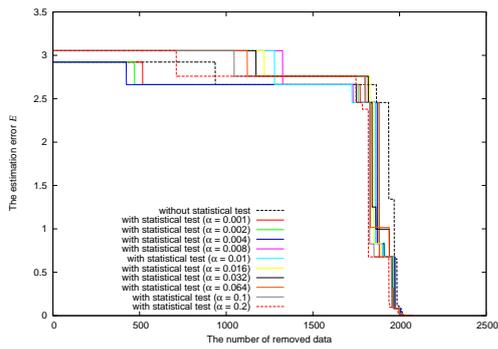(b) The 90th percentile value

(c) The worst value

Figure 10: Effect of the measurement data removal based on index I_2 after statistical test

(a) The mean value

(b) The 90th percentile value

(c) The worst value

Figure 11: Effect of the measurement data removal based on index I_3 after statistical test

5 Conclusions and future works

In this thesis, we proposed and evaluated the statistical processing methods of measurement results on the overlay paths to improve estimation accuracy of spatial composition-based measurement method for packet loss ratio. One of these methods is a statistical test for measurement results to exclude outliers from spatial composition. This method excludes outliers from measurement results of packet loss ratio. We showed this method reduces the estimation error, especially, when we set the significance level to 0.064, this method reduces the mean and 90th percentile estimation value of the estimation error by 25.8% and 36.1% , respectively. The other method is some statistical indexes for determining whether we should discard the measurement results and reconduct the measurement. We showed this method reduce the mean and 90th percentile estimation value of the estimation error significantly when the number of removed data sets increases.

For future works, we plan to evaluate estimation accuracy of spatial composition-based measurement method for other metrics, for example, TCP throughput or available bandwidth. We also plan to evaluate the proposed method by using various measurement results in addition to those obtained in PlanetLab environment.

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