PAPER

Accurate Parallel Flow Monitoring for Loss Measurements

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SUMMARY End-to-end loss and delay are both fundamental metrics in network performance evaluation, and accurate measurements for these end-to-end metrics are one of the keys to keeping delay/loss-sensitive applications (e.g., audio/video conferencing, IP telephony, or telesurgery) comfortable on networks. In our previous work [1], we proposed a parallel flow monitoring method that can provide accurate active measurements of end-to-end delay. In this method, delay samples of a target flow increase by utilizing the observation results of other flows sharing the source/destination with the target flow. In this paper, to improve accuracy of loss measurements, we propose a loss measurement method by extending our delay measurement method. Additionally, we improve the loss measurement method so that it enables to fully utilize information of all flows including flows with different source and destination. We evaluate the proposed method through theoretical and simulation analyses. The evaluations show that the accuracy of the proposed method is bounded by theoretical upper/lower bounds, and it is confirmed that it reduces the error of loss rate estimations by 57.5% on average.

key words: *Active Measurement, Packet Loss, Parallel Measurement, Probe Packet, QoS Monitoring*
[††]

1. Introduction

When we evaluate network performance, it is important to accurately measure metrics along an end-to-end path. End-to-end packet loss and delay are both fundamental metrics for network performance evaluations. Internet Service Providers (ISPs) normally monitor these metrics to keep the service levels of their networks. ISPs are under an obligation to keep network performance in compliance with Service Level Agreements (SLAs). Additionally, it is well known that real-time applications including audio/video conferencing, IP telephony, and telesurgery are sensitive to end-to-end packet loss and delay. Advanced SLAs which stipulate metrics including delay/loss along an end-to-end path are required for delay/loss-sensitive applications, though most of current SLAs stipulate only packet loss of each link monitored by a Management Information Base (MIB). Hence, the accurate measurement of end-to-end metrics is important for SLA monitoring, in order to provide advanced SLAs for delay/loss-sensitive applications.

It is valuable to measure the end-to-end metrics on a network without relying on the information inside the network such as MIB. If we are interested in end-to-end metrics across multiple ISPs, no one will have access to all the relevant network equipment. From the viewpoint of network researchers who do not have direct access to the network equipment, it is useful to achieve the measurement only from the information that can be accessed from the outside. In addition, it is difficult to accurately estimate a fine-grained loss rate along an end-to-end path due to the time synchronization problem.

In measurements of end-to-end metrics for networks, an active measurement in which probe packets are injected into a network is commonly used, and various measurement tools for active measurements have been proposed in prior works [3–8]. The literature details attempts to improve measurement accuracy without increasing the number of probe packets [9–11] since increasing the number of probe packets leads to greater communication overheads and the intrusiveness problem [8, 12]. In the modern Internet, a large delay (that exceeds 150 [ms] as mentioned in ITU-T Recommendation G.114 [13]) rarely occurs. Packet losses are also rare events as ITU-T Recommendation Y.1541 [14] defines QoS class with upper bounds 1.0×10^{-5} of end-to-end loss rate for emerging applications. It is difficult to capture such rare events using a limited number of probe packets of a single flow, even if active measurements are easy to perform.

While most of the prior works utilize only one probe flow to measure the end-to-end metric regarding one path, we proposed a parallel flow monitoring method in which delay on a flow is accurately measured by utilizing the observation results of other flows sharing the source/destination [1, 8]. In daily operations, ISPs are monitoring end-to-end metrics of the multiple paths on their network in parallel. The method in [1] utilizes this parallel monitoring.

In this paper, based on the delay measurement method in [1], we propose a loss measurement method that fully utilizes flows, including flows with different sources and destinations. We extend the delay measurement method to a loss measurement with a weighted loss estimator. In the proposed method, information regarding lost probe packets in the other probe flows is utilized in estimating the loss rate on a path of the target probe flow. As we mentioned above, it is difficult to capture packet loss events by the limited number of probe packets in a target probe flow since the packet losses

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are rare events. Even if a target probe flow fails to capture loss events, the proposed method can estimate the loss statistics on the path of the target probe flow since another probe flow may capture loss events. Therefore, the proposed method transcends a fundamental accuracy bound of conventional active measurements of the loss statistics. The method and network tomography are totally different from our method because our method estimates loss statistics along a path. Tomography estimates link-level statistics from statistics along a path. The proposed method does not compete with tomography. This is because the statistics along a path can be used as tomography inputs. By combining the proposed method and tomography, it may be possible to improve the accuracy of tomography. Additionally, we improve the accuracy of the extended method by fully utilizing information of all flows with a recursive conversion of the information of the other flows. The proposed method utilizes the information of all probe flows that share a part of the path with a target probe flow though the method in [1] only utilizes information of flows that has the same source/destination with a target probe flows.

The proposed method is extremely versatile under mild assumptions. The method does not require any internal information of a measured network, including the topology of the measured network, and it only uses delay and loss of each flow. Note that the method does not assume that all possible paths in a network are simultaneously monitored. It can appropriately perform when only a part of paths in a network are monitored.

In summary, this paper makes the following contributions.

- **Parallel loss measurements:** We propose a parallel monitoring method for packet loss. The method extends the delay measurement method that utilizes parallel active probe flows to a loss measurement, thereby improving measurement accuracy of loss statistics.
- **A recursive conversion technique:** Our loss measurement includes a novel technique called recursive conversion that is different from the previous delay measurement method [1] to improve accuracy in loss measurements. The technique enables us to fully utilize information of all probe flows for a measurement.
- **Theoretical accuracy analysis:** We provide a theoretical analysis of the accuracy of our method. The upper and lower bounds of the accuracy of the method are calculated.
- **Simulation-based evaluations:** We confirm that our method provides accurate measurements through simulations. It is also confirmed that the simulation results are consistent with analytical results.

The rest of the paper is organized as follows. First, we mention a network model and assumptions in Section 2. Next, Section 3 summarizes the parallel flow monitoring method for a delay measurement in our previous study [1]. In Section 4, we explain a proposed loss measurement method that fully utilizes information regarding all flows in a network. In Section 5 and 6, we provide theoretical analysis and simulation-based evaluation of the proposed method, respectively. After discussing some related works in Section 7, we conclude the paper and mention future works in Section 8.

2. A Network Model and Assumptions

Since the method we propose in this paper is based on the method [1], most of the assumptions are inherited from [1] to this paper. A wired network considered within the scope of this work is represented by a directed graph. A packet is delivered from a source to a destination along a path. Paths are stable in a measurement period (generally within several minutes) since paths are not changed frequently. Packets are delayed and may be lost at nodes or links on a path. We assume that an end-to-end delay consists of propagation delay and queueing delay since both delays are dominant in the modern Internet [15]. Propagation delay can be regarded to be a constant for a path while queueing delay dynamically changes reflecting traffic status.

In this paper, we assume that most of the loss events are caused by buffer overflows in interfaces placed on links with congestions. Inevitably, packet loss events highly depend on queueing delay. We assume that links with large queueing delay, i.e. links with many packet loss events, are sparse among all links in a network, and the ratio of periods with large queueing delay on a link to other periods is small. The validity of the assumption can be confirmed since the average link utilization of the modern Internet is maintained low [16]. Note that we do not assume a congested link is unique, and we do not need to know the topology of a network.

Though the metric we want to measure is loss statistics along a path in wired packet networks, we utilize delay information to improve accuracy of loss measurements. To measure packet loss and packet delay on paths, probe packets are periodically injected for all or a part of paths on a network. A delay or loss experienced by a probe packet can be obtained by matching the packets at the source and the destination. Generally, end-to-end delays on networks are the order of milliseconds. If we want to accurately measure end-to-end delays along with loss statistics, time synchronization on the order of microseconds like GPS network time synchronization is assumed on all senders and receivers. If we want to measure only loss statistics, strict time synchronization is not required. In our previous method [1], the time synchronization lag is treated like a propagation delay and is subtracted from the delay experienced by probe packets. Since sample conversion/uniting is executed based on the queuing delay that does not include the propagation delay and the time synchronization lag, the lag does not deteriorate the accuracy of the measurement.

3. Parallel Flow Monitoring for Delay

Since we assume sparseness of congested links, queueing de-

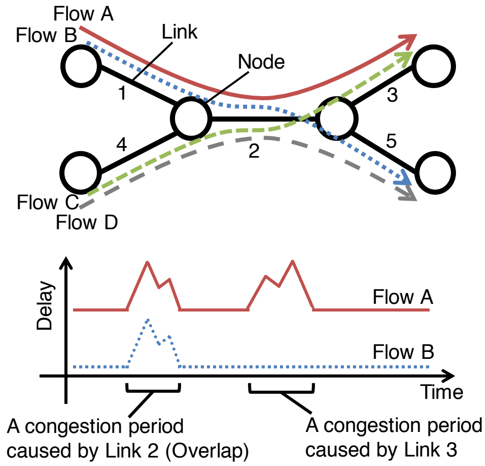

Fig. 1 Overlap of queueing delay processes in a congestion period.

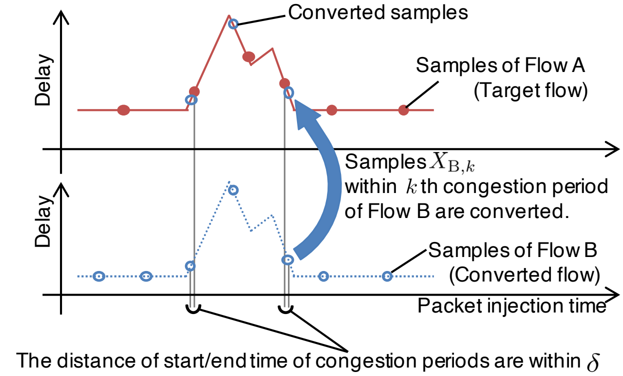

Fig. 2 Conversion of delay samples in congestion periods of multiple flows whose start and end times are respectively almost the same.

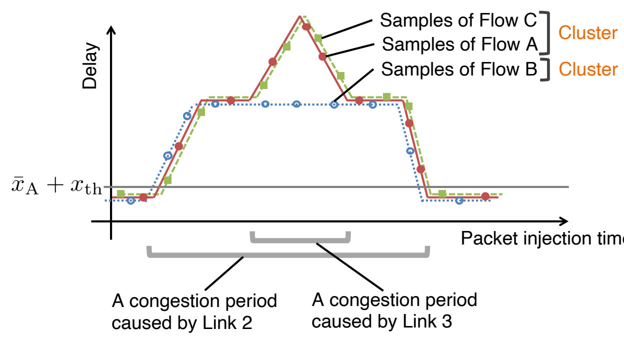

Fig. 3 Clusters for each common link that causes a large delay.

lay processes within a congestion period on multiple paths that have common links frequently overlap (see Fig. 1), and the samples within the congestion periods can be converted. In the method in [1], the ith sample for Flow A is expressed by (t^i_A, x^i_A) where t^i_A and x^i_A denote injection time and experienced delay of the ith probe packet, respectively. A congestion period is observed as consecutive samples that are larger than a threshold x_{th}. The set of samples within the jth congestion periods on the path of Flow A is denoted as $X_{A,j}$. If there are congestion periods of multiple flows whose start and end times are respectively almost the same (i.e., they are closer than a constant probe interval δ), the samples in the congestion periods are converted each other as shown in Fig. 2. After the conversion, clustering process starts. Delay samples in the congestion periods are formatted to n-dimensional vectors, and the vectors are divided into clusters for each common link that causes a large delay (Fig. 3). A clustering technique in machine learning is utilized to divide them into clusters. A queueing delay process captured by probe flows in the same cluster are determined to be overlapped, and the delay samples are converted between each other, by modifying the injection time and delay to that of the target flow. By the conversions, the number of delay samples of each flow increases, thereby improving the accuracy of the delay measurement.

4. Parallel Flow Monitoring for Loss Statistics

In this paper, we will extend the method of [1], which was mentioned in Section 3, to a loss measurement and improve its accuracy by utilizing information of all flows including flows with different source and destination. By utilizing all flows, the proposed method makes it possible to capture loss events that occur with extremely low probability, such as 1.0×10^{-5} defined as the strictest QoS class in ITU-T Recommendation Y.1541.

4.1 Extension to Loss Measurements

The proposed method achieves accurate loss measurements by uniting samples of loss events. As with the method in [1], the uniting in the proposed method is based on delay information, though the metric we want to measure in the proposed method is loss statistics. In the proposed method, samples that capture loss events are recorded for each congestion period, and samples are united each other at the time of conversion of delay samples (Fig. 4). Since we assumed that the main cause of packet loss is buffer overflows, most of packet loss events occur within congestion periods. Therefore, we can consider that loss events within a congestion period occur at the link which causes the congestion. First of all, a set $L_{A,j}$ of samples of loss events between the first and last samples in delay samples $X_{A,j}$ are recorded. A loss sample in $L_{A,j}$ is defined as (t^i_A, ∞) that corresponds to a lost probe packet within the jth congestion period of Flow A. Based on the method in [1], samples $X_{A,j}$ for delay are converted each other, thereby obtaining samples $\mathcal{X}_{A,j}$ which includes converted samples. When the samples $X_{B,k}$ are converted to the jth congestion period on the path of Flow A, samples $L_{B,k}$ of loss events are united to samples $L_{A,j}$ of loss events within the jth congestion period on the path of Flow A. As a result, the samples $\mathcal{L}_{A,j}$ which includes united samples within the

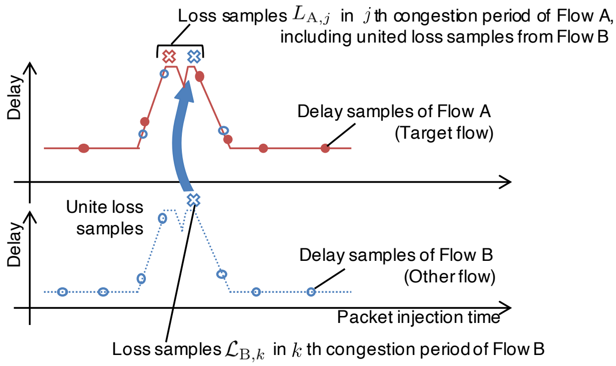

Fig. 4 United samples of loss events.

jth congestion period on the path of Flow A are updated to $\mathcal{L}_{A,j} \cup L_{B,k}$. Note that $\mathcal{X}_{A,j}$ and $\mathcal{L}_{A,j}$ respectively include converted and united samples from other flows while $X_{A,j}$ and $L_{A,j}$ represent the original samples of Flow A.

Using delay samples $\mathcal{X}_{A,j}$ and loss samples $\mathcal{L}_{A,j}$ that include converted/united samples, we can accurately obtain various statistics regarding delay and loss. These samples allow us to calculate not only the loss rate of packets for each flow over the entire measurement period but also the loss rate of any partial period in any granularity. By extracting a period when end-to-end delay exceeds a certain threshold, it is possible to detect congestion that occurred in an extremely short time. By calculating the loss rate within the short congestion, we can analyze the loss rate in detail for each individual congestion. Fine-grained measurement causes difficult estimation of the loss along a path from the link level measurement including MIB. This is because delay experienced by a packet before reaching each link is different, so that a packet sent at time t is not associated with the loss rate at time t on a link. In addition, even for long-term measurements, packet loss events for each link are not independent, so it is not possible to simply calculate a loss rate along a path. Moreover, it is noteworthy that the proposed method simultaneously measures delay and loss along a path. The obtained samples are also useful for analyzing the relationship between delay and loss along a path. The following is an example of an estimator of loss rate on each path.

To provide an unbiased estimator of loss rate on each path, samples should be weighted since the samples of loss events in the proposed method are biased on a time-space, while most of the conventional loss measurements using active probes assume that probe packets are uniformly distributed. The weight w_s of a sample s is given as

$$w_s = \frac{|X_{A,j} \cup L_{A,j}|}{|\mathcal{X}_{A,j} \cup \mathcal{L}_{A,j}|} \quad \text{for} \quad s \in \mathcal{L}_{A,j}.$$

Then,

$$\sum_j \sum_{s \in \mathcal{L}_{A,j}} \frac{w_s}{|X_A| + |L_A|}$$

provides an estimator of loss rate on the path of Flow A, where $|X_A|$ and $|L_A|$ denote the number of all delay samples and loss samples of Flow A, respectively.

The communication overhead of the proposed method is completely the same as the conventional method that measures delay and loss. The number of probe packets is not increased by the proposed method. Both the proposed method and the conventional method aim to measure loss statistics on N paths by obtaining samples of N probe flows. The number of injected probes and the number of probes that pass through each link are exactly the same. Both the proposed and the conventional method gather information of probe after a measurement from each endpoint to a measurement server. Because we consider the situation that a measurement server provides various packet-level statistics including delay distribution, loss duration, and so on. The calculation of these statistics requires packet-level delay/loss information. The communication overhead for the gathering process is common for both methods, and it is small compared to the overhead of probe packets. For example, each endpoint sends just 1 packet for the gathering process per 100 probe packets. The number of packets for the gathering process is proportional to the number of probe packets. Namely, less number of probe packets also reduces the number of packets for the gathering process.

The computational complexity of the proposed method is the same as the method in [1]. A measurement server checks the delay/loss status of each packet in reports from endpoints. The computational complexity of the process is $O(NP)$, where N and P denote the number of flows and the number of probe packets in a flow, respectively. The conventional method finishes after this process, then the computational complexity of the conventional method is $O(NP)$. Since the proposed method requires additional processes for conversion and uniting processes, the computational complexity of the proposed method is roughly $O(NP + N^2M^2 + NML + L^3K^3)$, where M denotes the maximum number of congestion periods of a flow. L and K denote the maximum number of samples in a congestion period and the maximum number of flows in a link, respectively. Since we assume sparseness of congested links M and L are significantly smaller than P. Moreover, in general networks, N, L, and K are small compared to P. Needless to say, the proposed method requires a longer processing time compared to the conventional method. However, the requirement of the processing time is not severe, since the packet-level statistics are calculated after a measurement period in an offline manner.

4.2 Recursive Conversion Technique to Utilize All Probe Flows

By repeatedly converting samples obtained from each probe flow, the proposed method utilizes information of all probe flows that include flows with different sources and destinations. Even if both source and destination are different, flows that share a part of paths includes information of the target

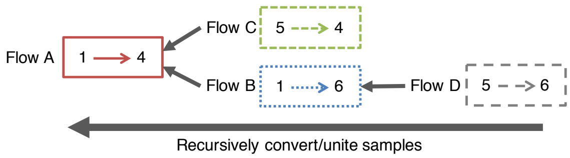

Fig. 5 An example of a dependency tree for a recursive conversion.

flow.

By checking whether conversion of samples is possible for all pairs of congestion periods of all probe flows, trees that represent dependency of conversions are generated for each congestion period (see Fig. 5). The proposed method recursively converts/unites samples from the leaves to the root of the tree. In the case of Fig. 5, the samples of Flow D can be converted/united to the samples of Flow B since Flow D and Flow B share their destinations in Fig. 10. These samples including samples converted/united from Flow D can be converted/united to the samples of Flow A that share the source with Flow B. As a result, the samples of Flow D that share neither sources nor destinations can be converted/united to the samples of Flow A through the samples of Flow B.

In the evaluation we will perform in Section 6, we measure the loss rate of the full-meshed paths, but the proposed method can also be applied to a subset of the universal path set. However, if the following conditions do not hold, the accuracy improvements by the proposed method will not be benefited.

- Two or more paths are measured at the same time.
- At least one link is included in multiple paths.
- In all path pairs that share a link, at least one pair has common a source or a destination.

If the number of measured paths or the number of shared links is small, the accuracy improvement may be limited. However, the accuracy of the proposed method is guaranteed to be equal to or higher than the conventional method in the measurement for any subset of paths.

The computational complexity of the conversion process of the proposed method is $O(NM)$ for each congestion period, where N and M denote the number of flows and the maximum number of samples in a congestion period, respectively.

5. Theoretical Accuracy

With an assumption regarding the injection time of probe packets, we provide a theoretical analysis of accuracy bounds. We assume that an injection time of a probe packet follows a uniform distribution on a measurement period $[0, T]$ and these injection times are independent and identically distributed (i.i.d.). If we decide times of probe packets in such a manner, an injection time of a packet that is decided later may be injected earlier than the first decided packet, namely, the order of decision will not correspond to the order of packet injection. However, the order of the injection is not important in the discussion of this section. The assumption of i.i.d. injection time is not always suitable for probe injection of conventional loss measurements or simulation settings in Section 6. However, the theoretical analysis under the assumption gives us a fundamental insight since the probe injection under the assumption corresponds Poisson process, one of the most basic probe injections, when $T \to \infty$. The theoretical analysis for the Poisson process is a lough approximation of analysis for periodical probe injection that we will perform in Section 6.

Under the assumption, an estimator of conventional loss measurements can be modeled by a binomial distribution. In conventional loss measurements, probe packets are injected, and the number $|L_\mathrm{A}|$ of loss samples is observed. If we assume the packet injection times of probe packets follow a uniform distribution on a measurement period, the trials to inject probe packets investigating loss events can be regarded as Bernoulli trials. Then, the number $|L_\mathrm{A}|$ of loss samples follows a binomial distribution $\mathrm{B}(n, p)$, where n and p represent the number $|X_\mathrm{A}| + |L_\mathrm{A}|$ of probe packets and the ground truth of the loss rate on path A, respectively. The conventional estimator $\hat{p}$ for path A is the random variable $|L_\mathrm{A}|$ (i.e., the number of loss samples) divided by the total number $|X_\mathrm{A}| + |L_\mathrm{A}|$ of probe packets.

When we evaluate the accuracy of the conventional method by using Root Mean Squared Errors (RMSE), we can analytically calculate the accuracy. From the definition of Mean Squared Errors (MSE), MSE can be expressed as a sum of variance $\mathrm{Var}[\hat{p}]$ and bias $\mathrm{E}[\hat{p}] - p$ of the estimator.

$$\begin{aligned}\mathrm{MSE} &= \mathrm{E}[(\hat{p} - p)^2] \\ &= \mathrm{Var}[\hat{p}] + (\mathrm{E}[\hat{p}] - p)^2.\end{aligned}$$

Since the conventional estimator with uniformly distributed probe packets is an unbiased estimator, MSE is equal to the variance of the estimator $\hat{p}$. As we mentioned above, the estimator is the random variable $|L_\mathrm{A}|$ that follows a binomial distribution divided by a constant $|X_\mathrm{A}| + |L_\mathrm{A}|$. Since the variance of $|L_\mathrm{A}| \sim \mathrm{B}(n, p)$ is $np(1-p)$, MSE can be derived as follows:

$$\mathrm{MSE} = \frac{p(1-p)}{|X_\mathrm{A}| + |L_\mathrm{A}|}. \tag{1}$$

In a similar manner, we are able to calculate the upper bounds of MSE of the proposed estimator. In the proposed method, when we measure the loss rate on a path, we convert and unite samples in congestion periods from the other flows. In the most inaccurate case of the proposed method, no samples are converted/united from the other flows, and the sampling rate is the same as the conventional method. Namely, the upper bound of MSE in the proposed method is MSE of the conventional estimator shown in Eq. (1).

On the other hand, the upper bounds of MSE of the proposed method are the MSE when all samples in the flows that share a part of paths with target flow are converted/united. By conversion and uniting process, the sampling rate increase in a pseudo manner. If the number of converted/united flows is m in a congestion period, the sampling rate increases $m + 1$

times in the congestion period comparing to the original rate. Though the pseudo increase of sampling rate is temporal, the temporal increase has the same effect as constantly increasing the rate of probe packet injection. Because we assume that most of the packet loss events are caused by buffer overflows. Consequently, the lower bound of MSE of the proposed method can be derived by

$$\mathrm{MSE}_{\mathrm{lb}} = \frac{p(1-p)}{m_{\max}(|X_{\mathrm{A}}| + |L_{\mathrm{A}}|)}, \tag{2}$$

where $m_{\max}$ denotes the maximum number of flows that pass links contained in the path of Flow A.

6. Evaluations

We perform ns-3 [17] simulations to confirm that the number of captured loss events increases and accuracy of a loss rate estimation is improved.

6.1 Simulation Settings

The network we simulated resembles Internet2 topology [18] with 9 nodes and 13 links whose capacities are 15.552 [Mbps] (see Fig. 10). The numerical values written beside the links in Fig. 10 indicate propagation delay in ms (milisecond), and we set them proportional to the distance between the nodes in Internet2. The topology of this simulation resembles the topology of Internet2 core transport network, but the assumptions of the proposed method shown in Section 2 are applicable to more general wired networks. Note that the simulation results are not limited to core transport networks.

2 types of user flows and 1 type of probe flow listed in Table 1 stream between all pairs of 9 nodes (i.e. $9 \times 8 = 72$ flows for each type in the entire network). Phases of packet injection are randomized while probe packets are injected periodically. The probe packets are commonly used for the proposed method and the conventional method. The communication overheads of the proposed method and the conventional method are completely equivalent in the simulation since the probe packets used by both methods are the same. Since the capacity of all the links are 15.552 [Mbps], if two or more flows of bursty traffic are joined at the link, traffic intensity on a link temporally exceeds the link capacity, thereby occurring a buffer overflow due to temporal capacity shortage. Though the congested links are sparse, congestions on multiple links can occur at the same time. Each node is configured with a drop-tail queue whose maximum size is 1024 for all interfaces. The simulation time is 1005.0 [s] and we only use the data from 5.0 [s] to 1005.0 [s].

To achieve valid evaluations through the simulation, it is important that the statistics regarding probe packet losses are accurately emulated in the simulation. First, the essential thing is to make the loss rate, which is one of the most important statistics, realistic. In the above simulation settings, we tuned the traffic intensity in the simulation so that the loss rate corresponds to QoS classes defined by ITU-T Recommendation Y.1541 [14]. Also, since the proposed method unites loss events observed on multiple flows in a congestion period, it is very important that the duration of the loss events in a congestion period is reasonable. In the above simulation settings, the duration of loss events at Link 3-2, which has the highest loss rate, ranges from 0.14 s to 1.01 s. The duration of the loss events in our simulation is consistent with the distribution of duration of loss events reported in [19], which is one of the few studies regarding the duration of loss events.

The parameters of the proposed method are set as follows. The delay threshold x_{th} to distinguish congestion period is set to 0.01 [s]. We use Minimum Entropy Clustering (MEC) [20] for clustering, and its radius parameter r is set to 0.1.

These improvements in accuracy have an extremely large impact on practical measurements. As a typical example, we focus on Link 3-2 where the most loss events were observed. The RMSE of Link 3-2 in the proposed method and the conventional method are 0.28×10^{-3} and 0.72×10^{-3}, respectively. Since the loss rate on the path is 1.5×10^{-3}, the ratio of RMSE to the loss rate is 47% and 19%, respectively. Assuming unbiased estimation and errors following a normal distribution, the probability that the conventional estimator is in range $[1.0 \times 10^{-3}, 2.0 \times 10^{-3})$ is 51%. In other words, the first digit of the estimator is not correct with a probability of 49%. In contrast, the first digit of the proposed estimator is correct with a probability of 91%. After all, when we estimate a loss rate 1.0×10^{-3} of classes 0-4 defined in ITU-T Recommendation Y.1541, the accuracy improvement by the proposed method has a large impact on the measurement. This tendency is even more pronounced for smaller loss rates. For Link 2-1 with the loss rate 2.1×10^{-4}, the ratio of RMSE to the loss rate is 27% for the proposed estimator, while it is 93% for the conventional estimator.

Table 1 Types of traffic in our simulations.

User (Stationary)	Packet size	600 [Byte]
	Traffic pattern	Poisson arrivals
	Traffic intensity	388.8 [Kbps] (4% of a link capacity)
User (Bursty)	Packet size	500 [Byte]
	Traffic pattern	On/off process with periodic arrivals in bursty periods
	Traffic intensity	10,000 [Kbps] in bursty periods
		0 [bps] in idle periods
	Bursty period	Exponential distribution with mean 1.0 [s]
	Idle period	Exponential distribution with mean 100.0 [s]
Probe	Packet size	74 [Byte]
	Traffic pattern	Periodic arrivals
	Packet intervals δ	200 [ms]

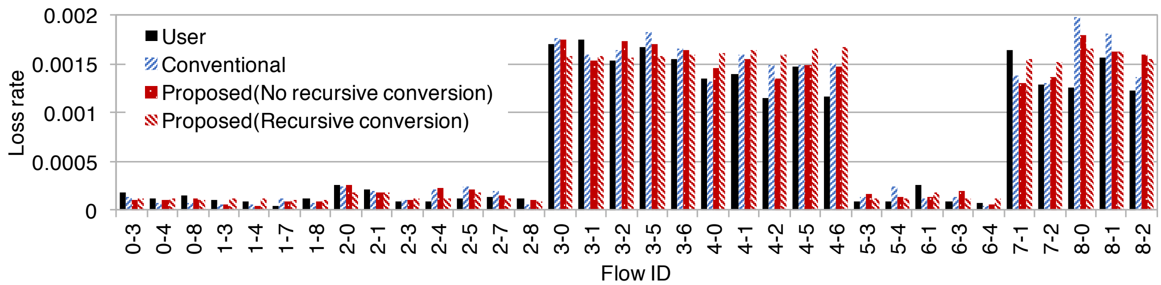

Fig. 6 Estimators of packet loss rate in the proposed and conventional methods.

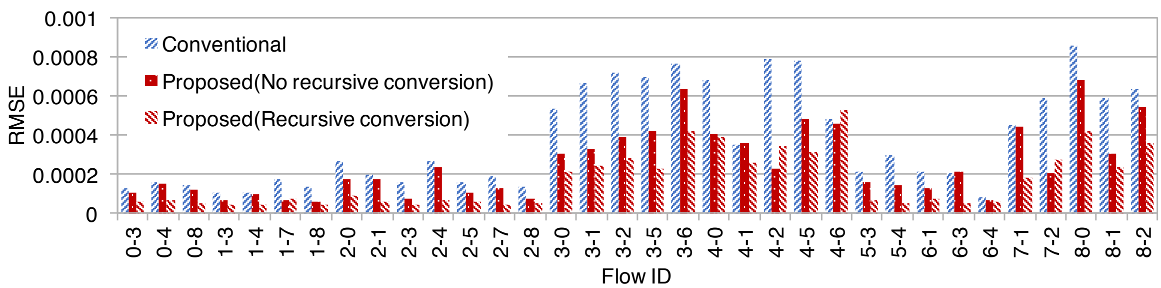

Fig. 7 RMSE of loss rate estimations.

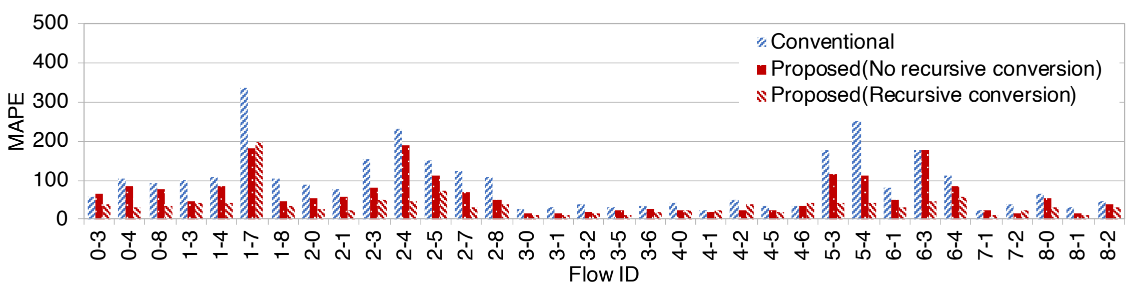

Fig. 8 MAPE of loss rate estimations.

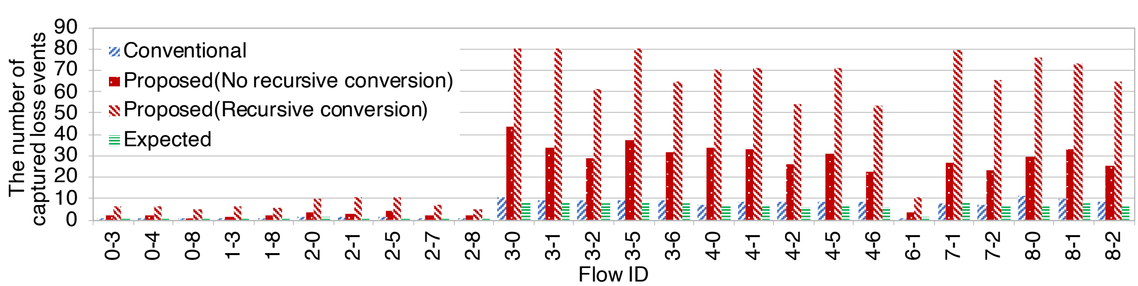

Fig. 9 The number of loss events that are captured by probe flows for each path.

6.2 Simulation Results

We evaluate the accuracy of the loss rate estimation of the proposed method. The simulation was repeated 10 times by changing the phase of the probe packet injection time. Fig. 6 shows the loss rate on the paths where loss events were captured at least once by stationary user flows. Root Mean Squared Errors (RMSE) between the estimator of loss rate and loss rate experienced by packets of the stationary user flows are calculated. Note that the loss rate experienced by packets with Poisson arrivals corresponds to the time average of the loss process due to PASTA (Poisson Arrivals See Time Averages) property [21]. The result is shown in Fig. 7. Note that we use RMSE instead of MSE to make it easier to compare with the estimator. The maximum loss

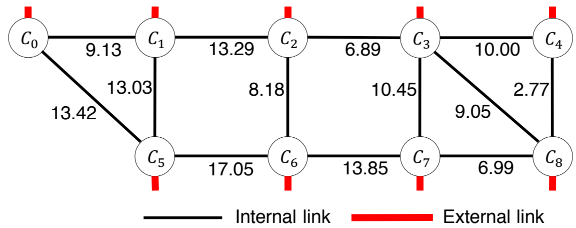

Fig. 10 Network topology on our evaluations.

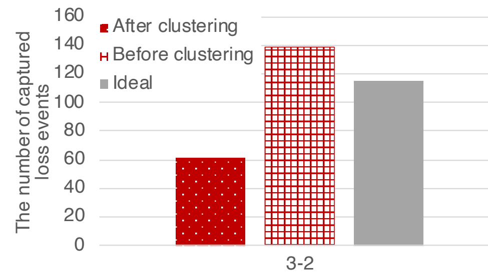

Fig. 11 The number of loss samples before and after clustering process.

rate experienced by stationary user flows was about 1.7×10^{-3}. The conventional estimator in this section is simply calculated as the ratio of the number of loss samples to the total number of samples. Note that it is not the method in [1]. The simple estimator is adapted by many prior works [10, 11, 22]. The results on paths in which any loss event is not captured by the stationary user flow are omitted in Fig. 7. In the results of no recursive conversion in Fig. 7, only samples of flows that have the same source/destination with a target probe flow are converted.

We can confirm that RMSE of each probe flow is reduced by the proposed method. Compared to the conventional method, the proposed method without recursive conversion provides 31.3% reduction of RMSE on average. Since the proposed method with recursive conversion achieves 57.5% reduction of RMSE on average, it can be confirmed that recursive conversion achieves further improvement in accuracy. Therefore, the proposed method can improve the accuracy of the loss rate measurement, though the number of probe packets in the entire network does not increase compared to that of the conventional method. The accuracy improvement is caused by the increase of samples that capture loss events. The increase of the samples is shown in Fig. 9. "Expected" in Fig. 9 represents the expected number of loss events experienced by probe packets on a path. The recursive conversion unites samples from more flows than the no recursive conversion, thereby increasing the number of captured loss events. In principle, it is impossible for the conventional method to estimate the loss rate less than 2.0×10^{-4} since the number of the probe packets per flow is 5000 in the simulation. However, the proposed method overcomes this fundamental limitation in accuracy. We also calculate Mean Absolute Percentage Error (MAPE) and show the results in Fig. 8. We got a similar result with the result of RMSE.

To analyze the ratio of inappropriate samples to the expected samples by an ideal measurement, we confirm the number of loss samples before and after the clustering process in the proposed method. In the proposed method, as in our previous method [1], after converting/uniting samples, inappropriate samples are excluded in the clustering process. To simplify the analysis, we consider the worst-case trials with the most loss samples united, focusing on Link 3-2, which causes the most loss events. We depict the number of the loss samples in the worst-case trial in Fig. 11. In Fig. 11, "Before clustering" and "After clustering" represent the number of loss samples before and after the clustering process. "Ideal" in Fig. 11 indicates the expected number of loss samples if we achieve perfect uniting. We can confirm that more loss samples were counted than expected due to falsely uniting loss samples before the clustering process. However, loss samples that may be falsely united are excluded (a little excessively) in the clustering process. As a result, the final samples obtained by the proposed method do not include false loss samples. Although excessive exclusion is not desirable, the estimator of the proposed method is more accurate than that of the conventional method while maintaining the unbiased estimator. The above results, in which the false loss samples are sufficiently excluded, are consistent with the result in Fig. 6 and Fig. 7.

6.3 Analytical Results

In this section, we compare the simulation results with the theoretical upper/lower bounds of the proposed method that we mentioned in Section 5. In the simulation settings of Section 6, we count the number of flows that pass through each link and calculate the maximum number $m_{\max}$ of flows that pass links contained in a path. Fig. 12 shows the results of the square root of Eqs. (1) and (2) based on $m_{\max}$ in the simulation. The two types of red bars are the same as the results of the proposed method shown in Fig. 7. The black lines show the upper/lower bounds of RMSE.

We can confirm that most of the results fall between upper and lower bounds in Fig. 12. Comparing the results of Fig. 6 and Fig. 12, the proposed method achieves a similar accuracy with the theoretical lower bounds in the measurement of paths with a relatively small loss rate such as Flow ID 0-3. On the other hand, it can be confirmed that RMSE of a part of paths with a large loss rate does not close to the lower bounds. This is because paths with a large loss rate have a relatively long delay period, and there is a high probability that other delays will occur during the delay period. The samples that observe the other delays are removed as shown in Fig. 3. In addition, since Eq. (1) represents the mean of MSE, the RMSE of the measurement results of some paths exceeds the upper bound due to the randomness of the measured values.

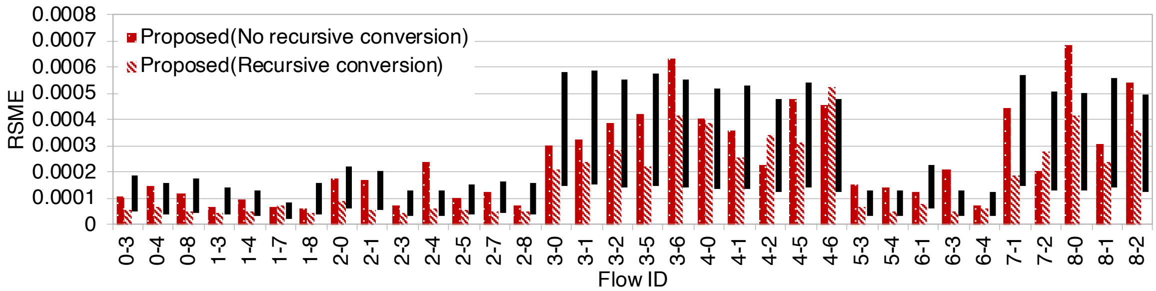

Fig. 12 Upper/lower bounds of theoretical accuracy of the proposed method.

7. Related Works

There is a rich collection of literature that aims at measuring end-to-end metrics [3, 8–10, 23–27]. Some prior works [9, 10] tried to estimate high quantile of end-to-end delays by active measurements. Choi *et al*. [9] proposed a scheme that estimates high quantile with bounded errors. The scheme allows us to know the minimum number of probe packets needed to bound the error of quantile estimation within a prescribed accuracy. Sommers *et al*. [10] also proposed an estimator of high quantile. Since the estimator provides confidence intervals, we can tune the number of probe packets to achieve the required accuracy. Some works [3, 25, 27] focus on loss measurements. Sommers *et al*. [3, 25] tackled the problem to estimate a mean loss duration by a statistical approach using back-to-back packets. Baccelli *et al*. [27] and Parker *et al*. [22] provided how to chose the best probing on an active measurement.

The effect of probe packets on the path quality has been also studied [4, 7, 8, 12, 21]. References [4, 21] showed that an arrival process of the probe packets affects accuracy of end-to-end delay/loss measurement. Degradation of measurement accuracy caused by probe traffic load were studied in references [7, 8, 12]. The limitation of single flow measurements can be understood by these works. The optimum probe rate that does not affect the path quality has been investigated in these works [6,7,11], and the proposed method provides a method to maximize the accuracy by utilizing the probe packets with this optimum probe rate.

In recent years, research on measurements with network telemetry has been actively studied. Network telemetry is a modern and excellent method. However, it depends on the functions of network devices, so it is not always available. Active measurements, including the proposed method, can be performed easily by sending packets to a network, and the measurements do not depend on the functions inside networks. Hence, traditional active measurements are still a powerful tool for network measurements, especially for researchers who do not have direct access to the functions of network devices. In addition, active measurements are also effective for measurements across multiple organizations, such as Internet-wide measurements.

8. Conclusions and Future Works

We proposed a loss measurement method that fully utilizes flows, including flows with different sources and destinations in this paper. We extended the delay measurement method [1] that utilizes parallel active probe flows to loss measurements. Additionally, our method includes a recursive conversion technique that enables us to fully utilize information of all probe flows for a measurement though the method [1] only utilize information of flows that have the same source/destination with a target probe flow.

We provided the theoretical analysis and the simulation-based evaluation for the proposed method. We show that the accuracy of the proposed method is bounded by upper and lower bounds in the theoretical analysis. Through simulation-based evaluation using ns-3 simulator, we confirmed that the proposed method can reduce estimation errors by 57.5% on average.

As future research, we plan to develop highly accurate delay/loss tomography using the parallel monitoring method. Additionally, we also have a plan to implement the proposed method for a real network, and evaluate the effectiveness of the method. Our future work includes the reduction of the computational complexity of the proposed method.

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