Accurate Delay Measurement for Parallel Monitoring of Probe Flows

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Outline

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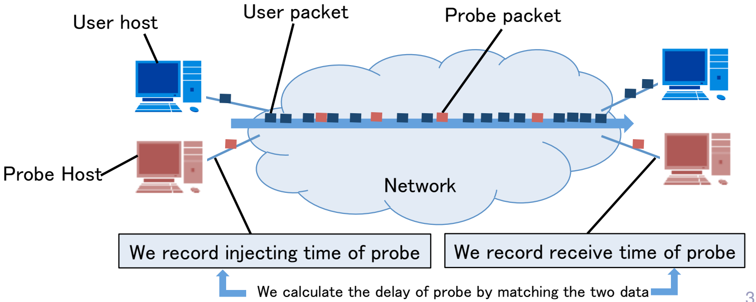
- Background
- Assumptions and models
- The key idea of the proposed method
- How to estimate delay metrics
- Experiments
- Conclusions and future works

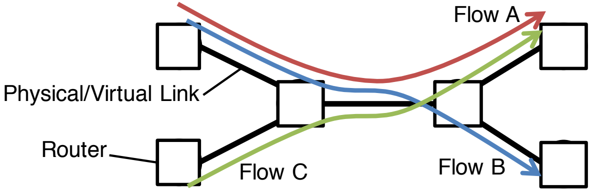
End-to-end Delay Measurements

- End-to-end delay is fundamental for a performance evaluation.
- An active measurement is a common method for end-to-end delay measurements.
  - Probe packets are injected into a network for measurement.
  - It is important to achieve accurate measurement without increasing the number of probe packets.
  - Since a large delay is a rare event in the modern Internet, high quantile of delay distribution is still hard to measure.



Parallel Monitoring of Probe Flows

- Multiple probe flows are monitored to measure delays on multiple paths in parallel for most measurement applications.
  - e.g., SLA monitoring by Internet Service Providers.
- In previous works, only one probe flow of the multiple probe flows is utilized to measure the end-to-end delay on a path.
- However, the information concerning a flow can be utilized supplementary for improving a measurement of another flow.



Objectives

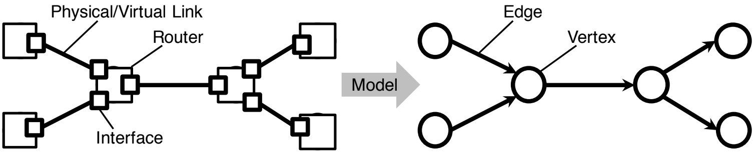
- We propose a novel parallel flow monitoring method in which information concerning all flow can be utilized.
  - The observation results of multiple flows are partially converted into the results of a flow that we want to measure.
  - It does not require any internal information of a measured network (i.e. a topology, current queue size).
- We evaluate the proposed method though simulations.
  - We confirm that the observation results of 72 parallel flows of active measurement are appropriately converted between each other.

Network Model

- A network considered within the scope of this work is represented by a directed graph.

  edge : a physical/virtual link and interfaces at both ends of the link.

  vertex : a part of a network device other than its interfaces.



- An end-to-end delay is consisted of propagation delay and queueing delay.
  - Propagation delay can be regarded as a constant.
  - Edges with large queueing delay are sparse.
- To measure delay on paths, probe packets are periodically injected for all or a part of paths.

Network Model (2)

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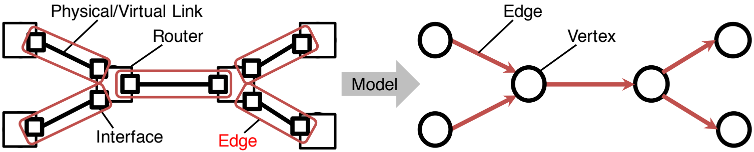

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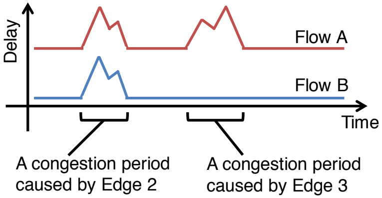
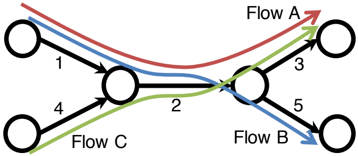
Overlap of Queueing Delay Processes

$\hat{\chi}_{\mathrm{A}}(t)$: A virtual delay which is the queueing delay experienced by a virtual packet injected into the path of Flow A at time t.

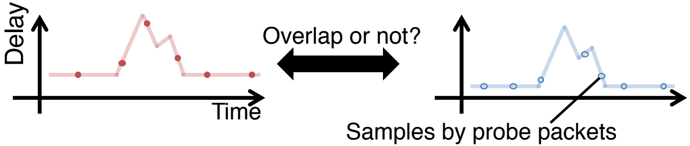




- If $\hat{\chi}_{\mathrm{A}}(t)$ and $\hat{\chi}_{\mathrm{B}}(t)$ in a congestion period tightly overlap, information of the period can be utilized each other.
- Sufficient conditions for overlap is as follows:
  1. The two paths of Flow A and B have the same source;
  2. Routes from the source to the last congested edge on the paths are common;
  3. A queueing delay that packets experience on edges after the last congested edge can be negligible.

Sample Conversion Technique

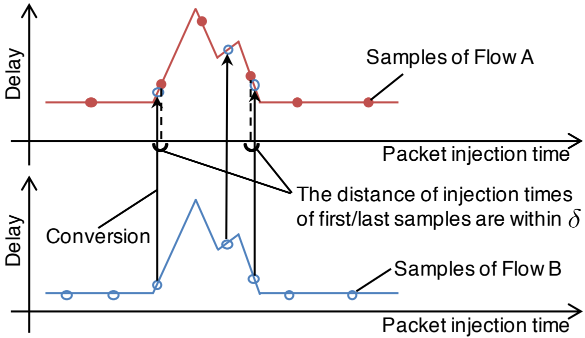
- It is, however, difficult to discriminate the above conditions 2 and 3 without using topology and current queue size.
- We design a method that uses samples of a virtual queueing delay process by probe packets.



- We discriminate whether processes overlap by the following two steps:
  1. Conversion Process
  2. Clustering Process

Conversion Process

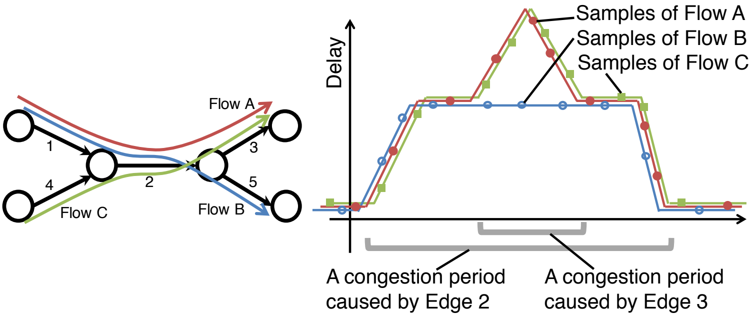
- We consider that virtual delay processes overlap if the two flows satisfy the following conditions:
  1. The two flows have the same source;
  2. The interval between the packet injection times of the first samples in a congestion period is smaller than δ;
  3. The interval between the packet injection times of the last samples in a congestion period is smaller than δ.



- Similar conversion can be considered for destination version.

Clustering Process

- If multiple edges are congested at the same time, the conversion process may convert inappropriate samples.



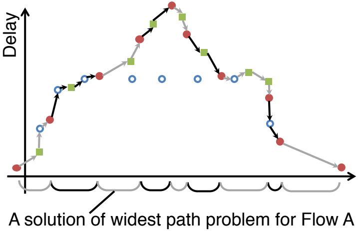
- To remove inappropriate samples, we utilize a clustering technique in machine learning.
- Based on samples that are converted, we construct clusters of flows using a clustering technique.

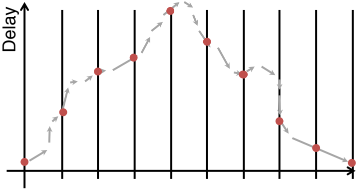
Clustering Process (2)

- To use general clustering techniques, we transform samples of each flow into n-dimensional vectors.
  1. Samples are connected by a solution of the widest path problem.
     - The cost of the edge between two samples is set to the reciprocal of distance
$$\frac{1}{\sqrt{\frac{\beta^2}{\delta^2}(t^i_\mathrm{A} - t^j_\mathrm{B})^2 + (x^i_\mathrm{A} - x^j_\mathrm{B})^2}}.$$

t^i_A : the injection time of ith probe packet of Flow A.
x^i_A : the delay of ith probe packet of Flow A.
β : a control parameter to tune scale of distance of injection time and delay.

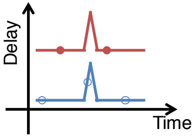
  2. For each flow, we transform the path into an n-dimensional vector by making the vertices evenly spaced.



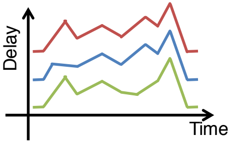


Limitations

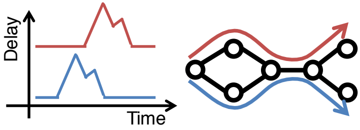
- The proposed method has the following limitations.
  - Momentary congestion: it cannot improve accuracy by converting samples in very short congestion periods.
  - Non-sparse congestion: it cannot detect start and end times of a congestion period if congested edges are not sparse.
  - Complex routes: it cannot convert samples between flows that are once forked and rejoined.



Momentary congestion



Non-sparse congestion



Complex routes

Estimators for Parallel Flow Monitoring

- The samples by our method is not uniformly distributed.
- It is needed to give weight w_i for ith sample with delay d_i.

$$w_i = \begin{cases} N_j/\mathcal{N}_j & \text{for samples in } j\text{th congestion period,} \\ 1 & \text{otherwise.} \end{cases}$$

  - Average end-to-end delay can be estimated by weighted average

$$\frac{1}{N}\sum_{s} w_i d_i,$$

  - q-quantile of end-to-end delay can be estimated by kth delay when delays are arranged in ascending order, where

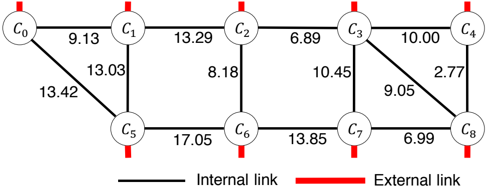
$$k = \arg\max_{j} \left\{ \sum_{i=1}^{j} w_i \leq qN \right\}.$$

N : The number of original sample.
N_j : The number of original sample in jth congestion period.
$\mathcal{N}_j$: The number of all sample in jth congestion period.

Simulation Settings

- We perform NS-3 simulations to confirm that samples of parallel flows are appropriately converted between each other.
- 3 types of traffic stream between all pairs of 9 nodes in a network (i.e., 72 flows stream for each type).

Stationary	Packet size	600 [Byte]
	Traffic pattern	Poisson arrivals
	Traffic intensity	388.8 [Kbps] (4% of a link capacity)
Burst	Packet size	500 [Byte]
	Traffic pattern	On/off process with periodic arrivals
	Traffic intensity	8,000 [Kbps] in burst periods
	Burst period	Exponential distribution with mean 0.1 [s]
	Idle period	Exponential distribution with mean 4.0 [s]
Probe	Packet size	74 [Byte]
	Traffic pattern	Periodic arrivals

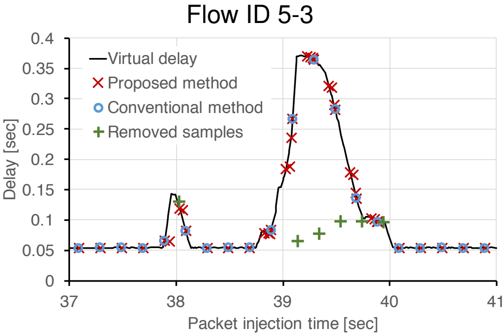


Simulation Settings (2)

- The parameters in the proposed method are as follows:
  - $\beta = 0.16$: The tuning parameter in clustering process.
  - $\delta = 0.2$: Probe packet intervals.
  - $x_{\mathrm{th}} = 0.01$: The threshold to define start/end time of congestion periods.
- In the clustering process, we use Minimum Entropy Clustering (MEC) with 2 parameters:
  - $\alpha = 0.001$: The radius parameter.
  - $e = 10$: The expected number of clusters.
- The simulation time is 42 [s] and we only use the data from 20 [s] to 42 [s].
- The simulation is repeated 10 times by changing the phase of the probe packet injection time.

Examples of Added/removed Samples

- We depict examples of samples by the conventional and the proposed method.



- The number of samples of the proposed method is larger than those of the conventional method.
- The samples tightly approximate the virtual delay.
- Most of removed samples are not on the virtual delay.

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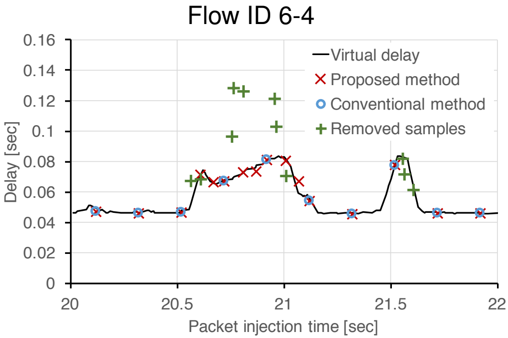

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Delays, Number of samples

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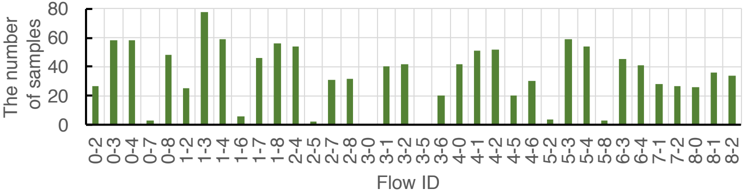
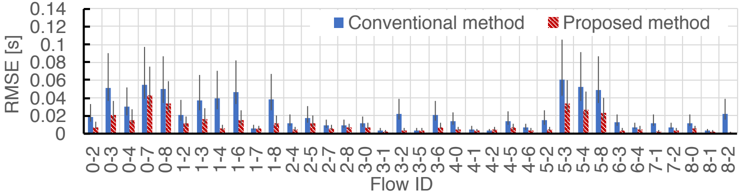
- The number of added samples by the proposed method is shown.
- We display only flows that experience large delay.



- The number of original samples that are obtained from probe packets is 110 samples.
- Up to 78 samples are converted into samples of a flow.

Delays, Number of samples (2)

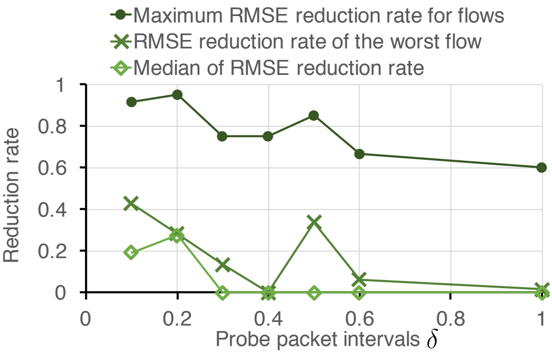
- We also evaluate Root Mean Squared Errors (RMSE) when the 99th-percentile of end-to-end delay is measured.
- The error bars represent 95% confidence intervals.



- The proposed method provides up to 95% reduction of RMSE (Flow ID 8-2).
- The RMSE reduction rate of the worst flow is reduced by 28% (Flow ID 0-7 vs 5-3).

Dependency of RMSE on Probe Intervals δ

- We compare RMSE of 99th-percentile of end-to-end delay by changing probe packet interval δ from 0.1 to 1.0 [s].



- The values of maximum RMSE reduction rate for flows are high.
- RMSE reduction rate of the worst flow and median of RMSE reduction rate occasionally decrease to nearly 0.

Independency of RMSE in MEC

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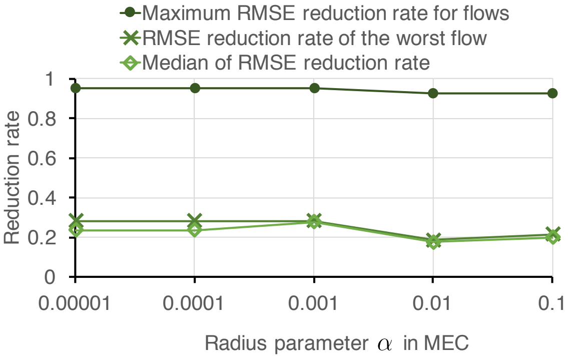
- We confirm the dependency of RMSE on parameters of MEC.



- It is confirmed that the RMSE is independent of the parameter from the figure.

Independency of RMSE in MEC (2)

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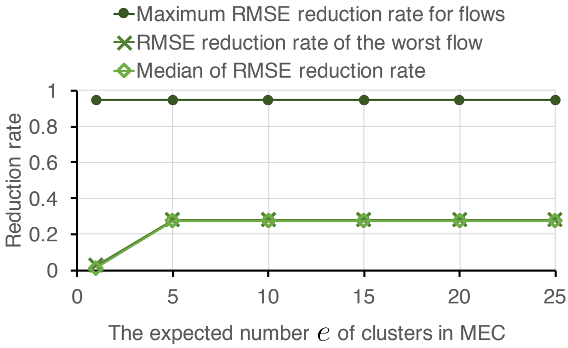
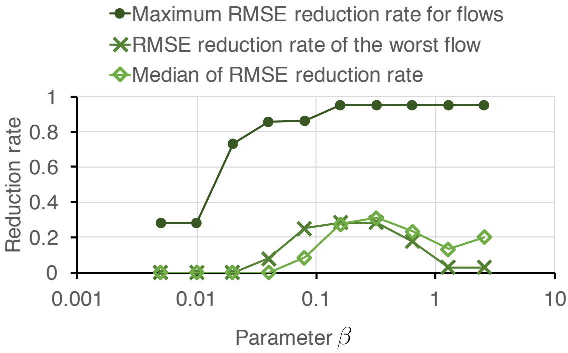


- It is confirmed that the RMSE is independent of the parameter from the figure.

Dependency of RMSE on β

- We verify the dependency of the performance of the proposed method on parameter β.



- The maximum RMSE reduction rate for flows increases as parameter β increases.
- The other reduction rate decrease due to the inappropriate conversions of samples when β is between 0.64 and 2.56.

Conlusion

In this paper, we proposed a parallel flow monitoring method that achieves accurate measurement by partially converting the observation results each other.

- The proposed method adds to samples of a flow from the samples of the other flows.
- It also removes inappropriate samples using a clustering technique in machine learning.
- It provides up to 95% reduction of errors, and the error of the worst flow among all flows is reduced by 28%.

Future Works

- We have the following 4 directions for future works.
  - Automatic tuning of the parameters.
  - Development of a method that utilizes a network topology for the conversion process.
  - Extension toword measurements of other metrics.
  - Evaluation of the proposed method using real network traffic.

Thank you for your kind attention.