Accuracy Improvement of CoMPACT Monitor by Using New Probing Method

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Abstract. CoMPACT monitor that we have proposed is new technique to measure per-flow quality of service (QoS). CoMPACT monitor provide scalable measurement of one-way delay distribution by the combination of active and passive measurement. Recently, a new probing method for improving the accuracy of simple active measurement have been proposed. In this paper, we adopt the new probing method as active measurement of CoMPACT monitor, and show that the combination improves the accuracy of measurement remarkably for UDP flows.

1 Introduction

As the Internet spreads, various new applications (telephony, live video etc.) appeared. On the other hand, the quality of service (QoS) that is required by these applications has become diversified, too. Moreover, it is expected that the diversification of application and requirement will continue in the future.

In order to meet such varied requirements for network control, we need a measurement technology to produce detailed QoS information. Measuring the QoS for each of multiple flows (e.g., users, applications, or organizations) is important since these are used as key parameters in service level agreements (SLAs). One-way packet delay is one of the most important QoS metrics. This paper focuses on the measurement of one-way delay for each flow.

Conventional means of measuring network performance and QoS can be classified into two types: passive and active measurements.

Passive measurement monitors the target user packet directly, by capturing the packets, including the target information. Passive measurement is used to measure the volume of traffic, one-way delay, round-trip time (RTT), loss, etc. and can get any desired information about the traffic since it observes the actual traffic. Passive measurement can be categorized into two-point monitoring with data-matching processes and one-point monitoring.

Passive measurement has the advantage of accuracy. However if we perform passive measurement in large-scale networks, the number of monitored packets is enormous and network resources are wasted by gathering the monitored data at a data center. Moreover, in order to measure delay, it is necessary to determine the difference in arrival time of a particular packet at different points in the network. This requires searching for the same packet pairs monitored at the

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different points in the monitored packet data. This packet matching process lacks scalability, so passive measurement lacks scalability.

Active measurement monitors QoS by injecting probe packets into a network path and monitoring them. Active measurement can be used to measure one-way delay, RTT, loss, etc. It cannot obtain the per-flow QoS, though it is easy for the end user to carry out. The QoS data obtained by active measurement does not represent the QoS for user packets, but only QoS for the probe packets.

By complementary use of the advantages of active and passive measurements, the authors propose a new technique of scalable measurement called *c*hange-*o*f-*m*easure-based *p*assive/*act*ive *monitor*ing (CoMPACT monitor) to measure per-flow QoS [1,2,3,4].

The idea of CoMPACT monitor is as follows. The direct measurement of the one-way delay distribution of the target flow by passive measurement is difficult due to the scalability problem. So, we try to obtain the one-way delay distribution of the target flow by using a transformation of one-way delay data obtained by active measurement. The transformation can be determined by passively monitored traffic data for the target flow of the measurement. The problem of scalability does not arise, because the volume of traffic can be measured by one-point passive measurement without requiring data-matching processes.

We have believed Poisson arrivals (intervals with exponential distribution) is appropriate to a policy of probe packets arrivals since we can apply PASTA (Poisson Arrivals See Time Averages) property to it.

However, recent work [5] indicates that many distributions exist that are more accurate than an exponential distribution if a non-intrusive context (ignoring the effect of probe packets) can be assumed. Moreover, according to [5] we can find a distribution that is suboptimal in accuracy by selecting an inter-probe time according to the parameterized Gamma distribution.

This study has applied this Gamma-probing to the active measurement part of CoMPACT monitor and tried to improve CoMPACT monitor's in accuracy. The effectiveness of this Gamma-probing was verified in case of the delay/loss process monitored by simple active measurement in [5]. However, CoMPACT monitor observes a process that depends on a value for traffic that is obtained by passive measurement. This process obviously differs from delay/loss processes that are influenced by all flows on the network. Therefore, it is necessary to confirm whether Gamma-probing is effective as a part of CoMPACT monitor.

This paper confirms that Gamma-probing is appropriate when measuring the complementary cumulative distribution function (CDF) of individual flows by simulation, and shows that the effect is remarkable for the flows that use the User Datagram Protocol (UDP).

2 Summary of CoMPACT Monitor

CoMPACT monitor estimates an empirical QoS for the target flow by converting observed values of network performance at timing of probe packet arrivals into a measure of the target flow timing. Now, let $V(t)$ denote the network process under observation (e.g. the virtual one-way delay in the network path at time t), and X_k denote a random variable which is observed $V(t)$ with a certain timing (e.g. the timing of user k's packet arrivals). The probability for X_k to exceed c is

$$\mathrm{P}(X_k > c) = \int 1_{\{x>c\}} \mathrm{d}F_k(x) = \mathrm{E}_{F_k}[1_{\{x>c\}}]$$

where $F_k(x)$ is the distribution function of X_k and 1_A denotes the indicator function that takes the value 1 if the event A is true and 0 otherwise.

If we can directly monitor X_k, its distribution can be estimated by $\sum_{n=1}^{m} 1_{\{X_k(n)>c\}}/m$ for sufficiently large m, where $X_k(n)$ $(n = 1, 2, \cdots, m)$ denote the nth observed value. Now, let us consider the situation that X_k cannot be directly monitored. Let Y denote a random variable that is observed $V(t)$ at a different timing (e.g. timing of probe packet arrivals) independent of X_k. Then we consider the relationship between X_k and Y.

Observed values of X_k and Y are different if their timing is different, even if they observe a common process $V(t)$. X_k and Y can be related by each distribution functions $F_k(x)$ and $G(y)$, and $\mathrm{P}(X_k > c)$ expressed by measure of X_k can be transformed into measure of Y as follows.

$$\begin{aligned}\mathrm{P}(X_k > c) &= \int 1_{\{x>c\}} \mathrm{d}F_k(x)\\ &= \int 1_{\{y>c\}} \frac{\mathrm{d}F_k(y)}{\mathrm{d}G(y)} \mathrm{d}G(y) = \mathrm{E}_G\left[1_{\{Y>c\}} \frac{\mathrm{d}F_k(Y)}{\mathrm{d}G(Y)}\right]\end{aligned}$$

Therefore, $\mathrm{P}(X_k > c)$ can be estimated by

$$\frac{1}{m}\sum_{n=1}^{m} 1_{\{Y(n)>c\}} \frac{\mathrm{d}F_k(Y(n))}{\mathrm{d}G(Y(n))}, \quad \text{for sufficiently large } m. \tag{1}$$

where $Y(n)$ $(n = 1, 2, \cdots, m)$ denote the nth observed value. Note that this estimator does not need to monitor the timing of X_k, if we can get $\mathrm{d}F_k(Y(n))/\mathrm{d}G(Y(n))$. This means the QoS of a specific flow (as decided by k) can be estimated by just one probe packet train that arrives with a timing of Y.

This subsection briefly summarizes the mathematical formulation of the CoMPACT Monitor [4]. We assume the traffic in the target flow can be treated as a fluid. In other words, we assume packets of the target flow are more numerous than active probe packets.

Let $a(t)$ and $V(t)$, respectively, denote the traffic in the target flow at time t and the virtual one-way delay on the path that we want to measure. $a(t)$ and $V(t)$ are a nonnegative deterministic processes assumed to be right-continuous with left limits and bounded on $t \geq 0$. Considering to measure the empirical one-way delay distribution, the value we want to measure is the ratio to all traffic of the target flow of traffic for which the delay to exceeds c, which is given by

$$\pi(c) = \lim_{t\to\infty} \frac{\int_0^t 1_{\{V(s)>c\}} a(s)\mathrm{d}s}{\int_0^t a(s)\mathrm{d}s} \tag{2}$$

This can be estimated through m times monitoring by

$$Z_m(c) = \frac{1}{m}\sum_{n=1}^{m} 1_{\{V(T_n)>c\}} \frac{a(T_n)}{\sum_{l=1}^{m} a(T_l)/m} \tag{3}$$

for sufficiently large m (see [4] for details), where T_n $(n = 1, 2, \cdots, m)$ denotes the nth sampling time, and each time of sampling corresponds to a time of probe packet arrival. Active and one-point passive measurement are used respectively to observe $V(T_n)$ and $a(T_n)$. Note that one-point passive measurement can be conducted very easily here, compared with two-point passive measurement for measuring the one-way delay.

If we extract the quantity $\sum_{n=1}^{m} 1_{\{V(T_n)>c\}}/m$ from (3), this quantity is a simple active estimator that counts the packets for the delay to exceeds c. However, (3) is weighted by $a(T_n)/(\sum_{l=1}^{m} a(T_l)/m)$, which is decided by the traffic in the target flow when probe packets arrive. This means that the one-way delay distribution (measured by active measurement without bias) is corrected to the empirical one-way delay distribution by the bias of the target flow (observed by passive measurement). $a(T_n)/(\sum_{l=1}^{m} a(T_l)/m)$ in (3) corresponds to $\mathrm{d}F_k(Y(n))/\mathrm{d}G(Y(n))$ in (1).

3 Suboptimal Probe Intervals

Since the PASTA property is good for non-biased measurement, Poisson arrivals (intervals with an exponential distribution) have been widely used as policy of probe packets arrivals for active measurement. However, if arrival process of the probe packets is stationary and mixing, under non-intrusive conditions, the following equation holds and we can also ignore the effects of probe packets under non-intrusive conditions.

$$\begin{aligned}\lim_{m\to\infty} \frac{1}{m}\sum_{n=1}^{m} f(X(T_n)) &= \lim_{t\to\infty} \frac{1}{t}\int_0^t f(X(t))\mathrm{d}t \\ &= \mathrm{E}[f(X(0))] \qquad \text{a.s.,}\end{aligned} \tag{4}$$

where f is an arbitrary positive function and the second equality follows from the stationary and ergodicity of the target process $X(t)$. [6] proved (4) and named this property NIMASTA (Non-Intrusive Mixing Arrivals See Time Averages).

For example, there are processes whose intervals obey the Gamma distribution, the uniform distribution, etc [6]. Note that periodic-probing, with determinate intervals is not a mixing process, and does not satisfy (4).

The recent study [5] also reported that NIMASTA-based probing is suitable for measurement. That provides an improvement in the accuracy of the measurement. We can select a suboptimal probing process in terms of accuracy under the specific assumption by using an inter-probe time given by the parameterized Gamma distribution.

If we estimate the mean of $X(0)$ by using active measurement, estimator $\hat{p}$ is

$$\hat{p} = \frac{1}{m} \sum_{n=1}^{m} X(T_n). \tag{5}$$

It is assumed that the autocovariance function $R(\tau) = \mathrm{Cov}\,(X(t), X(t-\tau))$ is convex. It can be proven that under the foregoing assumptions, no other probing process with an average interval of μ has a variance that is lower than that of periodic-probing (see [5]). A lower variance of the estimator is connected with accuracy. So, periodic-probing is the best policy if we focus only on variance.

On the other hand, periodic-probing does not satisfy the assumptions of NI-MASTA due to non-mixing, so periodic-probing is not necessarily the best. This is because a phase-lock phenomenon may occur and the estimator may converge on a false value when the cycle of the target process corresponds to the cycle of the probing process.

To tune the tradeoff between traditional policies obeying Poisson arrivals and periodic-probing, [5] proposes a suboptimal policy that gives an inter-probe time that obeys the parameterized Gamma distribution. The probability density function that is used as the intervals between probe packets is given by

$$g(x) = \frac{x^{\beta-1}}{\Gamma(\beta)} \left(\frac{\beta}{\mu}\right)^{\beta} \mathrm{e}^{-x\beta/\mu} \qquad (x > 0), \tag{6}$$

where $g(x)$ is the Gamma distribution whose shape and scale parameters are β and μ/β, respectively. μ denotes the mean, and β is the parameter. When $\beta = 1$, $g(x)$ reduces to the exponential distribution with mean μ. When $\beta \to \infty$, the policy reduces to periodic-probing because $g(x)$ converges on $\delta(x - \mu)$.

If the autocovariance function is convex, it is proven that the variance of estimator $\hat{p}$ sampled by intervals according to (6) monotonically decreases with β. We can achieve near-optimal variance of periodic-probing, since (6) corresponds to periodic-probing towards limit $\beta \to \infty$. The problem of incorrectness due to phase-lock phenomenon can be avoided if we tune β to a limited value (a probing process that has intervals as set by (6) is mixing). Solving the tradeoff between a traditional policy obeying Poisson arrivals and periodic-probing, we can get a suboptimal probing process if we give β an appropriate value.

The effectiveness of the Gamma-probing has been verified in the cases of simple virtual delay and loss processes using data from large-scale passive measurement and simulations [5]. However, these results do not directly mean that Gamma-probing can effectively be applied to CoMPACT. Comparing (5) with (3), we can consider that $X(t)$ as observed by CoMPACT monitor is

$$X(t) = 1_{\{V(t)>c\}} \frac{a(t)}{\overline{a}(t)} \tag{7}$$

where we let $\overline{a}(t)$ denote the time average of the traffic $a(t)$. Since this process is weighted by the traffic $a(t)$ of a specific flow, its propertyies are different from simple virtual delay or loss processes that is effected by all flows on the network. In this paper, we apply Gamma-probing to CoMPACT monitor and confirm its effectiveness.

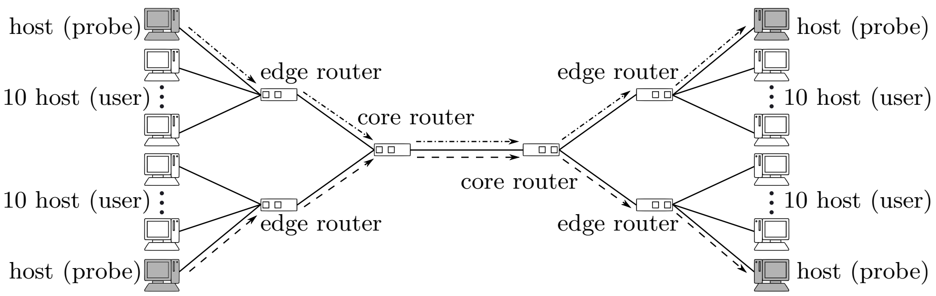

Fig. 1. Network model

4 The Effectiveness of Suboptimal Probe Intervals

4.1 Simulation Model

We investigated the effectiveness of Gamma-probing in the framework of CoMPACT monitor, through NS-2 based simulations [7].

The network model we used in the simulation is shown in Fig. 1. There are 20 pairs of source and destination end hosts. Each end host on the left in Fig. 1 is a source and transfers packets by UDP to the corresponding destination end host on the right. User flows are given as ON/OFF processes and categorized into the four types listed in Table 1, with there are five flows in each type.

Probe packet trains are categorized into the five types listed in Table 2. Mean probe intervals of each type is 0.5 s. Note that *Exp* and *periodic* in Table 2 are special cases of Gamma distribution. 300 trains of each type are streamed on the two routes shown in Fig. 1, so the total number of probe packet trains in the network is 3000. To analyze the variance of the estimator, we streamed a large number of probe packet trains. Of course we can estimate the empirical delay from only train. Note that parameters of *Exp* and *periodic* in Table 2 are parameters of the Gamma distribution corresponding to each probing.

User flow packets and probe packets are 1500 bytes and 64 bytes, respectively. Link capacities are identical at 64 Mbps. Delay occurs mainly in the link between the core routers, since it is a bottleneck, but no loss occures, because there is sufficient buffering.

We ran the simulation for 500 s. The non-intrusive requirement was satisfied, since the ratio of the probe stream to all streams is 0.00197%. We observed the traffic by passive measurement of queue for the edge router on the source side.

4.2 One-Way Delay Distribution

In this subsection, we show that CoMPACT monitor can estimate the empirical one-way delay when using Gamma-probing. The estimation of the complementary CDF of the one-way delay experienced by user flows will beshown below.

To estimate the complementary CDF of the one-way delay experienced by flow #1, we use probe packet trains with parameter $\beta = 1$, 25 and $\beta \to \infty$

Table 1. Type of user flows

Flow ID	Mean ON/OFF period	Distribution of ON/OFF length	Shape parameter	Rate at ON period
#1-5	10s/5s	Exp	-	6 Mbps
#6-10	5s/10s	Exp	-	6 Mbps
#11-15	5s/10s	Parete	1.5	9 Mbps
#16-20	1s/19s	Parete	1.5	9 Mbps

Table 2. Type of probing

Distribution of probe intervals	Parameter of Gamma distribution
Exp	$(\beta = 1)$
Gamma	$\beta = 5$
Gamma	$\beta = 25$
Gamma	$\beta = 125$
Periodic	$(\beta \to \infty)$

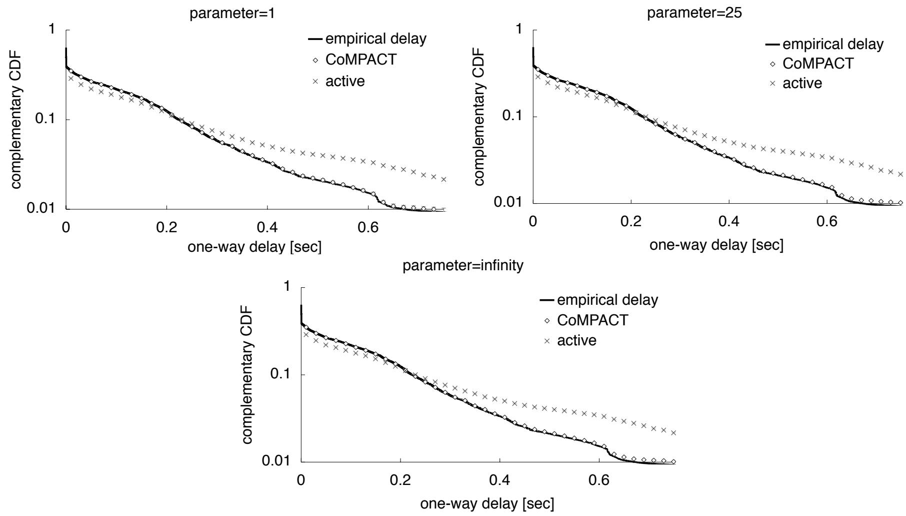

Fig. 2. The estimation of comprementary CDF (flow #1)

respectively. Each result, with 95% confidence intervals, is shown in Fig. 2. Note that the horizontal axis, which is the one-way delay, corresponds to c in (2). To compare the empirical delay with the estimate from CoMPACT monitor, we include the estimate from active measurement in the plot.

In Fig. 2, we can see that the CoMPACT monitor gives good estimates of the true value. We cannot judge the superiority or inferiority of any type of probe packet trains. To represent each flow type, we have plotted for flows #6, 11 and 16, getting results similar to Fig. 2.

4.3 Verification of Variance

In this subsection, we verify the relationship between the parameter of Gamma distribution that is used as the inter-probe time, and the variance of estimator. If we can apply the theory of [5] (explained in section 3) to CoMPACT monitor, the variance of the estimator decreases as the parameter increases.

Since we assume that the autocovariance function of the target process is convex, we will discuss its convexity. The target process observed by CoMPACT monitor is given by (7). We compute $V(t)$, which is the virtual one-way delay, by

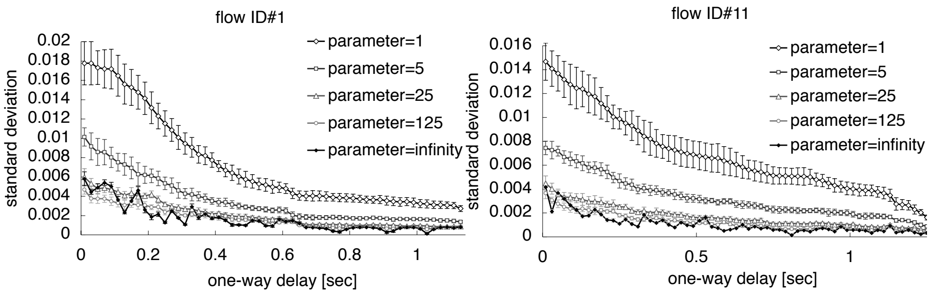

Fig. 3. Standard deviation of estimator

using the queue size (byte) of the core router on the source side. In our simulation model, the greatest part of the delay occurs at the core router on source side, because the link between the core routers is a bottleneck. Thus we can ignore any delay at other routers.

The autocovariance function for $c = 0.1$ for flow #1 with 95% confidence intervals is depicted in Fig. 4. To plot Fig. 4, we used data where the queue size and the traffic are recorded every 0.01 seconds. To represent at each flow type, we plotted flows #6, 11 and 16. This permitted the conclusion that none of these results contradicted the assumption that the autocovariance function is convex.

With the convexity of the autocovariance function confirmed, we will verify the relationship between the variance and parameter β. We plot the standard deviation of each point of the complementary CDF in Fig. 3. Note that the horizontal axis corresponds to the one-way delay, which is c in (2). Error bars indicate the 95% confidence interval when the standard deviation calculated from 30 probe packet trains is considered to be a single data point.

The standard deviation clearly decreases as β increases from $\beta = 1$ to $\beta = 125$. In periodic-probing corresponding to $\beta \to \infty$, the standard deviation is often larger than that for $\beta = 125$ and $\beta = 25$. This reversal is a sign of incorrectness due to the phase-lock that occurs when the cycle of the target process corresponds to the cycle of the probing process.

Consequently, for the case of UDP flow, it is confirmed that we can obtain adequate accuracy with a suboptimal probing process if we tune the parameter of Gamma distribution that we use as the inter-probe time.

4.4 Simulation in the TCP Case

We used UDP flows in the above simulation, but we also simulated the network for the case of TCP flows and obtained an interesting result. We replaced UDP flows with TCP flows in the above simulation model, but left other conditions the same. 300 packets was specified as the maximum window size.

In the case of TCP, user traffic is strongly affected by TCP traffic control. Therefore, the observed traffic of TCP flow may differ greatly depending on the timing of the sampling, compared with UDP. A condition of this simulation is

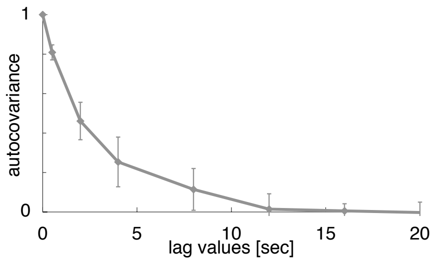

Fig. 4. The autocovariance function

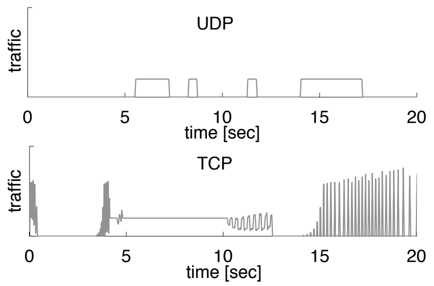

Fig. 5. Traffic process

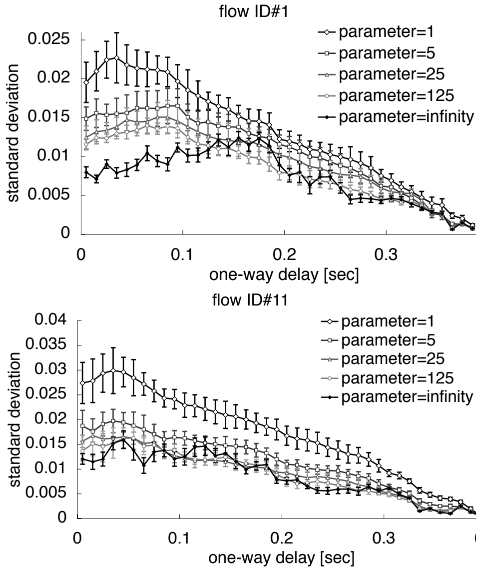

Fig. 6. Standard deviation of estimator in the TCP case

that user traffic is very unstable (see Fig. 5). Comparing these results with those from UDP simulation, we can confirm whether Gamma-probing can be applied to flows with a unstable traffic, or not.

In fact, we were able to confirm that the estimator converged to the true value and that the autocovariance function of the target process was convex, as in the UDP simulation.

However, the standard deviation of the estimator was different from that in the UDP simulation. Fig. 6 shows a plot of the standard deviation of each point versus the corressponding CDF point. The error bars idndicate 95% confidence intervals with the standard deviation calculated from 30 probe packet trains considered to be a single datum, as in the UDP simulation.

Now let us focus on $\beta \to \infty$ (corresponding to periodic-probing) in Fig. 6. The phase-lock phenomenon can be observed quite clearly by comparing these results to the UDP simulation. A clear reversal of the standard deviation is observed only with periodic-probing. This is the same as in the UDP simulation, though there the reversal does not necessarily happen. This result proves that periodic-probing is not optimal.

Moreover, we can confirm that there is no significant difference. From $\beta = 1$ to $\beta = 125$, there is a tendency to decrease. But confidence intervals overlap each other, which suggests that the reversal may be due to chance.

In short, the certainty of accuracy improvement by using Gamma-probing depends on the property of the target flow, though it is not completely ineffective. Comparing with small variable traffic, it can be concluded that no guaranteed improvement in accuracy is achieved by using Gamma-probing in a case with seriously variable traffic like this TCP simulation.

5 Conclusion

In a non-intrusive context where the effect of probe packets can be ignored, it was confirmed that the accuracy of estimating the complementary CDF of one-way delay can be improved by using Gamma-probing as part of applying CoMPACT monitor estimates.

However, the autocovariance function of the target process must be convex, obeying the assumption in [5]. Compared with simple delay/loss processes which are influenced by all traffic in the network, the traffic process in a specific flow some has periodicity. When we apply Gamma-probing to a real network, the convexity of the autocovariance function of the target process requires special attention.

We were able to show that the accuracy improvement due to Gamma-probing depended on the properties of the target process. In particular, there is a remarkable effect when gamma-probing is applied to UDP flows with stable traffic volumes, but there is no guaranteed improvement in accuracy when the same technique is applied to unstable traffic flows.

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