Micro Congestion Control: Every Flow Deserves a Second Chance

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Abstract
Today, a considerable Internet traffic is sent from the data-center and headed for users. With continuous upgrades in network infrastructure and user devices, the characteristics of connections served by servers in the datacenter are usually diverse and varied over time. As a result, one particular congestion control algorithm is hard to accommodate the heterogeneity and perform well in all scenarios. In this paper, we present Micro Congestion Control (MCC) — a novel framework for Internet congestion control. With MCC, diverse algorithms can be assigned to connections in one server to cover the heterogeneity, and multiple algorithms can be applied in each connection’s life cycle to keep pace with the dynamic of the Internet. We design and implement MCC in Linux, and experiments show that MCC is capable of smoothly switching among various candidate algorithms on the fly to achieve potential performance gain. Meanwhile, the overheads introduced by MCC are moderate and acceptable.

1. INTRODUCTION
Due to the Internet’s large-scale resource-sharing nature and continuous technology evolution in network infrastructure and user devices, the principles and techniques of congestion control have been unceasingly studied for decades [13]. Meanwhile, to support massive and various user needs whose quality of experience is severely affected by the Internet congestion control, datacenter to user are witnessed as the prevalent architecture. In such architecture, one server usually faces clients whose network path characteristics are diverse and dynamic.

To accommodate the heterogeneity, plenty of efforts have been devoted. For instance, dozens of classical congestion control algorithms are implemented in the Linux kernel, but the server operator usually set a unified algorithm for all connections in a server [15]. On the other hand, a trend [16] [10] [11] towards revolutionizing the very basic methodology of traditional congestion control emerges, which is based on the creed that the classical handcrafted approaches fail to accommodate the heterogeneity of the Internet and react ineffectively to the dynamic reality, resulting in less ideal performance. To make the congestion control adaptive to various network environment, Remy [16] utilize the machine-generated congestion control rules to replace manually designed algorithms, but the rules are mined from the offline data of given network condition, which can not summarize the dynamic of the network. PCC [10, 11] is a performance-oriented rate control architecture that adjusts the sending rate to maximize its utility value defined by several performance metrics.

Traditional handcrafted algorithms may fail to attain the ideal performance when they are exposed to the dynamics and diversity of Internet, unlike other works, we take a different road inspired from the following facts and trend. (1) One specific Congestion Control algorithm, even the state of the art, cannot excel in diverse scenarios, as described in §2. (2) The architecture of datacenter to user provides the opportunity to optimize Internet congestion control by mining volume data.

Therefore, we do not attempt to design an omnipotent algorithm to excel in all scenarios. Instead, we take a less radical reformism approach: With the fact that a set of algorithms outperform others for some specific scenarios, we do not invent new algorithms like existing work, we attribute the rigidity of applying the same pre-configured algorithm for all connections to the lack of fresh knowledge about each connection’s network environment, and we pin the performance degradation on the mismatch of algorithm adoption. We seek to bridge the gap by identifying the connection’s network characteristic and selecting the suited congestion control algorithm flexibly.

In this paper, we introduce Micro Congestion Control (MCC) — a framework for Internet congestion control, whose function is to select the proper algorithm for each connection. It has two “micro” features:

(1) Spatial: With MCC, diverse congestion control algorithms can be assigned to different connections in one server.

(2) Temporal: With MCC, different algorithms can be applied in each connection’s different phase to match its real-time network characteristics.

We implement MCC in Linux. Preliminary experiments show MCC provides the following benefits: 1) MCC ensures...
the transition between algorithms is smooth; 2) With suited algorithm applied to each connection, MCC performs better than utilizing a unified algorithm; 3) The overheads introduced by MCC are moderate.

The rest of the paper is organized as follows: In §2, we state our motivation and challenges to realize MCC; Then we describe how we design and implement MCC in §3 and §4. Preliminary experiments are presented in §5 and §6 concludes the paper.

2. MOTIVATION AND CHALLENGE

2.1 Motivation

One server in datacenter faces clients whose network path characteristics are diverse and dynamic. The heterogeneity can be largely attributed to the diversity of access network, carrier network and access time. Furthermore, especially for persistent connections, characteristic can also be time-varied, which is caused by factors such as competing flows’ joining/departing, route change, etc.

One particular congestion control algorithm cannot excel in all scenarios. Existing studies show that performance is dependent on the network environments. Results in [14] show the responsiveness, efficiency, fairness, and convergence time of different algorithms are varied by RTT (round-trip time) and loss rate. Findings in [18] show that the performance superiority of different algorithms can vary with network path and time. According to results in [11], PCC outperforms most of the tested algorithms but it is defeated by Sprout [17] in LTE environment.

However, nowadays servers usually apply a single congestion control Algorithm or a unified Congestion control configuration for all clients it serves. To accommodate the heterogeneity of diverse clients, server operators usually invent new handcrafted algorithms or modify existing ones, and tune the related parameters according to the common features of their clients [15].

To eliminate the rigidity of the unified congestion control approaches, we take a different road. Like recent works [16, 11, 10], we agree that unified algorithm configuration fails to accommodate the network heterogeneity, and admit traditional handcrafted algorithms, which are based on the

2.2 Challenges to Get MCC off the Ground

To realize MCC in practice, MCC needs to address the following challenges:

**Live migration between algorithms.** To achieve applying multiple algorithms in different phases of a connection, we need to migrate the states of the connection when algorithm switch happens. A smooth algorithm switch can be nontrivial for several reasons: To avoid performance degrading drastically, simply putting the new algorithm in initial phase is not an option; Besides, since different congestion control algorithms maintain individualized variables for their specific purpose, it is difficult for the new algorithm to maintain the performance if the necessary variables are not updated by the previous algorithm. For instance, observed maximum bandwidth is a performance-related variable in BBR, information loss happens if the previous algorithm such as Vegas [7] does not maintain the observed
Deployability. To realize MCC in practice, firstly, we need to ensure the introduced overheads are moderate. Characterizing connections online and deciding suitable algorithms requires analyzing the quickly generated feedback data in a real-time manner, because existed protocol implementation maintains only several accumulated variables like smooth RTT, minimum RTT, etc, which are just a profile of the raw data, but we need the connection’s evolution trace to characterize it. By collecting and analyzing the original data (e.g., the instantaneous RTT, loss rate, bandwidth), extra overheads are introduced, including huge-amount data extraction and high-frequency data analysis, which may harm the server’s performance. Besides, we need to ensure that the software architecture of MCC is deployable in servers of datacenter. To be specific, we need to drive MCC to scale to multicore and multi-server architecture. Because vast connections are handled by one server in datacenter, with multi-core processor and multi-queue NIC becoming ubiquitous. Furthermore, the rules of algorithm selection are from mining volume data collected from a huge number of connections, which can reside in multiple servers. These requirements pose difficulties in the software design of MCC [9].

3. DESIGN

We describe the details of MCC as well as how we address the above challenges in this section.

3.1 Architectural Overview

Figure 2 shows a high-level schematic description of MCC. We describe the profile of MCC first, and present design details later. MCC has two modules: Selector and Agent. Selector is in the user space and it identifies connections’ characteristic and maps the characteristics to congestion control algorithms according to given rules. Agent is responsible for coordinating information exchange between Selector and the kernel TCP stack. More specifically, Agent orchestrates information exchange in two directions:

The upward pipe transmits data collected by Agent from TCP stack and exposes them to Selector, the downward pipe transmit notifications generated by Selector, then Agent parses the notification and launches an algorithm switch in TCP stack.

The Rules Learner will be designed in the future work, who plays the role of setting rules to Selector by mining interested data.

3.2 Design Components

3.2.1 Agent

Agent mainly provides two functions: Data collection and Algorithm switch.

Data collection. MCC agent data-receiving procedure is invoked every time an ACK is received in the TCP stack, the procedure first extracts the information (e.g., the instantaneous RTT, loss rate, bandwidth), then it writes the collected data to the upward pipe that is read by the Selector later.

Algorithm switch. Specifically, we focus on how to ensure the smoothness of the transition between algorithms. We firstly set the initial congestion window of the new algorithm by inheriting the previous algorithm’s evolutional value to avoid drastic performance degradation. As for the algorithms that utilize pacing rate, such as BBR, we set the initial pacing rate to the value of congestion window divided by the value of recent sampled RTT. And the transition from pacing-rate based algorithm to window-based algorithm is symmetric. With inheriting the congestion window as a start point to avoid performance degrading drastically, we then consider other influential factors. To support their speed adjustment, algorithms maintain observed variables such as the minimum observed RTT, the maximum observed bandwidth, etc. We abstract the most common variables by looking into the implementation of congestion control algorithms in Linux, and the abstracted variables include the minimum RTT, the maximum RTT, the maximum congestion window, and the maximum bandwidth. To enable the new algorithm to obtain these important variables in the first place, we deliberately maintain these variables for each connection. As for other individualized variables, we first set them to their initial values, and then put the new algorithm in bandwidth probing phase to update them.

To sum up, we take the following steps to ensure the smoothness of the algorithm switch.

Preparation: We first deliberately maintain the described common variables of each connection during each connection’s whole life cycle.

Inheritance: The new algorithm’s initial congestion window is directly inherited from the last one’s evolutional value, and we set the new algorithm’s other variables as much as we can by the values of common variables we maintain.

Probing: Then, we put the new algorithm in the bandwidth probing phase after the inheritance. As for the individualized variables, we set them to their initial values, which are updated shortly in the probing phase.

3.2.2 Pipes

The pipes transmit the data between the Agent and the Selector. Specifically, the upward pipe transmits data collected...
by Agent from the TCP stack and exposes them to Selector, the downward pipe transmits notifications generated by Selector, then Agent reads and parses the notification.

To optimize the data exchange, we choose the ring buffer as the data structure of the upward and downward pipe. Agent is the data producer and Selector is the consumer for upward pipe, and the downward pipe is symmetric. Then we minimize the two kinds of overheads: The overheads of memory allocation / release, and the overheads of data access. We first pre-allocate memory pools for upward and downward pipe respectively, and the necessity of memory pre-allocation is: The rate of writing data into the upward pipe is the same as the ACK arriving rate, for we collect data from each ACK. This fast generation rate of data requires we collect and consume the data quickly, the pre-allocation avoids the frequent memory allocation and release. Second, we decrease the data access overheads by memory mapping design. Take upward pipe for instance, for the data are collected in the kernel and analyzed by Selector in the user space, memory mapping avoids the overheads of user / kernel mode switch and system calls to read and write data.

3.2.3 Selector

The functions of Selector contains: Reading collected data from upward pipe, analyzing the data with given rules to select the algorithm for each connection, send the notifications by downward pipe to signal Agent to switch algorithm. Then we describe the details of these functions. The selector maintains per-connection states in its memory to store the necessary information for algorithm selection. Each time it reads collected data from upward pipe, it updates the per-connection states of the connections who own the data. After the updates, If the per-connection states and given rules indicate a new algorithm is selected, the Selector informs the Agent to switch algorithm by sending a notification through the downward pipe.

Selector optimization: To amortize the overheads of upward pipe synchronization between Agent/Producer and Selector/Consumer, Selector reads a batch of data from the upward pipe rather than a single one each time, the downward pipe is symmetric. Besides the synchronization overheads amortization, we take the data analyzing as a compute-intensive process, which can benefit from the advantages the batch processing provides: Cache locality. Due to the pre-allocated memory strategy, most of the adjacent data in the ring are continuous in virtual-address, which can be exploited by cache’s data pre-fetching strategy. Besides, the batch processing is basically a loop process, where a fragment of code is executed repeatedly, which satisfies the instruction temporal locality and spatial locality. Instruction-level parallelism exploitation. Since all data’s processing is isomorphic, that is, they all flow through specific classification rule after unified pre-processing. For example, after a batch of data are read, the current-round RTT sample values are utilized to update connections’ estimated RTT respectively, which is independent and identical. Therefore, the isomorphism provides opportunities for parallelism, which can be exploited by vector instructions [1] or GPU.

3.3 Multi-core Support

To make MCC deployable in multi-core server, we minimize the synchronization overheads and inter-core contention by employing two techniques: per-core data structure and lock-free synchronization. Per-core data structure. For each core, we localize one Selector, one Agent and two pipes. Since our framework does not interfere with packet processing, we achieve load distribution of analyzing data, that is, we map connection’s data to cores by NIC’s RSS (receive-side scaling), and a suite of Selector thread, kernel TCP stack thread are bound to the same core to ensure all data of a specific connection are processed by one core throughout its life cycle, which avoids the inconsistency. Otherwise, if multiple cores analyze different parts of one connection’s data, they may have disagreement in algorithm selection due to the limitation of the partial information they extract from a fragment of data. Lock-free synchronization. With per-core data structure, the synchronization between Selector and Agent can be modeled as the single-producer-single-consumer model, which can be implemented to be lock-free.

4. IMPLEMENTATION

We implement MCC in the Linux kernel 4.14.29 and the associated user level library.

4.1 MCC Kernel Implementation

MCC contains two parts in the kernel: an external kernel module and modifications to the TCP stack.

4.1.1 Kernel Module

Selector interacts with Agent through a special device file: /dev/mcc. Selector calls open() system call to open the file to create a suite of pipes, which is also accessible from Agent. A handle is returned to Selector for manipulating the pipes. Besides that, pre-allocated memory pool is allocated by the driver of the /dev/mcc in the open() system call. In addition, the driver implements the ioctl() system call to realize the synchronization between Selector and Agent, memory mapping is achieved by implementing the mmap() interface of the device. Pipe implementation The pipe is maintained as a lock-free ring structure which are pre-allocated and memory mapped. The batch processing is implemented by Selector polling the pipe, that is, Agent continuously writing collected data to the modules’ shared area, where Selector periodically reads a batch of data by timer triggering. The timer interval naturally becomes a prominent performance-influent factor that directly influences the batch size and data freshness. We currently adopt an empirical approach of setting timer interval around one-tenth of the modal number of the RTTs, for data arriving is per-ACK, and RTT is typically millisecond-level, which is far larger than the CPU
cycles consumed by one timer waking up operation.

4.1.2 Kernel TCP Stack Modification

We make minor modifications to Linux kernel TCP stack to cover Agent’s functions including: data collection and algorithm switch.

Data collection. We instrument the ACK processing procedure to generate the raw data, and currently extracted per-ACK information contains RTT, loss rate, delivery rate, ECE (ECN-Echo) mark. More information will be extracted if future usage requires.

Algorithm switch. Dozens of congestion control algorithms are implemented in the Linux kernel in the form of loadable modules. Changing a TCP connection’s algorithm is achieved by replacing the function pointer of the previous algorithm to the new one’s.

The switch starts by Selector writing a group of connections’ algorithm decision in the downward pipe and calling ioctl, which signals Agent to set algorithm switch flags for the related connections’ TCP control blocks. The flag will directly trigger an algorithm replacement when kernel congestion control component are invoked. The state migration for the replacement is in accordance with the steps we state in §3, including preparation, inheritance and probing.

4.2 MCC User Interface Implementation

MCC user library is essentially a simple wrapper of the kernel module, which contains: mcc_open() returns a handle to manipulate MCC, mcc_ioctl() is implemented to synchronize the data exchange in upward and downward pipe. User’s customized characteristic identifying and algorithm selection logic are implemented in mcc_update_state(), which returns the selected algorithm.

5. PRELIMINARY EVALUATION

Experiment Setup: We set up one server machine and two client machines. The server and two clients are all equipped with a 12-core CPU (Intel Xeon E52620 @ 2.4GHz), 64GB RAM and one dual-port Intel 82599 10G NIC, respectively. The two 10G ports of 82599 NIC in the server are directly connected to client machines’ NIC ports. To regulate the network environment, we use the Linux traffic shaper (TC) [2].

5.1 State Migration

To observe MCC’s effects on algorithm switch, we utilize the traffic shaper to regulate the link characteristics to: bandwidth: 2 Mbps, RTT : 30ms, loss rate: 4%. By utilizing MCC, we switch the algorithm from CUBIC to BBR, then TCP Westwood. To observe each algorithm’s behavior, we use the dynamic probe [3] technique to obtain metrics including sender congestion window, inflight packets and instantaneous throughput as shown in Figure 3. The result shows no drastic performance degradation is observed and the jitter of performance is modest in the transition phase.

5.2 Performance Gain

We create two scenarios to emulate the heterogeneity of network by utilizing traffic shaper on two client machines: C1, C2 respectively, and compare the performance of MCC, TCP Westwood, and BBR in both throughput and retransmission rate. We set rules of MCC as selecting TCP Westwood if the observed loss rate is more than 3%, otherwise, BBR is selected.

C1 network condition: Bandwidth : 2Mbps, RTT : 30ms, Loss rate : 4%, Concurrent connections: 10. C2 network condition: Bandwidth: 5Mbps, RTT : 30ms, Loss rate: 0.5%, Concurrent connections: 5.

Table 1 shows that MCC selects TCP Westwood for connections in C1 and selects BBR for connections in C2, the total performance of MCC is better than the performance of adopting only one algorithm in two different scenarios.

5.3 Overheads

In order to test the overheads of MCC in high-load server with multi-core, we conduct two experiment: single-core and two-core experiment. We only conduct single-core and two-cores experiment for two cores are enough to saturate the dual-port 10G NIC for persistent connections.

In the single-core experiment, to achieve high loads, we combine the multi-queue of 10G NIC into a single queue, and bind the single queue to one specific core in the server, that is , we utilize one core to versus one 10G NIC. Then we apply MCC to Nginx [5] and ensure the MCC, Nginx, kernel network stack all run in the same core which is bound with the single queue NIC. To find out the overheads introduced by the framework itself, Selector only pre-processes the data by computing the average RTT, loss rate, and throughput, computation of characterizing connections’ class is not applied. This concludes the configuration of the server. One client firstly regulate the RTT to 20 ms, then 250 persistent-connection are generated in this client by an HTTP benchmark tool (wrk) [4] to download files of 1MB from the server, which nearly saturates the 10G port.

In two-core experiment, we configure the server with two
cores, and bind the two 10G NICs to the two cores, both of the NIC is configured to combine the multi-queue into single queue, which makes the two cores versus the two 10G NIC respectively. For each core, a suite of MCC, Nginx and kernel network stack is bound to it as the single-core experiment. Two client machines with RTT equals to 20ms simultaneously sends requests to the server, each client generates 250 persistent-connection to download the 1MB file.

We then collect the metrics of microbenchmark and macrobenchmark for the above two experiments. In microbenchmark, we profile the CPU cycles cost proportions by Linux performance profiling tool (Perf) to evaluate the overheads of MCC in the server. As shown in Table 3, MCC contains two parts, Selector in the user space and Agent in the kernel. To make the overheads concrete, we compare MCC’s overheads with Nginx and tcp_ack procedure. (Nginx runs in user space as the application while tcp_ack() is the original kernel procedure we add Agent in). Results in Table 3 are divided into two parts. The left part is results of single-core experiment, the right part is the percentages of the total CPU cost of two-core for each entity. The result shows the overheads introduced by MCC is moderate and remain relatively small as more cores are utilized. In macrobenchmark, performance metrics are observed from clients and presented in Table 2 for both experiment. The left part of the data in each grid is for single-core experiment, and the right is for the two-core experiment. It shows that the total performance is not affected prominently by utilizing MCC.

Table 3: CPU cost percentages of single-core and two-core experiment

| Entity         | Space CPU cost | User | Kernel |
|----------------|----------------|------|--------|
| MCC (Westwood+BBR) | 0.54 / 0.54 | Nginx 29.24 / 38.26 | Agent 0.08 / 0.08 |
| Westwood       | 0.54 / 0.54 | Nginx 29.24 / 38.26 | Agent 0.08 / 0.08 |
| BBR            | 0.54 / 0.54 | Nginx 29.24 / 38.26 | Agent 0.08 / 0.08 |

Table 1: Performance gain

| Entity         | Throughput (KB/sec) | Retransmission rate |
|----------------|----------------------|---------------------|
| MCC (Westwood+BBR) | 233.29 | 3.52% |
| Westwood       | 233.91 | 3.51% |
| BBR            | 233.08 | 3.80% |

http://nginx.org

6. CONCLUSION

In this paper, we present MCC to drive the congestion control to be adaptive to the heterogeneity and dynamic of the Internet. The limitation of MCC is that it is only effective in the architecture of datacenter to user. The future work includes: 1) To design and implement Rules Learner for mining rules of algorithm selection from network data; 2) To deploy the MCC in datacenter to attain real performance gain.

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