Toward Adaptive DDoS-Filtering Rule Generation

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***Abstract*—Despite various distributed denial-of-service (DDoS) filtering solutions proposed and deployed throughout the Internet, DDoS attacks continue to evolve and successfully overwhelm the victims with DDoS traffic. While current DDoS solutions in general employ a fixed filtering granularity (e.g., IP address, 4-tuple flow, or service requests) with a specific goal (e.g., maximum coverage of DDoS traffic), in this paper we investigate adaptive DDoS filtering. We design and experiment algorithms that can generate and deploy DDoS-filtering rules that not only adapt to the most suitable and effective filtering granularity (e.g., IP source address and a port number vs. an individual IP address vs. IP prefixes at different lengths), but also adapt to the first priorities of victims (e.g., maximum coverage of DDoS traffic vs. minimum collateral damage from dropping legitimate traffic vs. minimum number of rules). We evaluated our approach through both large-scale simulations based on real-world DDoS attack traces and pilot studies. Our evaluations confirm that our algorithms can generate rules that adapt to every distinct filtering objective and achieve optimal results.**

***Index Terms*—distributed denial-of-service; DDoS; DDoS filtering; DDoS filtering rule; adaptive DDoS filtering**

I. Introduction

Despite years of research and industry efforts that have led to a myriad of defense approaches, the Internet continues to be severely susceptible to distributed denial-of-service (DDoS) attacks and see DDoS attacks increase in both the amount and scale [1]. Among the most common DDoS attacks are high-volume DDoS that overwhelm a victim's bandwidth, in which such attacks can reach as high as 1.2 Tbps [2], 1.35 Tbps [3], 2.4 Tbps [4], or even 3.47 Tbps [5], with largest ever recorded packet per second-based DDoS at 809 Mpps [6].

Continuous improvement of DDoS defense is therefore critical. DDoS defense is usually composed of three complementary (and often combined) processes: DDoS detection and DDoS traffic classification that detects DDoS attack and classifies DDoS traffic and legitimate traffic; DDoS path discovery that discovers the paths of DDoS traffic; and DDoS mitigation that filters, throttles, or redirects DDoS traffic. This paper is focused on DDoS mitigation via filtering.

Depending on the solution in place, DDoS filtering can happen at the victim end, the sources of DDoS, or in network. A key challenge facing DDoS solutions is the *proper* granularity of DDoS traffic filtering. For example, although it is probably suitable to filter traffic from an entire IP prefix when a victim is under a severe DDoS attack, if the volume of DDoS traffic from the prefix is low and the volume of legitimate traffic from the prefix is high, it may be more preferable to only filter traffic from individual IP addresses of DDoS bots instead to minimize collateral damage, which however will incur a higher overhead.

Or, for another example, if there are two traffic flows appearing from the same IP address, one of which is benign traffic and the other is DDoS traffic spoofing the source, filtering traffic from the IP address becomes a dilemma unless it happens only on the paths of the DDoS flow, or the filtering must use both IP address and port numbers if the two flows share the same path but use different port numbers. Interestingly, as shown in this example, the filtering granularity can be different depending on the location of filtering.

Of further challenge is that there can be thousands of DDoS flows at prefix level, millions of DDoS flows at IP address level, and potentially even more at IP address plus port number level. It will be prohibitively expensive to monitor traffic for every granularity. Furthermore, while in general one cannot accomplish all objectives simultaneously, every victim may have different first priorities, such as maximum coverage of DDoS traffic, minimum collateral damage to legitimate traffic, or minimum overhead—which we use number of filtering rules to represent in this paper.

While numerous research has been conducted on detecting and mitigating DDoS, filtering DDoS has basically based on a single granularity, such as IP address, IP prefix, or IP address and port number, or a flow (which is usually a 4-tuple flow defined by the source IP and port and destination IP and port). If DDoS defense is at the application layer, the granularity can also be the user requests to a service. The filtering has not been considered to be adaptive to filtering locations, either. Moreover, rigorous study and approach has been lacking in terms of finding the best tradeoff between different objectives, particularly DDoS traffic coverage, collateral damage from dropping legitimate traffic, and the number of DDoS-filtering rules.

In this paper, we investigate adaptive DDoS filtering. We allow a DDoS defense to adaptively generate DDoS-filtering rules at the proper granularity and then deploy them at the most suitable filtering nodes along the paths of DDoS traffic. We develop efficient rule-generation algorithms that can not only generate rules with different granularities toward different objectives, but also help determine where to deploy generated rules for the best efficacy. We then evaluate our system that embraces the algorithms. We first use large-scale simulations based on real-world DDoS attack traces to study the efficacy of rules generated, then study their deployment success rate under different distributed Internet-scale filtering

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profiles, and also experiment the efficacy and scalability of the entire system for DDoS mitigation in real time against real-world DDoS attack traces.

The rest of this paper is organized as follows. We first describe related work in Section II. We then describe our design of adaptive DDoS-filtering rules in Section III, followed by the implementation in Section IV. We detail our results from evaluating our solution through simulations and pilot studies in Section V and conclude the paper in Section VI.

II. Related Work

Different solutions in filtering DDoS can be based on a different granularity. DDoS filtering in early days is primarily based on IP addresses. An exemplary approach is AITF ([7]), which filters DDoS traffic based on individual IP addresses of DDoS bots as close to the source as possible. However, because IP addresses can be spoofed, a great deal of research has been devoted to IP traceback, such as those discussed in [8], [9], [10], [11]. Before long flow-based DDoS filtering also became common, in part due to the development of network telemetry which supports network traffic data collection and analysis at a finer granularity. While most solutions are at the victim end (e.g., FastNetMon [12], some are at the source end (e.g., [13]). The development of software-defined networking further strengthened this trend, as exemplified by FlowGuard [14]. Lastly, DDoS filtering can also happen at application layer, in which the filtering is usually about discarding illegitimate requests to a service under DDoS attack, as demonstrated by research in [15] and [16]. In all these cases, DDoS filtering has basically based on a fixed granularity. What set our research apart from the previous work is that our research studies how a DDoS defense can adapt its filtering granularity based on various factors for the best efficacy and tradeoff, and choose the granularity that is most effective or is the best tradeoff to filter DDoS traffic.

Filtering DDoS has also mostly focused on maximizing the amount of DDoS traffic filtered. While DDoS filtering research has primarily been focused on the accuracy, i.e., filtering DDoS traffic without falsely filtering legitimate traffic, as those in [17], [18], [19], recent studies have been also on boosting the throughput of filtering DDoS traffic [20], [21]. Nonetheless, less has been studied in detail on DDoS filtering methodologies if the top priorities of filtering change. In this paper we develop DDoS-filtering rule generation algorithms corresponding to different top priorities, including maximum DDoS traffic filtered, minimum collateral damage, *or* smallest number of filtering rules, while still imposing constraints on secondary priorities.

III. Design

A. Assumptions

We focus on a *distributed filtering model* as a basis for our adaptive filtering, where the DDoS mitigation happens in multiple different locations. As a DDoS attack is to launch DDoS traffic from DDoS bots throughout the Internet towards a victim along many different paths, the DDoS traffic can be filtered along these paths before they reach the victim, so long as on the paths there are nodes that are set to help filter DDoS traffic and know what traffic are DDoS traffic to filter. Our study is centered on deploying *effective* DDoS filtering rules at *effective* nodes along DDoS paths, including adaptively determining these effective rules and nodes.

We assume a DDoS defense system is constantly running on behalf of a DDoS victim and can employ a third-party DDoS detection software such as FastNetMon [12] with a usable accuracy to detect DDoS attacks and classify "flows" to be DDoS flows or legitimate flows.

We also assume a DDoS defense can track the DDoS traffic, such as knowing the paths of a DDoS flow before they reach the victim, so it can select the most suitable filtering nodes along the paths to filter the DDoS traffic. Example solutions include those using marking techniques [8], [22], [23] and those based on logging [9], [24], [25].

B. Rationale

Once a DDoS defense detects DDoS "flows", it then can request filtering nodes on the path(s) of these flows to filter them. Certain types of DDoS traffic are straightforward to filter, including those flows defined by the Protocol, TCP flags, and/or Destination attributes. However, flows that are defined by different source attributes, with or without other attributes, are challenging to handle. Such flows correspond to three different filtering granularities:

- *IP-prefix-based filtering* that discards all traffic from an IP prefix.
- *IP-address-based filtering* that discards all traffic from an IP address.
- *IP-and-port-based filtering* that discards all traffic from an IP address with a given source port number.

All three filtering granularities have their advantages and disadvantages. IP-prefix-based filtering results in the least number of DDoS "flows" to filter, i.e., the least number of filtering rules as every DDoS flow maps to a filtering rule. It thus in turn leads to least networking, storage, and management overhead. It could also lead to faster deployment of all the rules and, with less rules to search, better performance in matching every DDoS packet to a rule and taking actions. However, IP-prefix-based filtering may lead to collateral damage, sometimes perhaps even severe, when traffic from a legitimate IP in an IP prefix is filtered. Nonetheless, certain amount of collateral damage may be still acceptable, especially when the victim is under a severe DDoS attack. IP-address-based filtering will cause less collateral damage, but it can still happen if there is also legitimate traffic from the same IP address of a DDoS bot, or worse, if a DDoS bot spoofs the IP address of a benign host who happens to be also sending traffic to the victim. IP-and-port-based filtering has the least possibility of collateral damage. It also makes IP spoofing hard to succeed, unless a DDoS bot can spoof both the IP address and the source port number of an active legitimate flow with the victim, the chance of which is extremely slim. However, IP-and-port-based filtering usually does not scale.

We thus introduce adaptive filtering to seek the best trade-off among all the competing factors. In particular, a DDoS defense can enforce filtering at different granularities. A simple adaptive filtering strategy could be as follows. For an IP prefix that originates DDoS traffic, if the volume of legitimate traffic from the prefix is low, assuming the victim is under a severe DDoS attack and can afford losing some legitimate traffic, a rule that filters the entire IP prefix is probably applicable. Otherwise, we can look at every sub-prefix of the prefix. We can generate a rule for every sub-prefix that primarily originates DDoS traffic, skip every sub-prefix that primarily originates legitimate traffic, and apply the same filtering strategy here recursively on every sub-prefix that originates both DDoS and legitimate traffic. If in this recursive process a sub-prefix becomes an IP address that originates both DDoS and legitimate traffic, we can check which ports of the IP address originates DDoS traffic, and only filter traffic from those ports of the IP address.

With such an adaptive filtering, the DDoS defense is not limited to a single granularity of filtering DDoS traffic. Instead, it is able to elect to use different filtering granularities as needed. This simple strategy, however, leaves many key questions unanswered. A major challenge is that there can be thousands of DDoS flows from different IP prefixes, millions of DDoS flows from different IP addresses, and potentially even more from different IP address and port number combinations. It will be prohibitively expensive to monitor traffic for every granularity and then determine filtering rules accordingly.

Also, for a flow from an IP prefix or IP address, it does not take advantage of the paths of the flow. For example, if traffic from an IP address consists of DDoS traffic from one path and legitimate traffic from another distinct path, we can employ IP-address-based filtering at a node that is on the former path but not on the latter path, without resorting to the more specific but less scalable IP-and-port-based filtering.

Moreover, it does not consider the preferences of a DDoS defense, such as its objectives and constraints in terms of DDoS traffic coverage, collateral damage, and the number of DDoS-filtering rules. Ideally, a defense wants to generate rules that are optimal for three objectives, including a full coverage of DDoS traffic, no collateral damage from dropping legitimate traffic, and only using a small number of rules. In practice, however, a DDoS defense must compromise one or two objectives in order to optimize for another objective, and each DDoS defense may have different prioritized objectives. In our design, we allow a defense to optimize for one objective, but it must also meet the constraints for other objectives.

Finally, the simple adaptive filtering strategy is a top-down approach, moving from IP prefixes to sub-prefixes to IP addresses and then to ports. However, DDoS detection and classification solutions usually classifies traffic flows into a fine granularity such that every flow is either DDoS traffic or legitimate traffic (rather than a mixture of both) (Section III-A). To run adaptive filtering on top of DDoS classification, it is more natural for it to be bottom-up instead.

We incorporate all these observations next.

C. Problem Formulation

We now formulate the problem of rule generation. For a given rule r, we define $d(r, T)$ and $l(r, T)$ to be respectively the DDoS traffic and legitimate traffic that rule r filters from the traffic set T, respectively. As such, if we have a set of rules R=$\{r_i|i$=1, …, $n\}$, where r_i is a rule, we have $d(R,T)$=$\sum_{i=1}^{n} d(r_i,T)$ and $l(R,T)$=$\sum_{i=1}^{n} l(r_i,T)$ to respectively represent the DDoS traffic coverage and collateral damage of the rule set R over traffic T. Assuming the DDoS defense's constraints for the minimal amount of DDoS traffic that must be filtered is D, the maximal amount of legitimate traffic that could be filtered is L, and the maximal number of rules that is allowed to generate and deploy, which we also call **rule budget**, is M, we define three distinct single-objective rule-generation problems as follows:

- **Rule-generation Problem 1:** In case the defense is most concerned about filtering as much DDoS traffic as possible, for traffic T, output a set of rules R=$\{r_i|i = 1,...,n\}$ that maximizes $d(R,T)$, whereas $l(R,T) \le L$ and $|R| \le M$. Example scenario 1: the victim is overwhelmed by a severe DDoS attack and eager to have as much DDoS traffic as possible filtered.
- **Rule-generation Problem 2:** In case the defense is most concerned about avoiding collateral damage due to the filtering of legitimate traffic, for traffic T, output a set of rules R=$\{r_i|i = 1,...,n\}$ that minimizes $l(R,T)$, whereas $d(R,T) \ge D$ and $|R| \le M$; Example scenario 2: the DDoS attack is not that severe, and the victim does not wish legitimate traffic to be filtered by mistake.
- **Rule-generation Problem 3:** In case the defense is most concerned about minimizing the number of generated rules, for traffic T, output a set of rules R=$\{r_i|i = 1,...,n\}$ that minimizes $|R|$, whereas $l(R,T) \le L$ and $d(R,T) \ge D$. Example scenario 3: deploying filtering rules costs a certain amount of money, and the defense may have a limited budget to defend against an attack.

The defense then can choose which problem to solve, depending on which metric to optimize and which metrics to impose constraints.

D. F-tree

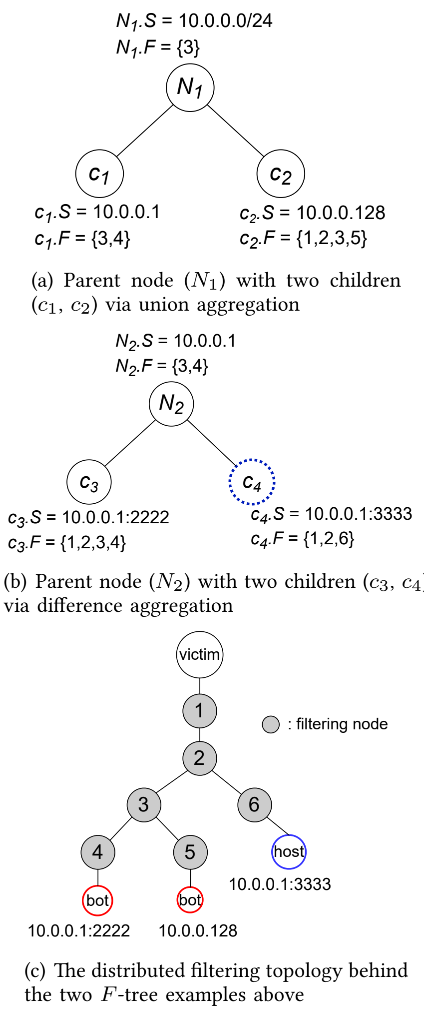
We now describe a data structure called F-tree, which we will use to generate DDoS-filtering rules as described in Section III-E. An F-tree is a tree in which every node records a traffic source and every parent node records an aggregated source that aggregates all the sources represented by its child nodes. Specifically, every node in an F-tree records the following information of a source:

- S: The source of traffic. It can be an IP source address and a port number, an IP address, or an IP prefix. We call all packets from S toward the victim a "flow" from

S. Note the source is not necessarily a single end point on the Internet. Even if it is a single IP address, because of IP spoofing, there may be more than one path.

- F: A set of candidate filtering nodes on the path(s) of the flow that may be used to filter packets from the flow.
- d: The amount of DDoS traffic from the flow in terms of number of bytes, packets, or TCP or UDP connections, that can be filtered by F. This is also the DDoS coverage when using a node from F to filter traffic from S.
- l: The amount of legitimate traffic from the flow that can be filtered by F. This is also the collateral damage when using a node from F to filter traffic from S.

Basically, every node N on an F-tree can be mapped to a rule that requires traffic originating from $N.S$ to be dropped, with a DDoS coverage of $N.d$ and collateral damage of $N.l$. The rule must be deployed on any one of the nodes in $N.F$ to be able to intercept the traffic. Figures 1(a) and 1(b) show two toy F-tree examples.



(a) Parent node (N_1) with two children (c_1, c_2) via union aggregation

(b) Parent node (N_2) with two children (c_3, c_4) via difference aggregation

(c) The distributed filtering topology behind the two F-tree examples above

Figure 1. **F-tree for DDoS-filtering rule generation.**

Every node N with a set of child nodes $c_1, ..., c_n$ (in a binary tree n is 1 or 2) derives its four values from those of its children through aggregation. First, the source value of N is the aggregation of the source values of all its child nodes. Specifically, $N.S$=*prefix*$(c_1.S, \ldots, c_n.S)$, where *prefix()* is a function to extract the longest common prefix from input prefixes. For example, in Figure 1(a), if node N_1 has two children c_1 and c_2, $c_1.S = 10.0.0.1$ and $c_2.S = 10.0.0.128$, then $N_1.S = 10.0.0.0/24$. Or for another example, in Figure 1(b), if node N_2 has two children c_3 and c_4, $c_3.S = 10.0.0.1 : 2222$, $c_4.S = 10.0.0.1 : 3333$, where 2222 and 3333 are source port numbers, then $N_2.S = 10.0.0.1$.

There are two types of aggregation: **union aggregation** or **difference aggregation**. Both can only happen if they do not lead to an empty $N.F$. A union aggregation is to derive information for filtering all the flows represented by child nodes. It is as follows:

- $N.F = \cap_{i=1}^{n}(c_i.F)$;
- $N.d = \sum_{i=1}^{n}(c_i.d)$; and
- $N.l = \sum_{i=1}^{n}(c_i.l)$.

Assume node N_1 above is derived via a union aggregation. If $c_1.F = \{3, 4\}$ and $c_2.F = \{1, 2, 3, 5\}$, then $N_1.F = \{3\}$, $N_1.d$ = $c_1.d + c_2.d$, and $N_1.l$ = $c_1.l + c_2.l$.

A difference aggregation is to derive information for filtering only certain flows represented by child nodes and avoid filtering certain flows represented by child nodes. Assume among child nodes $c_1, ..., c_n$, we want to filter flows from $c_1, ..., c_k$ but not flows from $c_{k+1}, ..., c_n$, a difference aggregation is as follows:

- $N.F = \cap_{i=1}^{k}(c_i.F)$ - $\cup_{i=k+1}^{n}(c_i.F)$;
- $N.d = \sum_{i=1}^{k}(c_i.d)$; and
- $N.l = \sum_{i=1}^{k}(c_i.l)$.

Assume node N_2 above is derived via a difference aggregation. If $c_3.F = \{1, 2, 3, 4\}$, $c_4.F = \{1, 2, 6\}$, and N_2 wants to filter traffic from c_3 but not c_4, then $N_2.F = \{3, 4\}$, $N_2.d$ = $c_3.d$, and $N_2.l$ = $c_3.l$.

Finally, if we combine our above examples for nodes N_1 and N_2 and map N_2 to c_1 (they have the same values), we can obtain a bigger F-tree. Figure 1(c) shows the underlying topology. We can see if we want to filter DDoS traffic from $10.0.0.1 : 2222$ (c_3) and $10.0.0.128$ (c_2) without a collateral damage on traffic from $10.0.0.1 : 3333$ (c_4), we will obtain a rule represented by N_1, i.e., filter traffic from $10.0.0.0/24$, to be deployed in one of nodes in $N1.F$, i.e., node 3.

E. Rule Generation Algorithms

We now describe how a defense generates rules using an F-tree. First, as a DDoS victim continuously receives traffic, the defense acting on behalf of the victim can classify/label incoming traffic flows to be DDoS flows or legitimate flows, and also know the nodes on the path(s) of the flows that can filter traffic (Section III-A). With such information for every incoming flow, the defense can accordingly initialize all the leaf nodes in the F-tree. For all labeled traffic from the same source, the defense casts them into a leaf node, say N, on the F-tree, where $N.S$ is the source, $N.F$ are all the filtering nodes on the path of traffic from $N.S$, and

$N.d$ and $N.l$ are the amount of DDoS and legitimate traffic from $N.S$, respectively. ($N.d$ and $N.l$ are respectively zero for legitimate and DDoS flows.) It then runs a loop process which recursively aggregates leaf nodes to generate parent nodes, using the procedure in Section III-D. The key at every iteration of the loop is to determine which nodes to aggregate based on the rule-generation problem in place, as follows.

For the rule-generation problem 1 (which maximizes the DDoS coverage), in each iteration, the algorithm first finds leaf nodes, if aggregated, that will bring the highest increase of the DDoS coverage without violating the collateral damage constraint. It then derives their parent node as described in Section III-D, prunes the leaf nodes, and makes the parent node a new leaf node. Note while a union aggregation can lead to a higher d value per node, a difference aggregation can aggregate leaf nodes into a parent node to further run a union aggregation with other nodes. The loop process continues until no further aggregation can be done. The defense then maps the top up to M leaf nodes with the highest d-values to the rules to use.

For the rule-generation problem 2 (which minimizes the collateral damage), in each iteration, the algorithm first finds leaf nodes, if aggregated, that will introduce the least collateral damage. It then derives their parent node, prunes the leaf nodes, and makes the parent node a new leaf node. The loop process continues until in the current F-tree there are M or fewer leaf nodes whose sum of d values are at least D. It then maps these M or fewer leaf nodes to the rules to use.

Finally, for the rule-generation problem 3 (which minimizes the number of rules), in each iteration, the algorithm first finds the largest number of leaf nodes whose aggregation into a parent node, whether a union aggregation or a difference aggregation, will not violate the collateral damage constraint. It then derives their parent node, prunes the leaf nodes, and makes the parent node a new leaf node. The loop process continues until no such aggregation can be done. It then returns the least number of leaf nodes whose total collateral damage is less than L and total DDoS coverage is at least D, and maps these leaf nodes to the rules to use.

F. Rule Placement

Once rules are generated, the defense can inspect all the rules and deploy them. For every rule, it can look at the F-tree node that corresponds to the rule, say N, and choose one of the filtering nodes in $N.F$ to place the rule. It then can contact the node for rule placement; if the node is unavailable, the defense can choose another node in $N.F$ for rule placement. If no node in $N.F$ can place the rule, this rule cannot be placed. The defense can first try to deploy rules that only have a single possible deployment location ($|N.F| = 1$), and then those with two locations, and so on.

IV. Implementation

A. Adaptive DDoS Filtering Software Suite

We have developed an adaptive DDoS filtering software suite composed of a set of independent applications, including the filtering-rule application and the filtering-node application. The filtering-rule application takes classified/labeled traffic as input and includes modules on rule generation and rule placement. The filtering-node application can interact with a wide range of filtering capabilities, including BGP FlowSpec, Cisco ACL, and all major SDN controller software (e.g., OpenDaylight[26], ONOS[27], and Ryu[28]). Due to space limitations we skip the complexity analysis of our implementation here.

B. Adaptive Filtering Protocol

We developed a protocol to define the messages between a filtering-rule application and any filtering node. The most important message type is **rule submission**. It includes a version number, a message type, the rule ID, and the rule itself that is defined by the four fields (source, protocol, TCP flags, and destination). Further, it includes a starting time field regarding when the rule should start taking effect and an ending time field indicating when the rule should expire. Also, we define a type of message called **rule submission acknowledgment**, which is sent in response to a rule submission message. It also contains a version number, a message type, a rule ID that is the ID of the rule being acknowledged. Moreover, it includes an error code that indicates either the rule is installed successfully (with error code being zero), or what error has occurred, such as verification error, timing error, out of rule space, or internal error.

C. Security and Privacy Considerations

To ensure our system is not misused or abused, we tackle the following security and privacy issues:

Privacy: The most essential information sharing in the system is that when a DDoS defense runs the rule generation process, it may learn newly detected DDoS flows and their paths from the DDoS detection, classification and tracking components. It may also learn who the filtering nodes are on each path. However, as these paths are the same paths meant to be announced and propagated for packet routing on the Internet, there is thus no privacy concern here.

Authentication: Every party in the system (filtering nodes, DDoS defense, or DDoS victim) must have a signed, verifiable certificate so that other parties can verify its identity, IP address(es), public key, and other metadata. If it does not have a certificate signed by a public-key infrastructure (PKI) that our system recognizes, it can obtain a certificate from an internal PKI of our system through a registration process.

Traffic Ownership: When a DDoS defense requests a filtering node to deploy a rule, the rule must only filter traffic to the victim that the defense protects. To ensure this, our system mandates that the defense have a **traffic control authorization (TCA)** ticket issued and signed by the victim to prove that the defense is allowed to issue rules against traffic to the victim. The defense must also sign the rule. This design also allows our system to protect any link of an ISP from the Crossfire DDoS [29]: the ISP can contact each downstream network beforehand for a TCA ticket to become its defense and then generate and deploy rules to filter the Crossfire traffic toward each downstream network.

Message Protection: Communication within our system must achieve confidentiality, integrity, and authentication. To do so, each communication channel will leverage the certificate obtained from the PKI to open an HTTPS connection.

V. Evaluation

A. Overview

We built a simulation platform consisting of the actual implementation of our system and a simulation of the Internet data plane. We measured our system's ability at the Internet scale to defend a victim against real-world, large-scale DDoS attacks. We replayed three real-world DDoS attacks of different sizes and attack dynamics: RADB-DDoS [30] with the DNS protocol and ∼16,000 DDoS sources, Booter1-DDoS [31] with the DNS protocol and ∼4,500 DDoS sources, and CAIDA-DDoS [32] with the ICMP protocol and ∼7,000 DDoS sources. Note that we have yet to find DDoS solutions that are based on assumptions similar to ours (Section III-A) to be able to compare.

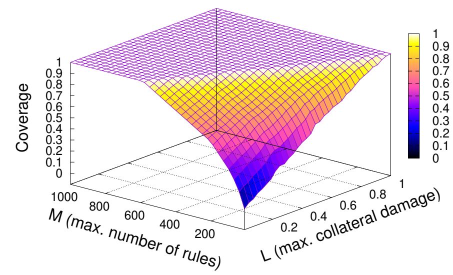
We first evaluated rule generation in Section V-B, focusing on the efficacy and tradeoffs of different rule generation objectives, and rule deployment in Section V-C, focusing on the percentage of rules for which suitable locations are found (i.e., success rate). In Section V-D, we assessed our system's efficacy in mitigating DDoS in real time. Lastly, in Section V-E we deployed and evaluated our system on the GENI testbed [33] and two real-world IXPs.

B. Rule Generation

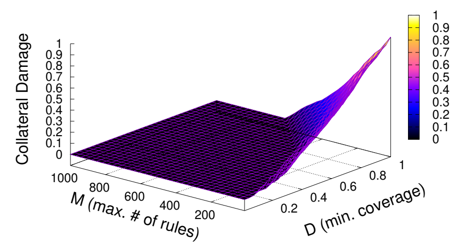
We evaluated the rule generation algorithm and measured the resulting DDoS coverage, collateral damage, and number of generated rules for each of the rule-generation problems, and compared the tradeoffs of differing rule generation strategies. We focused on rules based on source IP addresses of the traffic. While rule generation is a continuous process running in real time and handles a batch of DDoS and legitimate flows each time, we focused on one batch of traffic over a second composed of 1000 attack sources and 500 legitimate sources, all randomly generated. The size of the batch is not too big to cause a slow response with many DDoS flows, but not too small either to result in too many batches.

We found the algorithm achieves optimal results for all three rule-generation problems (1, 2 and 3). We first examined our algorithm for rule-generation problem 1 described Section III. Here, the goal is to maximize the DDoS coverage, while satisfying constraints on the maximum number of rules M and the maximum amount of acceptable collateral damage L. We vary the values for L and M and examine the DDoS coverage. As shown in Figure 2(a), 100% DDoS coverage is achieved easily, except when L and M are both low. In these cases, however, the DDoS coverage is still maximized subject to the stringent constraints on L and M.

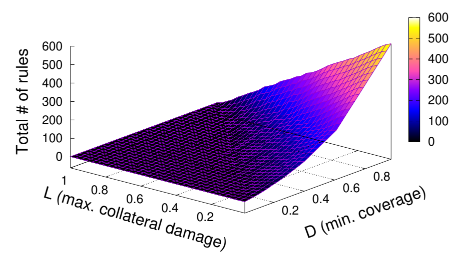
We then examined our algorithm for rule-generation problem 2 described in Section III. The goal of this algorithm is



(a) Maximizing DDoS Coverage vs. L and M



(b) Minimizing Collateral damage vs. D and M



(c) Minimizing Number of Rules vs. D and L

Figure 2. **Rule generation with constraints** (D: minimum DDoS coverage; L: maximal collateral damage; M: rule budget).

to minimize the collateral damage, subject to constraints on the minimum DDoS coverage and maximum number of rules. Figure 2(b) shows that the collateral damage vary as expected according to the values of the minimal DDoS coverage D and the maximum number of rules M. In particular, collateral damage is indeed minimized, and is zero in most cases. When D is high and M is low, some collateral damage is incurred, since the only way to cover a large percentage of unwanted flows with a relatively small number of rules is to allow some collateral damage to occur.

Finally, we examined our algorithm for rule-generation problem 3 described in Section III. The goal of this algorithm is to minimize the number of rules, while satisfying the constraints on the minimum DDoS coverage and maximum acceptable collateral damage. Figure 2(c) shows the results. We can see that in most cases only one or a small number of rules are generated, except when the minimum DDoS coverage (D)

is high and the maximum collateral damage (L) is low.

C. Rule Deployment

Continuing with rules generated in Section V-B, we evaluated the distributed deployment of DDoS-filtering rules against a number of distinct, Internet-scale distributed filtering profiles. Each profile represents different rates of ASes on the Internet that participate distributed filtering of DDoS traffic, as shown in Table I. The total number of ASes in tiers 1, 2, and 3 is 89, 8442, and 47052, respectively. Full-participation profile is clearly unrealistic, but we use this profile as a baseline. The "victim only" profile serves as another baseline, in which the victim's ISP is the only AS that filters DDoS traffic and all rules must be deployed there.

Table I
Distributed filtering profiles for rule deployment experiments. (These numbers are the same as the real Internet.)

Name	Tier 1	Tier 2	Tier 3	Total #
Full-participation	100%	100%	100%	55583
Tier-1-only	100%	0%	0%	89
Top-centered	100%	50%	0%	4310
Middle-centered	0%	80%	20%	16163
Bottom-centered	0%	20%	80%	39330
Victim-only	0%	0%	0%	1

We evaluated the rule deployment success rate, i.e., the percentage of rules for which suitable locations are found. With rules from Section V-B as input, Figure 3 depicts the success rate under each profile. The first and most obvious trend displayed is that the success rate for all profiles either remains stable or generally increases as we increase the per-AS rule limit from 1 to 1000. Another trend is the impact of a higher overall rate of ASes participating the distributed DDoS filtering. Overall, the rule deployment success rate increases with a higher rate of participating ASes, though increasing the participation rate for some AS tiers has different effects than for others. As expected, the lowest success rate belongs to the victim-only profile, while the highest rate is achieved by the full-participation profile. The four profiles in between generally perform much better than the victim-only profile, and slightly or moderately worse than the full-deployment profile, where the top-centered profile is the only profile of these four to reach nearly 100% success rate, and generally performs better than the others. The middle-centered profile is not far behind, however, and actually reaches higher success rates than the top-centered profile when the number of rules per AS is low. The tier-1-only profile is the most sensitive to the per-AS rule limit, as with only 89 tier-1 ASes each AS faces pressure to deploy more rules than other profiles; it thus has a lower success rate than other profiles (except for victim-only) when the per-AS rule limit is low, but gradually improves as the limit gets higher.

D. DDoS Mitigation

We also evaluated the overall efficacy of adaptive distributed filtering as we defend in real time against real-

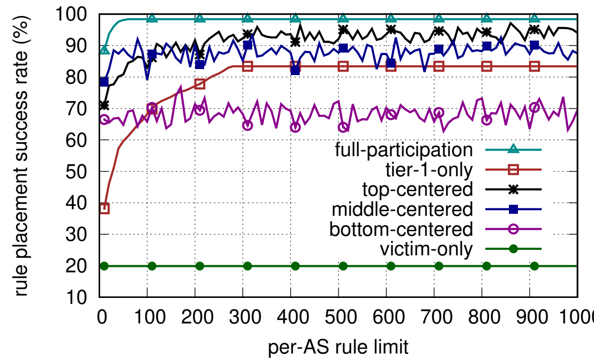


Figure 3. **Rule deployment success rates.**

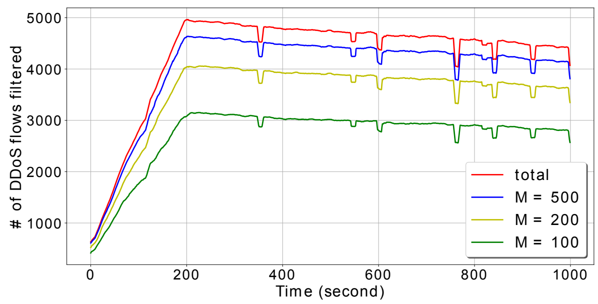
world DDoS attack traces with continuous rule generation and placement. Figure 4 shows two representative time series for our defense against two DDoS attacks with dissimilar dynamics (CAIDA-DDoS and RADB-DDoS). For each attack, we show the number of DDoS flows filtered at each second during the attack as well as the number of flows that arrive at the victim when no filtering is performed; although not shown, no legitimate flows are ever filtered.

More specifically, Figure 4(a) applies rules that are generated based on source addresses of the traffic toward maximal DDoS coverage under *zero* collateral damage requirement *and* three different rule budgets (100, 200, and 500, which represent roughly 1.5%, 3%, and 7%, respectively, of the total approximately 7,000 DDoS sources). Here, even with a tight budget of 100 source-based rules, which is only 1.5% of DDoS sources, 60-70% of DDoS flows will be filtered, and a higher value for the rule budget leads to more effective filtering.

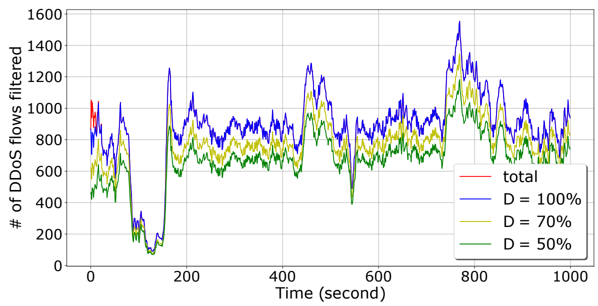
Figure 4(b) instead applies rules that are generated toward minimum number of rules under *zero* collateral damage requirement *and* three different requirements on minimum DDoS coverage (100%, 70%, and 50%). The generation and placement of rules tracks very closely the spikes in the attack traffic, demonstrating the overall accuracy of our rule generation algorithm. In particular, with rules required to cover 100% DDoS, although initially not all DDoS flows are filtered, it takes only about 13 seconds to begin filtering *all* DDoS flows at every second afterwards.

E. Pilot Studies

We have deployed and tested a distributed DDoS filtering pilot system on the GENI (Global Environment for Network Innovations) testbed [33]. Based on a recent Internet topology that consists of all Internet ASes, we chose a subgraph of 1 tier-1 AS, 18 tier-2 ASes, and 31-tier3 ASes where each of the total 50 ASes participates the filtering of DDoS traffic. We also attached a local machine to one of the 50 ASes as a DDoS victim running a DDoS defense. Each of these 50 ASes is supported with two virtual machines provided by GENI. The first virtual machine for each AS runs a Ryu controller as an SDN controller and an Open vSwitch[34] as an SDN switch

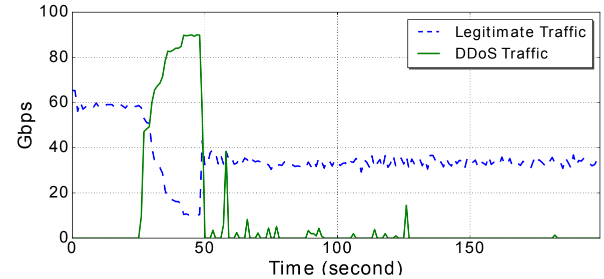


(a) CAIDA-DDoS attack under rules for maximal coverage with varying rule budgets.

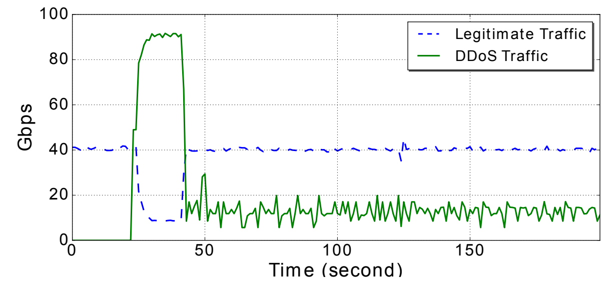


(b) RADB-DDoS attack under rules for minimal number of rules with varying coverage.

Figure 4. **Time series of filtering of DDoS flows.** The "total" curve shows DDoS flows without filtering.



(a) Traffic time series under rules for maximal DDoS coverage



(b) Traffic time series under rules for minimal collateral damage

Figure 5. **Volume of legitimate and DDoS traffic over time before and during distributed filtering of DDoS traffic during a pilot study.**

that can deploy OpenFlow rules to filter traffic. The Open vSwitch is populated with a forwarding table by running the OSPF routing protocol [35]. The second virtual machine for each AS acts as an end-host in the AS that can generate benign traffic toward a destination from different IP addresses of the AS. More, in order to emulate large-scale DDoS attacks on the topology, we installed a DDoS agent on each AS's second virtual machine. It can receive commands about a variety of DDoS attacks from a bot master that we deployed on GENI and generate DDoS traffic toward a victim at a scheduled time from different IP addresses of the AS.

Our system runs smoothly on this platform with good performance and low network overhead. It also runs fast with rule generation at 105 milliseconds on average and the network overhead is no more than 10 kilobytes each round for rule deployment.

Below we exemplify our system's effective filtering of DDoS traffic by launching an emulated 100-Gbps DDoS attack toward the victim from ∼1000 source addresses, together with 40- to 60-Gbps legitimate traffic to the victim from ∼200 sources. The DDoS defense will then generate rules based on the newly incoming DDoS traffic and have these rules eventually converted to OpenFlow rules and deployed at selected Open vSwitches to filter the DDoS traffic.

Figure 5 shows our defense in two different scenarios. In the first scenario (Figure 5(a)) where the defense begins at second 48, it takes *only about 3 seconds* for the filtering of DDoS traffic to reach 100%. Since we are using source-based filtering, and the number of attack sources (1000) is relatively high compared to the rule budget (150), some collateral damage has to happen, preventing the volume of legitimate traffic since second 48 from fully recovering; nonetheless, relative to the sharp dip of DDoS traffic, the legitimate traffic does recover to be between 30 and 40 Gbps. In the second scenario (Figure 5(b)), we increase the rule budget to 200 and minimize the collateral damage. Although we no longer filter as much of the DDoS traffic as the first scenario, we filter enough to relieve the link congestion, while all the legitimate traffic can continue to flow at its previous rate.

Finally, we conducted a pilot study with major IXPs to test the scalability of our system in the wild against real, large-scale DDoS attacks. The results are promising. For example, over a month at one IXP, our system was able to generate rules towards minimal collateral damage that covered 90% of the attack traffic from all 46,552 attack IPs in less than 7 seconds.

VI. Conclusion

DDoS attacks are notorious for the damage they can cause to network users and services. In this paper we focused on making DDoS filtering adaptive. We depart from the state of the art in which filtering DDoS is usually based on a fixed granularity and enabled the filtering of DDoS to adapt to the most effective granularity. Further, we designed rule-generation algorithms that correspond to different top priorities in DDoS filtering, including maximizing the DDoS coverage, minimizing the collateral damage, and minimizing the number of rules. A DDoS defense can run a rule-generation algorithm to derive an F-tree which, by tracking the traffic toward the victim and strategically aggregating flows from different sources, can help derive traffic-filtering rules that are adaptive to different objectives and deploy the rules at the most effective filtering nodes.

We thoroughly evaluated our system through large-scale simulations based on real-world DDoS attack traces, including (i) the quality, quantity, and the tradeoff of rules generated with different objectives; (ii) rule deployment success rates with different Internet-scale filtering profiles; and (iii) the system's overall efficacy. We also conducted pilot studies on a large-scale testbed as well as major IXPs, showing our system can filter the DDoS traffic from large-scale DDoS attacks with as little as zero collateral damage within several seconds. Future work may include revisiting the assumptions of this work, performing more theoretical analysis of the algorithms, and comparing performance with other approaches to DDoS.

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References

[1] A. Research, "2020 state of the Internet / security: 2020 – a year in review," https://www.akamai.com/us/en/multimedia/documents/state-of-the-internet/soti-security-a-year-in-review-report-2020.pdf, 2020.

[2] K. York, "Dyn's statement on the 10/21/2016 DNS DDoS attack," *Dyn Blog*, 2016. [Online]. Available: https://dyn.com/blog/dyn-statement-on-10212016-ddos-attack/

[3] S. Kottler, "February 28th DDoS incident report," *GitHub Engineering*, 2018. [Online]. Available: https://githubengineering.com/ddos-incident-report/

[4] S. Vaughan-Nichols, "Microsoft azure fends off huge DDoS attack," https://www.zdnet.com/article/microsoft-azure-fends-off-huge-ddos-attack/, 2021.

[5] A. Toh, "Azure ddos protection: 2021 q3 and q4 DDoS attack trends," https://azure.microsoft.com/en-us/blog/azure-ddos-protection-2021-q3-and-q4-ddos-attack-trends/, 2022.

[6] T. Emmons, "Largest ever recorded packet per second-based DDoS attack mitigated by Akamai," https://www.akamai.com/blog/news/largest-ever-recorded-packet-per-secondbased-ddos-attack-mitigated-by-akamai, 2020.

[7] K. Argyraki and D. R. Cheriton, "Active Internet Traffic Filtering: Real-time Response to Denial-of-service Attacks," in *USENIX Annual Technical Conference*, 2005.

[8] S. Savage, D. Wetherall, A. Karlin, and T. Anderson, "Practical Network Support for IP Traceback," in *ACM SIGCOMM*, 2000.

[9] A. C. Snoeren, C. Partridge, L. A. Sanchez, C. E. Jones, F. Tchakountio, S. T. Kent, and W. T. Strayer, "Hash-Based IP Traceback," in *ACM SIGCOMM*, 2001.

[10] J. Li, J. Mirkovic, M. Wang, P. L. Reiher, and L. Zhang, "SAVE: Source address validity enforcement protocol," in *INFOCOM*, June 2002, pp. 1557–1566.

[11] K. Singh, P. Singh, and K. Kumar, "A Systematic Review of IP Traceback Schemes for Denial of Service Attacks," *Computers & Security*, vol. 56, 2016.

[12] P. Odintsov, "FastNetMon community - very fast DDoS analyzer with sFlow, NetFlow, mirror support," https://github.com/pavel-odintsov/fastnetmon, 2019.

[13] J. Mirkovic, G. Prier, and P. Reiher, "Attacking DDoS at the source," in *Network Protocols, 2002. Proceedings. 10th IEEE International Conference on.* IEEE, November 2002, pp. 312–321.

[14] Y. Jia, F. Zhong, A. Alrawais, B. Gong, and X. Cheng, "Flowguard: An intelligent edge defense mechanism against iot ddos attacks," *IEEE Internet of Things Journal*, vol. 7, no. 10, pp. 9552–9562, 2020.

[15] Y. Feng, J. Li, and T. Nguyen, "Application-layer DDoS defense with reinforcement learning," in *IEEE/ACM International Symposium on Quality of Service (IWQoS)*, Virtual conference, June 2020.

[16] Q. He, C. Wang, G. Cui, B. Li, R. Zhou, Q. Zhou, Y. Xiang, H. Jin, and Y. Yang, "A game-theoretical approach for mitigating edge ddos attack," *IEEE Transactions on Dependable and Secure Computing*, vol. 19, no. 4, pp. 2333–2348, 2022.

[17] G. Oikonomou, J. Mirkovic, P. Reiher, and M. Robinson, "A framework for a collaborative DDoS defense," in *Computer Security Applications Conference (ACSAC)*, 2006, pp. 33–42.

[18] X. Liu, X. Yang, and Y. Lu, "To filter or to authorize: Network-layer DoS defense against multimillion-node botnets," *ACM SIGCOMM Computer Communication Review*, 2008.

[19] Y. Li, H. Li, Z. Lv, X. Yao, Q. Li, and J. Wu, "Deterrence of intelligent ddos via multi-hop traffic divergence," in *CCS*, 2021, p. 923–939.

[20] M. Zhang, G. Li, S. Wang, C. Liu, A. Chen, H. Hu, G. Gu, Q. Li, M. Xu, and J. Wu, "Poseidon: Mitigating volumetric DDoS attacks with programmable switches," in *The 27th Network and Distributed System Security Symposium (NDSS)*, 2020.

[21] Z. Liu, H. Namkung, G. Nikolaidis, J. Lee, C. Kim, X. Jin, V. Braverman, M. Yu, and V. Sekar, "Jaqen: A high-performance switch-native approach for detecting and mitigating volumetric DDoS attacks with programmable switches," in *USENIX Security Symposium*, 2021.

[22] A. Yaar, A. Perrig, and D. Song, "FIT: fast Internet traceback," in *Proceedings IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies*, vol. 2, 2005, pp. 1395–1406.

[23] K. J. Argyraki and D. R. Cheriton, "Active Internet Traffic Filtering: Real-Time Response to Denial-of-Service Attacks," in *USENIX annual technical conference, general track*, 2005, pp. 135–148.

[24] J. Li, M. Sung, J. Xu, and L. Li, "Large-scale IP traceback in high-speed Internet: Practical techniques and theoretical foundation," in *IEEE Symposium on Security and Privacy*, 2004, pp. 115–129.

[25] L. Shi, J. Li, M. Zhang, and P. Reiher, "On capturing DDoS traffic footprints on the Internet," *IEEE Transactions on Dependable and Secure Computing*, vol. 19, no. 4, pp. 2755–2770, 2022.

[26] OpenDayLight. (2018) Opendaylight platform overview. https://www.opendaylight.org/what-we-do/odl-platform-overview.

[27] P. Berde, M. Gerola, J. Hart, Y. Higuchi, M. Kobayashi, T. Koide, B. Lantz, B. O'Connor, P. Radoslavov, W. Snow *et al.*, "ONOS: Towards an open, distributed SDN OS," in *Proceedings of the third workshop on Hot topics in software defined networking*, 2014.

[28] Ryu. (2017) Ryu SDN framework. https://osrg.github.io/ryu/.

[29] M. S. Kang, S. B. Lee, and V. D. Gligor, "The crossfire attack," in *IEEE Symposium on Security and Privacy*, 2013, pp. 127–141.

[30] M. Network, "Merit RADb," http://www.radb.net, 2016.

[31] J. Santanna, R. van Rijswijk-Deij, R. Hofstede, A. Sperotto, M. Wierbosch, L. Zambenedetti Granville, and A. Pras, "Booters - an analysis of DDoS-as-a-service attacks," in *IFIP/IEEE International Symposium on Integrated Network Management (IM)*, 2015.

[32] C. for Applied Internet Data Analysis. (2007) The CAIDA UCSD DDoS attack 2007 dataset. http://www.caida.org/data/passive/ddos-20070804_dataset.xml.

[33] M. Berman, J. S. Chase, L. Landweber, A. Nakao, M. Ott, D. Raychaudhuri, R. Ricci, and I. Seskar, "GENI: A federated testbed for innovative network experiments," *Computer Networks*, vol. 61, pp. 5–23, 2014.

[34] B. Pfaff, J. Pettit, T. Koponen, E. Jackson, A. Zhou, J. Rajahalme, J. Gross, A. Wang, J. Stringer, P. Shelar, K. Amidon, and M. Casado, "The design and implementation of Open vSwitch," in *12th USENIX Symposium on Networked Systems Design and Implementation (NSDI)*, 2015.

[35] J. Moy. (2017) OSPF Version 2. https://tools.ietf.org/html/rfc2328.