Early detection of Crossfire attacks using deep learning

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ABSTRACT
Crossfire attack is a recently proposed threat designed to disconnect whole geographical areas, such as cities or states, from the Internet. Orchestrated in multiple phases, the attack uses a massively distributed botnet to generate low-rate benign traffic aiming to congest selected network links, so-called target links. The adoption of benign traffic, while simultaneously targeting multiple network links, makes the detection of the Crossfire attack a serious challenge.

In this paper, we propose a framework for early detection of Crossfire attack, i.e., detection in the warm-up period of the attack. We propose to monitor traffic at the potential decoy servers and discuss the advantages comparing with other monitoring approaches. Since the low-rate attack traffic is very difficult to distinguish from the background traffic, we investigate several deep learning methods to mine the spatiotemporal features for attack detection. We investigate Autoencoder, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) Network to detect the Crossfire attack during its warm-up period. We report encouraging experiment results.

1 INTRODUCTION
A novel class of an extreme link-flooding DDoS (Distributed Denial of Service) attack [11] is the Crossfire attack [7]. It is designed to cut off a targeted geographic region from the Internet by simultaneously targeting a selected set of network links [3], [2]. The most intriguing property of this attack is the usage of legitimate traffic flows to achieve its devastating impact by making the attack particularly difficult to detect and, consequently, to mitigate [7].

In this paper, we propose a new detection approach that uses the traffic volume (or intensity) on specific network regions for any subtle changes on some of the links. Depending on the resolution of the monitoring scheme, we show that this leads to an early detection of the attack. In particular, we argue that monitoring the traffic of the public servers near a target area could facilitate early detection. We describe several deep learning based methods to extract useful features from the traffic volume: Autoencoder, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network. We show the feasibility of early detection in our simulation.

1.1 Crossfire attack
The Crossfire attack uses a massively large-scale botnet for attack execution [7]. The success of the attack depends highly on the network structure and how the attacker plans and initiates the attack sequence [12]. The attacker aims to find a set of target links, which connects to the decoy servers such that if the target links are flooded, traffic destined to the target area is prevented from reaching its destination. Reciprocally, access from the target area to Internet services outside the target area will be cut off.

For the adversary to achieve its goal, it chooses public servers either inside of the target area or nearby the target area, which can be easily found due to their availability. The quality of the attack depends on the specific selection of servers and the resulting links to be targeted.

The Crossfire attack consists of three phases: (a) the construction of the link map, (b) the selection of target links, and (c) the coordination of the botnet. While phases (a) and (b) are sequentially executed only initially, once triggered phase (c) is executed periodically. Figure 1 illustrates the dynamics of the Crossfire attack.

Link map construction: The attacker creates a map of the network along the ways from the attacker’s bots to the servers using traceroute [7].

Target links selection: After the construction of the link map, the adversary evaluates the data for more stable and reliable routes to decide on its selection of the target links.

Bot coordination: In the final phase of the attack, the adversary coordinates the bots to generate low-intensity traffic and to send it to the corresponding decoy servers. The targeted aggregation of multiple low-intensity traffic flows on the target link ideally exhausts its capacity, hence, congesting the link.

Because the Crossfire attack aims to congest the target links with low-rate benign traffic, neither signature based Intrusion Detection
Therefore, we propose to perform detection at the decoy servers,
(a) gradually increasing bot traffic intensities, (b) estimating the
decoy servers’ bandwidth to avoid exceeding their bandwidth, (c)
evenly distributing the traffic over the decoy servers, (d) alternating
the set of bots flooding a target link, and (e) alternating the set
of target links [7]. Although these techniques further sophisticate
the attack, the inherent complexities of the attack also create sub-
stantial execution obstacles, which exposes the attack to detection
vulnerabilities.

2 MONITORING AND DETECTION
APPROACH
Considering the described Crossfire attack execution sequence, we
argue that there are potentially four ways to detect the attack [10]:
(a) detection at the traffic flows origin, i.e., bot sides, (b) detection
at the target area, (c) detection at the target link, and (d) detection
at the decoy servers. Following, we address the advantages and
disadvantages each of the four ways to finally justify our choice for
traffic monitoring.

• Detection at the origin can be the fastest way to stop an attack
before even it is initiated. However, versatility and spatial
distribution of bots (source of the attack traffic) makes it the
most challenging option.
• Detection at the target area is the most reasonable approach
as any target areas should be equipped for self- defense. However, assuming not all decoy servers are inside the target
area, early detection is impossible [11].
• Detection at the target link might be the simplest form of
detection as simple a threshold based detection system that
could detect the trend of the incoming traffic. However, the
locations of the target links may be unknown to the defender.
• Detection at decoy servers can be the best approach to detect
Crossfire attack. Assuming the target area is not far from the
decoys servers (3 to 4 hops [7]) detecting at the decoy servers
might reduce the impact of the attack.

Therefore, we propose to perform detection at the decoy servers,
because it is the exclusive area that the defender can detect the
attack while actively responding to it. To emphasize the effective-
ness of our detection approach at the decoy servers, we address
the question of where is the best location to probe the network. In a
high resolution, this probing can be placed either at the target link,
before or after the target link. Monitoring a single link as a target
link is not considered as a solution because of two reasons:
• Any links can be targeted for an attack. Therefore, there
should be a one-to-one detector for every link in the network.
However, in our proposal, there is only one detector but
many probing points.
• Monitoring and detecting based on a single link will fail in
distinguishing between link attack and flash-crowd.

Our main goal is to detect the Crossfire attack without the need
of having the target link information. Depending on the budget of
the adversary, the number of bots purchased for an attack can be
in the range of thousands to even millions. If the sources of the
attack traffic, i.e., bots, are geographically spread out, the variation
of the traffic volume on most of the links is very small (for many
routes, there might be only one or few attack flow before they
are aggregated at the target link). That leaves only few link closer
to a target link worth to examine. However, the chosen decoy
servers should not be very far away from the target area (if they
are not inside the target area). Since there is a smaller number of
destinations for the attack traffic than the number of sources of
generating them, it can be assumed that the variation of the volume
of the traffic caused by the attack traffic on the links after the target
link is higher than the links before the target link (even at the edge
of the network). Therefore, we propose to monitor links around
servers or data centers that can result in more successful detection
than around clients.

The approach of evenly distributing the traffic for decoy servers
[7], might even support the above reasoning and rather make it
simpler to detect some variation in the traffic volume across several
links. The important element in this method is to be able to monitor
the traffic at several links and send the information to a detector
decision making.

3 ATTACK CHARACTERISTICS AND
EXPERIMENT SET-UP
Since our focus is on the detection of the attack, we ignore the first
few steps of the Crossfire attack such as link map construction,
finding link persistence, or target link selection. We assume that
all attack preparations have been made and the attacker is ready to
attack.

When the preparations have been made, to bring down the target
link, the bot-master initiates the attack by sending the attack order
to the Command and Control (C&C) server or some selected peers
depending on the structure of the botnet. Bots usually update each
other in a polling or pushing mechanism.

When designing Crossfire detection mechanisms, an often ig-
nored part of the Crossfire attack is the phase from the attack
initiation and the successful impact of the attack [7]. This often
gnored part of the Crossfire attack, which we call it warm-up pe-
riod, is the time difference between the time of the first bot- flow of
the attack reaches the target link and the moment the target link is
down. By definition, the attack actually happens at the end of the
warm-up period when the target links are down. Since, reaching a
zero time warm-up period is hard, this period can be used for early
detection and before the attack successfully takes place.

In fact, for several reasons reaching a zero warm-up time is hard.
One reason is the dynamic delay of packet arrival at the target link.
That could be because of variations of hop distances from bots to
target link, or the delay in receiving attack order from the adversary.
Any sudden significant change on traffic volume can be detected
by firewalls and IDSs. Therefore, adversaries gradually increase the
attack traffic volume to prevent being detected.

Another important factor for generating the bot traffic is the
duration of the attack. The attack duration is the time difference
between the end of the warm-up period and the end of the attack.
Usually, bot-masters (adversaries) tend to reduce the duration of the
attack to prevent being detected. In the case of the Crossfire attack,
a rolling mechanism is introduced to keep the attack at the data
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Figure 2: The simulated low-rate network utilization data for 2 decoy server locations when all servers are under attack. The link utilization is normalized to a range of 0-1 with 0 and 1 corresponding to the minimum and maximum of all measurements respectively. Note that the low rate traffic in the warm up period is very difficult to distinguish from the background traffic.

plane (evade activating control plane which redirects the traffic) [7]. In the rolling scheme, a set of target links are only used for a specific period of time before switching to another set of target links. The duration they used in the rolling scheme is 3 minutes or less where 3 minutes is the keep-alive messages time interval for the BGP algorithm.

To generate data for the training Crossfire detectors, we simulate link utilizations of a network with 80 decoy servers under attack in two different conditions. In the first case all the 80 decoy servers are under attack and in the other case 70 decoy servers which are randomly selected each time are under attack. We also study the case when not all decoy servers are under attack as we cannot know in advance exactly which all servers would the attacker target. We sample the average link utilization every 1 minute. When not under an attack, the servers have a background traffic which is simulated by a random Gaussian process assuming the server is communicating with many clients. The background traffic for each server has a different mean between 100Kbps-150Kbps and a standard deviation between 0.45Kbps-2.45Kbps.

To simulate an Crossfire attack, an extra attack traffic is added to the background traffic. The attack starts with a warm-up period where the attack traffic slowly increases in intensity. The warm-up duration is 30 minutes (samples). The warm-up period corresponds to a randomized ramp function. When the attack manages to flood the target link, the attack traffic reaches its peak and stays there till the attack is over. The intensity of the low rate network traffic from the bot for the attack ranges from 0.43Kbps-2.2Kbps. The dataset for both the conditions has 6000 separate attack instances. The data is labeled true only for the warmup period as we attempt to do early detection before the attack has flooded the target links. Figure 2 illustrates the link utilization for 2 decoy servers during 3 separate attack instances when all the decoy servers are under attack. Note that it is difficult to distinguish the attack traffic from the background traffic.

4 CROSSFIRE DETECTION WITH DEEP LEARNING

Crossfire attack poses numerous challenges for security researchers and analysts both in detection and mitigation as the packets streaming from bots in the network are seemingly legitimate. While the objective of the Crossfire attack is to deplete the bandwidth of specific network links, a distinct traffic flow between each bot to server, i.e., "bot-to-server" is usually very less intensive flow, and consumes a limited bandwidth at each link. Thus detecting a single flow (or very few number of them) at a link is hard to detect and filter. On the defender’s side, Traffic Engineering (TE) is the network process that reacts to link-flooding events, regardless of their cause [9]. The goal of an attacker is to hide the variation of traffic bandwidth as much as possible from the TE module.

Following this direction, we leverage deep learning approaches to detect the Crossfire attack from available traffic data. Recently, deep learning has achieved breakthrough results in many natural language processing and computer vision problems [1, 4, 8]. Here we investigate its usefulness and performance for traffic data analysis to detect Crossfire attack in the early stage.

4.1 Deep Autoencoders

We investigate using deep-autoencoder [5] to extract intrinsic low-dimensional information from the traffic. This is followed by Random Forest for anomaly detection.

Here we propose a deep-autoencoder structure to exploit spatiotemporal information. We uses a window of 5 consecutive time steps by concatenating data from 5 consecutive samples. Each sample contains 80 measurements that correspond to the traffic volumes of the 80 decoy servers in the simulated network. Thus the input dimension of the data for the autoencoder is 400. The autoencoder contains 2 hidden layers and its structure is as such: (400)-390-370-390-400. Figure 3 shows the area under the Receiver Operating Characteristic (ROC) curve of this approach.

4.2 Convolutional Neural Network

A Convolutional Neural Network (CNN) can be utilized for detecting by considering the data as a 2 dimensional grid spanning across time and decoy server dimensions. The dataset is divided into separate windows with 80 servers we are monitoring as columns and across 15 time steps as rows. We label the entire window as an attack window if the warmup period of the attack occurs in at least 5 out of 15 time steps. The CNN is arranged in two separate convo-
4.3 Long Short-Term Memory Network
An LSTM[6] is used as a sequence classifier for detecting whether each time sample is a warm-up period of Crossfire attack or not. We use a stacked LSTM configuration having 2 consecutive LSTM cells as shown in Figure 5. Each of the LSTM cells have 64 hidden units. Each output sample from stacked LSTM is classified into an attack or non-attack by a fully connected layer. The input to the LSTM network are windows of 64 time samples of 80 dimensional vectors for decoy traffic. Adam optimizer is used to train the network with learning rate as 0.001 till the Early stopping condition.

![Figure 4: The CNN architecture used to detect crossfire attacks. The output layer is a binary predictor predicting the two categories of attack and non-attack](image)

LUTional operations. The first step learns a convolutional filter that spans only across the time axis(rows) and has dimension of 1 across the server axis(columns). This filter is expected to learn the pattern for the attack only in the time axis independent of the servers. We call this as a temporal filter. The second convolutional filter spans across all the 80 servers and a few rows. We call this as the spatial filter as it extends through space for all the servers. This filter is expected to discover the correlation between different servers as they are under attack at the same time. The intuitive reasoning behind such a network configuration was validated by a hyperparameter search across various configurations. The activation function used is ReLu and to improve network performance each convolutional step is batch normalized. A final fully connected layer with softmax activation does a binary classification of the window as attack or non-attack. The network architecture is demonstrated in figure 4.

The shape of the temporal filter is 9x1x16 (height x width x depth). The spatial filter dimension is 6x80x20 (height x width x depth). The filter strides for each case is 1. An Adam optimizer with learning rate of 0.3x10^{-5} is used to train till the early stopping condition. The dataset is divided into Training, Validation and Test set in the ratio of 70:20:10.

The results on the test dataset for two different attack conditions is shown in Table 1.

![Figure 5: The LSTM architecture for detecting Crossfire attacks](image)

To improve on the per sample prediction of learned LSTM and also to exploit the fact that warm-up samples are consecutive, we keep the history of the per sample prediction of LSTM Network in a circular buffer of length 7. The scalar value in the buffer cell is 1 if there is an attack and 0 otherwise. Only if all the samples in the buffer are attacks, do we finally predict an attack. This increases latency in predicting an attack but dramatically increases attack detection accuracy. With a buffer of length 7, we find that we can predict almost perfectly for the warm-up period with a maximum latency of 13 samples. The precision of the detector is 1.0 and recall is 0.998, shown in Table 2. We can also trade-off between the latency of detection and the performance of detection by changing buffer size.

![Table 1: Performance of CNN.](image)

| Servers under attack | Precision | Recall | F1 Score |
|----------------------|-----------|--------|----------|
| 80/80                | 0.74      | 0.97   | 0.84     |
| 70/80                | 0.759     | 0.788  | 0.773    |

5 CONCLUSIONS
The Crossfire attack is considered to be one of the most difficult target-area link-flooding attacks to be detected. The attack uses a distributed botnet to generate multiple low-rate benign traffic flows aiming to congest selected network link with the ultimate goal to disconnect the target area from the Internet. In this paper, we have demonstrated the effectiveness of monitoring link utilizations at the decoy servers to detect Crossfire attacks. Out of the different deep learning methods we have investigated, we find that the LSTM detection approach achieves encouraging performance under different attack conditions. For future work, we investigate the performance under different network structures.

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