Fuzzing Based on Function Importance by Attributed Call Graph

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Abstract—Fuzzing has become one of the important methods for vulnerability detecting. The existing fuzzing tools represented by AFL use heuristic algorithms to guide the direction of fuzzing which exposes great randomness. What’s more, AFL filters seeds only by execution time and seed length. Meanwhile there is no in-depth consideration of the instruction information covered by the trace.

In this paper, we propose a fuzzing method based on function importance. First, we propose a data structure called Attributed Call Graph to characterize function feature and the relationship. On this basis, we use an improved PageRank algorithm to further strengthen ACG’s characterization of the importance of function position. We score the seeds according to the feature vector of the ACG covered in the seed execution trace and optimize the seed filtering and according to the scoring results. In addition, fuzzing is a process of dynamic change. We will adjust the feature vector range according to the number of function hits. The change of a node attribute will affect the importance of its surrounding nodes. Here we use the improved Weisfeiler-Lehman The algorithm propagates the node attributes to reflect this influence relationship.

We implemented our fuzzer FunAFL based on the above method. Our tool found 18 bugs on the LAVA-M dataset exceeding the fuzzers such as AFL and AFLFast. The coverage rate in real-world programs is higher than that of AFL and AFLFast. At the same time, 10 bugs were found in real-world programs and 3 CVE numbers were assigned.

Index Terms—Function Importance, Attributed Call Graph, PageRank, Weisfeiler-Lehman Graph Kernels

I. INTRODUCTION

Fuzzing is widely used by academia and industry as the main means of vulnerabilities mining because of its easy expansion and high degree of automation. Mutation-based gray box fuzzing is currently a mainstream fuzzing method. Alternative tools for this kind of fuzzing include AFL [1], AFLFast [2], etc. These tools use lightweight instrumentation to obtain coverage and other information, combined with dynamic or static information to guide the fuzz direction. The workflow of the fuzzing includes several processes such as seed filtering and selection, seed mutation location selection, seed mutation method selection and energy schedule.

There is a lot of work on fuzzing optimization. For example, NeuFuzz [3], FuzzGuard [4], etc. use neural networks to filter out seeds that are meaningless and retain seeds that have greater coverage and vulnerability mining gains which improves the efficiency of fuzzing. The starting point of MOPT [5], Angora [6], and Augmented-AFL [7] is that different mutation methods and mutation locations have different sensitivity to path discovery. These works select mutation locations and mutation methods that are more sensitive to the results with higher probability during the fuzzing process. Work such as AFLFast [2], AFLGo [8] and Hawkeye [9] optimizes fuzzing from the perspective of energy scheduling. By increasing the energy of potential seeds and reducing the energy of seeds with less potential, more time of fuzzing spent on seeds with greater potential.

The existing methods of fuzzing optimization have some limitations. The existing methods of fuzzing optimization still do not make full use of the information provided by the program code and fuzzing history. First of all, the current seed filtering and selecting strategy is based on the isolated characteristics of the nodes corresponding to the specific attributes on the execution path of the seeds. Some are based on the execution depth of the seeds [10], some are based on whether they are close to the unknown area [11], and some are based on coverage of the rare edges [12] [13] [17], and some are based on the closeness of specific instructions [3] [9] [14] [15] [16]. We believe that multiple attributes determine the value of each node on the execution path for the fuzzing coverage, and there is a correlation between the nodes which will affect the gain effect of the seed on the test coverage. For a node C, if the comprehensive attributes of C reflect higher importance, such as the number of comparison instructions and the number of memory operation instructions are more, then C has a higher probability of generating more gains in coverage. The probability of C being tested should be increased. Suppose
the node C has two parent nodes L and R. If both L and R are tested frequently after a period of testing, then C has a high probability of being tested frequently. No matter how deep C is, whether it is close to an unknown area or close to a specific vulnerability characteristics, the seed passing C does not need to increase its priority; The opposite is true. In addition, this correlation causes the influence of each node on the coverage gain to change continuously with the fuzzing process. The existing method can only update the attribute of a single node on the execution path at runtime, and lack of mechanism to propagate this change to reach different areas of the program. What’s more, if L and R change from being less tested to being tested by high frequency within a period of time, this means that C has also been frequently tested during this period. Then the priority of seeds that have passed C can be appropriately lowered, and assign computing resources to other areas that have not been fully tested. To eliminate these limitations, we have to answer two questions.

1) How to characterize the priority of seeds?
2) How to dynamically adjust the priority of seeds according to the fuzzing?

A. How to characterize the priority of seeds?

To solve this problem, the first thing to consider is the granularity of modeling. The traditional method is based on the Control Flow Graph (CFG). But for the two problems mentioned above, there are two shortcomings in characterizing seed priority based on CFG: First, the importance of the same basic block in different functions is also different. For example, the same program statement i++, this risk in the error handling function and memory allocation function is different, and it is difficult to reflect this point based on the attribute characterization of CFG. Second, if attribute propagation is based on CFG, the computational cost is too great. A common program usually has thousands basic blocks. The computational complexity of the graph propagation algorithm is usually $O(x)$, and it is too time-consuming to do attribute propagation on such a large graph. Therefore, we propose to describe the priority of seeds with the granularity of the function.

The previous research on binary similarity detection used a data structure called Attributed Control Flow Graph (ACFG for short) [18], which uses the statistical and structural features of each basic block to represent functions on the basis of CFG. Binary similarity detection is based on function as the basic unit, so ACFG proposed with basic block as the granularity is a suitable data structure. The fuzzing test is carried out in the unit of the entire program. In this application scenario, the granularity of ACFG is too small. Therefore, we propose the data structure Attributed Call Graph (ACG for short) according to the ACFG, which represents the program as a call graph and each function node of the graph uses features vector composed of function statistical features and structural features.

The second question to be considered is how to measure the priority of each seed based on the correlation of the function on the ACG. How to obtain the most important nodes from the interconnected network structure is a common problem in data mining. Therefore, we borrowed the PageRank [19] algorithm commonly used in data mining to solve the second problem. Why can we use the PageRank algorithm to solve this problem? The reasons are as follows: We observed the different positions of the function also determine the importance of the function in the fuzzing process. If a function has fewer parent nodes, then the node is not easy to reach, so the node is more important and worth exploring which we call quantity assumption. In addition, if the importance of the function pointing to a function is higher, then the function being pointed will get higher importance from the parent node, which we call quality assumption. This is very similar to the PageRank algorithm. PageRank is a method for Google to identify the rank and importance of web pages through the link analysis of graphs. We improve the PageRank algorithm based on the above quantitative and quality assumptions and use the improved PageRank algorithm to analyze the ACG. The function feature vector after analysis reflects the importance of function location and content for fuzzing. For a seed, we divide its corresponding trace into the unit of function, and score the function according to the feature vector obtained after each function is calculated by PageRank. For those seeds with high overall importance, priority is given a higher level, because such seeds have more potential to find vulnerabilities and new paths.

B. How to dynamically adjust the feature vector of ACG according to the fuzzing?

Static analysis is an important method for obtaining program internal information and structure for security research, and it also plays an important role in fuzzing. However, we have observed that the information from static analysis often shows stable and excellent ability in the early stage of the fuzzing, and poor performance in the later stage. The reason can be explained by the example below. If there are functions A and B in a program, we know that the importance of function A is much higher than the importance of function B through static analysis, that is, we have to increase the exploration of function A. It seems correct. But we are aware of a problem. After a certain period of fuzzing, function A may have been tested enough times, but function B has not been explored enough. Therefore, we need to dynamically adjust the static analysis information used in the fuzzing process.

The difficulty now lies in how to update and how to determine the update frequency. In order to avoid the shortcomings of the above examples, and combined with our representation of the program, we propose to use the number of function hits to adjust the function attributes. That is, the adjustment will expand the data range of the feature vector of the function that has not been tested enough, and reduce the data that has not been tested enough. After adjusting the data range, the story is not over yet. The importance of a node often affects the importance of surrounding nodes. We need to take the change of a node’s attributes into a global perspective. Therefore, when the function attribute range is adjusted, we should analyze the influence of node attribute changes on the surrounding nodes. Weisfeiler-Lehman [20] is a classic...
graph algorithm, which is often used in the fields of graph similarity and graph isomorphism. According to the relabel process of the Weisfeiler-Lehman algorithm, we perform attribute propagation on the ACG after the adjustment of the characteristic vector range to characterize the influence of the change of node attributes on surrounding nodes. Fuzzing is a long-term process, so we believe that the frequency of attribute updates and propagation every 25 minutes is appropriate.

Time is life, and time for fuzzing is also precious. Invalid seeds will greatly waste the time of fuzzing and reduce the efficiency of fuzzing. Seed filtering is the most direct way to improve the efficiency of fuzzing. So our work will optimize the fuzzing from the perspective of seed filtering based on the answer to above questions.

In summary, this paper makes the following contributions:

- We propose a seed priority assignment method based on the function correlation. On this basis, we propose a data structure called ACG to characterize functions importance, and use the PageRank algorithm to operate on ACG, so that ACG can accurately reflect position importance and content importance of the node. The so-called importance refers to the probability that the function will bring greater gains to path and vulnerability discovery in terms of location and content. The higher the importance, the more worth exploring the function.

- We propose a method to update the ACG according to the historical state of the fuzzing which periodically adjust the attribute range of the feature vector of each function in the ACG, and give higher importance weights to the functions that have not been fully tested, so that the seeds with higher path weights will be tested first. ACG can accurately reflect the importance of each function of the current time node at this time, and guide the fuzzing to keep seeds with greater potential for path discovery and vulnerability discovery.

- Based on the above method we implemented our prototype tool FunAFL. Evaluation shows that our tool found 18 bugs on the LAVA-M dataset exceeding the fuzzers such as AFL and AFLFast. The coverage rate in real-world programs is higher than that of AFL and AFLFast. At the same time, 10 bugs were found in real-world programs and 3 CVE numbers were assigned.

II. BACKGROUND AND RELATED WORK

A. Classification of Fuzzing

From the perspective of the cognition of the source code, fuzzing can be divided into three types: black box fuzzing, white box fuzzing and gray box fuzzing. Among them, black box fuzzing refers to the fact that the internal structure of the program under test is not known. On the contrary, whitebox fuzzing refers to testing under the condition of having all the internal structure information of the program, and gray-box fuzzing is a test method between black-box fuzzing and white-box fuzzing. Gray-box fuzzing cannot fully obtain the internal information of the program, but it can obtain feedback information such as coverage rate during program execution through lightweight instrumentation and use the information feedback to guide the direction of mutation, thereby improving the efficiency of fuzzing. The gray box fuzzing using genetic algorithm has found many vulnerabilities in the program in practice with relatively low consumption which achieved great success. Therefore, the method studied in this paper is the gray box fuzzing method.

B. A Representative Tool for Mutation-Based Gray Box Fuzzing

AFL (American fuzzy lop) is one of the most classic mutation-based gray box fuzzing tools. The overall process of AFL for fuzzing is shown in Figure 1.

AFL’s algorithm includes the following process:

1) Select the next seed file to be tested from the seed queue.
2) Perform deterministic mutations on the selected seeds and monitor the results of their execution.
3) Assign energy to the selected seeds and carry out non-deterministic mutations and monitor the execution results.
4) If the execution result shows that the seed caused the crash of the tested program, then save the seed in the crash seed queue for subsequent security analysis.
5) If the execution result shows that the seed brings new coverage, then save the seed in the seed queue.
6) According to certain rules, select the smallest seed set that can cover all bits in the current bitmap.

According to the fuzzing process represented by AFL, existing research can divide the optimization of fuzzing into the following categories: optimization of seed selection strategy, optimization of seed mutation method, optimization of seed mutation location selection, and energy scheduling optimization for non-deterministic mutations.

C. Optimization of Seed Selection and Selection Strategy

An important reason why fuzzing can efficiently find vulnerabilities in software is that it can quickly perform mutation tests on seeds. During the mutation process, a large number of seeds will be generated. AFL retains the smallest set of seeds while maintaining the current bitmap coverage. The criteria for seed filtering is to retain seeds that are faster and smaller. However, this kind of seed filtering strategy will miss
some vulnerabilities. For example, some vulnerabilities require a specific relatively long path. However, according to AFL’s seed filtering strategy, such seeds may be filtered out while ensuring coverage. As shown in Figure 2, there are now five seeds corresponding to the three paths 1234, 154, 156, 12354 and 12356 respectively. Among them, the seed corresponding to path 12356 takes the longest time to execute. Assuming its length is also the longest, according to the AFL filtering rules, path 12356 will be eliminated. However, if the vulnerabilities occur on the path 12356, AFL will miss the path. It can be seen that the orientation of AFL’s seed filtering strategy may cause the omission of important paths, so many researches are aimed at optimizing fuzz testing for seed selection strategies.

Fig. 2. AFL Seed Select Example.

For research in this area, VUzzer [10] prioritizes the seeds to reach deeper paths with the goal of reaching parts of the code that are not easily accessible for testing. SlowFuzz [24] targets algorithm complexity vulnerabilities, so it will consider giving higher priority to seeds that consume more resources during program execution. On the basis of solving the problem of edge coverage hash collision, CollAFL [11] proposes three seed selection strategies, namely, the following types of seeds are preferentially mutated: a. There are more unexplored adjacent branches on the path. b. The offspring with more adjacent branches on the path are unexplored. c. There are many memory access operations on the path. This tendentious seed selection strategy will accelerate the exploration of specific scenarios. NeuFuzz [3] uses a neural network to predict the probability of vulnerabilities in each path and then uses the probability of vulnerabilities in the path to sort the seeds. Every time it will select the seeds with a higher probability of vulnerabilities to be placed in the front of the seed queue, so that the fuzzing test can more quickly find the existence of the program bug, but NeuFuzz [3] is implemented under the support of a specific operating system and hardware. Peiyuan Zong et al. proposed FuzzGuard [4] for directed fuzzing. The method is to use deep learning to filter out the input that cannot reach the target code area, so that it can reach the designated code area more quickly for fuzzing.

D. Optimization of Seed Mutation Method

The seed mutation methods currently used by AFL include the following:

1) bitflip, flip every bit in the seed
2) arithmetic, integer addition/subtraction arithmetic operations
3) interest, replace some special content into the seed
4) dictionary, replace/insert the token generated during the test or provided by the user into the seed
5) havoc, randomly select a certain number of mutation operations in a, b, c, d to continuously mutate the seed
6) splice, splice two seeds together to get a new seed

Among them, the four mutation methods of 1, 2, 3 and 4 are deterministic mutations, 5 and 6 are non-deterministic mutations. AFL [1] executes 1-6 in order according to the incoming parameters to mutate the seeds while monitoring the execution status and responding. MOPT [5] found that different mutation operations have different effects on one target program and the same mutation operation has different effects on different target programs. Therefore, MOPT [5] proposes to use particle swarm algorithm to dynamically evaluate the effectiveness of mutation operations and adjust the selection of mutation operations probability which improves the efficiency of fuzzing. TIFF infers the byte in the input file corresponding to the operand of the comparison instruction through dynamic taint analysis, which is called the control offset. TIFF [25] infers the type of bytes other than the control offset, which is called data offset. TIFF [25] performs type-based mutation based on control offset and data offset which makes the mutation more targeted and achieving higher test efficiency.

E. Optimization of Seed Mutation Location Selection

When AFL [1] performs fuzzing, whether it is the deterministic mutation stage or the non-deterministic mutation stage, the selection probability for each byte of the input file is the same. However, the study by Rajpal M et al. found that all bytes in the input file are not completely equal [7]. Mutations in the file header or other key positions are more likely to produce new coverage, while mutations in the data part of the file are less likely to produce new coverage. Therefore, Rajpal M at el. use neural networks to predict the importance of each byte of the input file, and then guide the fuzzing. FairFuzz [13] dynamically calculates the “mask” to make the location of the mutation tend to hit the rare path, enhance the fuzzing test for the rare path and improve the coverage of the fuzzing test. Profuzzer [26] analyzes the execution path after mutation, then composes the related byte positions into an input field.
Then it determines the type of the input field according to the different modes of "mutation-execution path". It mutates multiple bytes in the same input field according to a predefined type strategy. Angora [9] believes that most path constraints depend on a few specific bytes and track which bytes will be checked by path constraints through taint analysis, so that the range of input mutation can be restricted to these bytes which compresses the state space and improves test efficiency.

F. Optimization of Energy Scheduling

The mutate of a seed is divided into deterministic mutate and non-deterministic mutate. Deterministic mutate is described in section B. Non-deterministic mutate is random to select several types of deterministic mutate continuous perform. The so-called energy schedule refers to the times of non-deterministic for a seed. If the energy assigned is too much, it will waste the time of the fuzzing. On the contrary, if the energy assigned of the fuzzing is too small, it may miss the vulnerabilities that should have been discovered in this mutation stage. AFL's energy schedule strategy is comprehensively evaluated based on the execution time of the seed, the number of seed mutations and the coverage of the seed, etc. This energy schedule strategy can stably perform mutation and testing in practice, but the energy schedule strategy of AFL has a certain degree of blindness and cannot be adapted to some specific situations. Therefore, there is research to improve the energy shedule strategy of AFL. AFLFast [2] will assign higher energy to the seeds that have been selected more times but have been executed less times to increase the exploration of low-frequency paths. As a directed fuzzing tool, AFLGo [8] will assign more energy to the seeds that reach the target code closer to the target code area so as to make the fuzzing mutate in the direction of the target code area. Hawkeye [9], also as a tool for directed fuzzing, gives an example to illustrate that the vulnerability may occur on a longer path. Therefore, Hawkeye [9] weighs the path length and the similarity of the function to assign energy to achieve fuzzing for stronger directional mutation.

III. METHOD

Our method is as follows: Before the fuzzing starts, we first disassemble the tested program to obtain ACG (subsection A), and calculate the initial attribute vector of each node through static analysis. The vector is composed of the statistical attributes such as the number of cmp instructions, the number of memory read and write instructions, the total number of instructions, the total number of basic blocks and the structural attributes such as Betweenness and Offspring. Then the ACG’s representation ability is further enhanced according to the PageRank algorithm (subsection B). During the fuzzing, set the dictionary $P_f$ to count the hit count of each function. Then every 25 minutes of the fuzzing, the attribute vector of each node on the ACG is updated according to the hit count, and then the Weisfeiler-Lehman algorithm is used for attribute propagation (subsection C). In this process, an asynchronous execution and lazy loading strategy is used to reduce the time-consuming of the Weisfeiler-Lehman algorithm. After the propagation is completed, when the fuzzing of the current seed ends and the next seed is selected, the seed filtering strategy is improved according to the calculated priority (subsection D). The whole process is shown in Figure 3. Among them, the green box is the standard process of fuzzing, the dark green is the original function been modified, and the orange boxes such as static analysis, ACG characterization and dynamic property adjustment are added components. The key technologies of each step are introduced below.

A. Function and Calling Relationship Representation based on Attributed Call Graph

Function is a common granularity for program analysis and security research. The most commonly used form to represent functions and their relationships in a program is call graph. The call graph is a directed graph with functions as nodes and edge directions indicating function call relationships. Although the call graph characterizes the calling relationship between functions, it lacks the representation of the information inside the functions. In other words, this granularity is too coarse. Feng Q et al. proposed a data structure called Attributed Control Flow Graph (ACFG) [18] during the study of binary code similarity detection. This structure adds the statistical information and structural information of the basic block corresponding to each node in the graph on the basis of the control flow graph, that is, using feature vectors to represent each function in the graph, giving the control flow graph more Semantic information. Inspired by this research, we propose to use a data structure called Attributed Call Graph (ACG) to characterize program, that is, each function node is represented by a feature vector composed of its statistical characteristics and structural characteristics and call relationships are represented by edges. We selected four statistical features and two structural features. Table I lists these features.

Our consideration for selecting these statistical attributes and structural attributes is: the number of cmp instructions is positively correlated with the number of branches in the function and the number of instructions related to memory read/write operations has a strong correlation with the probability of memory errors. Meanwhile, the number of instructions and the number of basic blocks indicate the size.
In this case, the probability of reaching the function fun5 is function represented by its child node with equal probability. and fun6 are the ends of the program. From a structural aspect, fun1 is the beginning of the program while fun5 is tested. Therefore, we need to determine its importance for fuzzing according to the location of the function and its own attributes.

For the figure 4, let’s compare the functions fun5 and fun6. Consider the relative position of the function in the program.

Moreover, the number of read and write instructions of this function indicates how much a function’s own attributes are worth exploring. For example, there is a strong correlation between the number of read and write instructions of this function and the probability of a memory error in this function. In addition, structural attributes characterize the importance of its position in the fuzzing process. The larger the offspring of the node, the more nodes need to be explored after passing through the node.

\[ c_B(v) = \sum_{s,t\in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \]  

(1)

**B. Enhanced Representation of Function Call Relations Based on Improved PageRank Algorithm**

Fuzzing is for the entire program. One of our important observations is that the importance of each function is not only determined by itself, but also determined by the relative position of the function in the fuzzing process. The importance of the function itself is obtained by calculating the statistical and structural characteristics of the function. The importance indicates how much a function’s own attributes are worth exploring. For example, there is a strong correlation between the number of read and write instructions of this function and the probability of a memory error in this function. In addition to the importance of the function itself, we should also consider the relative position of the function in the program. For the figure 4 let’s compare the functions fun5 and fun6. The function fun1 is the beginning of the program while fun5 and fun6 are the ends of the program. From a structural point of view, it is assumed that each function calls the function represented by its child node with equal probability. In this case, the probability of reaching the function fun5 is \( \frac{1}{3} \ast 1 + \frac{1}{3} \ast 1 + \frac{1}{3} \ast \frac{1}{2} \) which is \( \frac{5}{6} \) and the probability of reaching fun6 is \( \frac{1}{2} \ast \frac{1}{2} \) which is \( \frac{1}{4} \). Fuzzing will generate a large number of test cases for testing, that is to say, from the structural point of view, fun6 in this example has a relatively low probability of being tested which is not fully tested during the fuzzing process while fun5 has a higher probability of being fully tested. Therefore, we need to determine its importance for fuzzing according to the location of the function and its own attributes.

\[ PR(A) = \sum_{i=1}^{B|} \frac{PR(B_i)}{L(B_i)} \ast q + (1 - q) \]  

(2)

**TABLE I**

| Type         | Feature                           |
|--------------|-----------------------------------|
| statistical feature | No. of cmp instructions |
|               | No. of basic block                 |
|               | No. of sum instructions            |
|               | No. of memory read/write           |
| structure feature | betweenness offspring            |

ACG characterizes the static information of the program, including the statistical information, the structure information of the location in the function and the call relationship between the function. However, for the entire call graph, the importance of a node will also affect the importance of surrounding nodes and the call relationship between functions should also be more clearly characterized. In addition, through the above example, we observe that the importance of a function’s location will also affect the results of the fuzzing. In other words, in addition to its own attributes, the importance of a function will also be determined by the number and quality of its adjacent functions. This is very similar to the PageRank algorithm.

PageRank is a connection analysis algorithm proposed by Larry Page and Sergey Brin to improve the quality and speed of web search, which enables important pages to be presented first. The algorithm regards web pages as interconnected nodes and ranks the importance of web pages based on quantity hypothesis and quality hypothesis.

The quantity hypothesis refers to that in the Web graph model, if a page node receives more links from other web pages, the more important this page is. The quality hypothesis refers to that the quality of the links to a page is different, and pages with high quality will pass more weight to the page. Therefore, the higher quality pages point to a page, the more important the page is.

We set the PageRank value of node \( x \) as \( PR(x) \), assuming that the nodes pointing to node \( A \) is a set \( B, \forall B_i \in B, i \in [1, |B|] \), then the PageRank value of \( A \) is calculated as shown in formula 2. Among this formula, \( L(x) \) represents the out-degree of \( x \), and \( q \) is the damping coefficient.

\[ PR(A) = \sum_{i=1}^{B|} \frac{PR(B_i)}{L(B_i)} \ast q + (1 - q) \]  

(2)

The PageRank algorithm is used to indicate the importance of each web page in the process of web page testing.
clicks. According to the quality hypothesis and quantity hypothesis of the PageRank algorithm, we also put forward quality hypothesis and quantity hypothesis for the current data structure ACG in our application scenarios. The quantitative hypothesis of our application scenario is that in the fuzzing, if a function is called less frequently by others, the static analysis results will show that there are fewer functions pointing to this function, then this function is more important. That is, this function is not easy to reach in structure. The quality hypothesis is that the quality of the function that points to a function is different, and the function with high quality will transfer more quality than other functions through the link. Therefore, the more higher quality function point to a function, the more importance the pointed function gets. The practical significance of this is that the difficulty of reaching the parent node of the function will be passed to the son function. Based on the quality and quantity hypothesis analyzed above, in order to achieve a trade-off of quantity and quality, we give the calculation formula of the function node PageRank in the current application scenario. For the node corresponding to function $A$, if there are functions $B_1, B_2, \ldots, B_n$ that calls $A$, that is, the node set $B, \forall B_i \in B, i \in [1, |B|]$ points to $A$, the formula $3$ shows the PageRank vector of the function node $A$.

$$PR(A) = \sum_{i=1}^{\left|B\right|} \frac{PR(B_i)}{L(B_i) \ast IN(A) \ast IN(A)} \ast p + (1 - p) \ast PR(A)$$  \hspace{1cm} (3)

Among the formula $3$, $A, B_1, B_2, \ldots, B_n$ are function nodes, $L(x)$ represents the out-degree of $x$, and $IN(x)$ represents the in-degree of $x$.

When the attribute extraction and the PageRank algorithm are completed, we found that the function feature vector has the following problems:

1) For the same function, the magnitude difference between different attributes is too large.

2) For the same dimension, the magnitude difference between different functions is too large. As shown in the figure $5$, it is the first component of the feature vector of different functions, that is, the number of compare instructions. It can be seen that most points are not very distinguished in the figure, and the values of individual points are too large.

Therefore, we normalize each dimension according to the formula $4$, $5$, and $6$. The $\mu$ and $\delta$ in formula $4$ represent the mean and variance of the data in this dimension. The $min\_value$ and $max\_value$ in formula $5$ respectively represent the maximum and minimum values of the data in the dimension. The $min\_value\_component$ in formula $6$ represents the non-zero minimum value of the data in this dimension. Formula $4$ makes the mean and variance of each dimension of the data in an order of magnitude. Formula $5$ keeps the data range of each dimension within the specified interval. After normalization by formula $6$ the original size relationship can be maintained while the data points are evenly distributed without too much difference. We use formula $4$, formula $5$, formula $6$, and formula $5$ in order to scale the data processed by the PageRank algorithm to the range of $0$ to $100$.

$$y = \frac{x - \mu}{\delta}$$  \hspace{1cm} (4)

$$y = \frac{x - min\_value}{max\_value - min\_value}$$  \hspace{1cm} (5)

$$y = log_{min\_value \_component}(x)$$  \hspace{1cm} (6)

The normalized comparison instruction data image is shown in the figure $6$. It can be seen that for the dimensions shown in the figure, the data is evenly distributed between $0$ and $100$ while maintaining the size relationship. In addition, the order of magnitude between different dimensions also maintains a comparable relationship.

C. Dynamic Adjustment of Function Attributes Based on Improved Weisfeiler-Lehman Algorithm

Our another observation is that existing work obtains the importance or other indicators of each function through static analysis are fixed and unchanged. The importance obtained at the initial stage of the fuzzing may lose its effectiveness...
with time going by. For example, there are functions A and B. The importance of function A is far greater than that of function B. After fuzzing for a period of time, function A was tested 10,000 times and function B only hit 1 time. If you still use the initial static information to guide the fuzzing, a lot of time will be spent on function A at this time which is obviously not enough smart. At this point, although the importance of A is higher and the importance of B is lower, function A has been fully tested and function B has not been fully tested, so we need to reduce the importance of A and increase the importance of B which makes fuzzing spend more time exploring function B.

Fuzzing is a process that requires continuous generation of seed to test for a long time. Our static analysis before fuzzing, that is, ACG and PageRank processing, can be regarded as the extraction of function attributes of start time. We also need to consider the change of function attributes of other time during the fuzzing process. With the progress of fuzzing, if a function is hit enough times, then we have reason to think that the function has been tested enough times, and we should not continue to waste time on this type of function. we adjust the node attribute range of the function according to the number of hits of the function. Then, in order to reflect the influence of the change of a node on the surrounding nodes, we use the graph algorithm to perform a propagation of the node attributes.

Therefore, we have to finish two tasks here, one is to scale the range of node feature vectors, and the other is to propagate node attributes.

We set the feature vector corresponding to the function $f$ as $[s_1, s_2, s_3, ..., s_n]$, where $n$ represents the dimension of the feature vector. According to the above, we know that $n=6$ here. For the first task, after the fuzzing is executed for a certain period of time, we set the number of times function $f$ is executed as $p_f$. we adjust the attribute feature vector of each function as follows: $\alpha = \alpha \cdot [s_1, s_2, s_3, ..., s_n]$, where $\alpha = adjust\_time(p_f)$, the function $adjust\_time$ should be satisfied that the larger the $p$, the smaller the $\alpha$, and vice versa. One question is, how often is it appropriate to conduct attribute propagation? If our update frequency is too high, it will affect the efficiency of fuzzing and waste valuable resources. Conversely, if our update frequency is too low, it will cause the accuracy of the fuzzing to decrease. We know that fuzzing takes between 6 and 72 hours one time, so we think that every 25 minutes per time is a appropriate update frequency.

The feature vector of the function is expanded or reduced according to the number of function hits. The number of hits of the function increases with time. Therefore, function $adjust\_time$ uses an exponential function with an adaptive base to normalize the number of function hits. Such a function satisfies two points as below.

1) For the number of function hits, the larger the value, the smaller the value after normalization.
2) The normalized value can be guaranteed to be within a reasonable data range, and the distribution of the data is clearly distinguished, that is to say, the data will not be too concentrated in a certain interval.

The function $adjust\_time$ is shown as formula $7$. Among the formula, $MaxCount$ represents the maximum number of hits of the function, $lower$ represents the minimum value after normalization, and $p$ represents the number of function hits. The normalization method adjusts the data range to $[lower, 1]$. In order to ensure that the data is stable without large fluctuations while normalizing, the value of $lower$ is empirically set to 0.5.

$$adjust\_time(p_f) = (lower \frac{1.0}{MaxCount})^{p_f}$$

For the second task, we used the Weisfeiler-Lehman [20] algorithm for reference. The Weisfeiler-Lehman [20] algorithm is a classic graph algorithm which has guided many traditional and deep learning graph algorithms. The relabelling process in Weisfeiler-Lehman [20] is the process of spreading node information to the surroundings, which coincides with our needs, so we use the idea of Weisfeiler-Lehman [20] algorithm to complete our attribute propagation process. Next, let’s briefly introduce relabelling process of the Weisfeiler-Lehman [20] algorithm.

Figure 7(a) is a graph with a label for each node. For each node, the labels of its adjacent nodes and the current node are linked together as a new label, as shown in Figure 7(b). According to the result of relabelling, the node label is compressed as shown in Figure 7(c). We use the result of label compression to relabel and finally get the new label of the figure as shown in Figure 7(d).

![Fig. 7. relabel process of Weisfeiler-Lehman algorithm.](image)

In our application scenario, each node is composed of a feature vector. After using the number of function hits to adjust the range of the function node attributes, we define our node feature vector propagation algorithm according to the Weisfeiler-Lehman algorithm label compression iteration...
corresponding to the function \( f \) we score the seeds according to formula 9.

\[
v_i = p \times v_i + (1 - p) \times \frac{1}{n} \sum_{j \in M(i)} v_j
\]  

(8)

Among the formula 8, \( p \) is the damping coefficient and \( M(i) \) represents the adjacent node of node \( i \). According to the size of the graph, we dynamically adjust the number of node propagation times. Every iteration, the node attributes will be propagated to the node with a distance of 1. The more node propagation times. Every iteration, the node attributes

**D. Seed Filtering Strategy Based on Function Granularity**

Score

Each input seed \( seed_i \) will generate a trace after execution. This trace corresponds to multiple functions. We set the corresponding functions as \( f_1, f_2, ..., f_n \). The feature vector corresponding to the function \( f_i \) is \( v_i = [s_{i1}, s_{i2}, ..., s_{im}] \), and we score the seeds according to formula 9.

\[
score(seed_i) = \frac{1}{n} \left( ||v_1||_2 + ||v_2||_2 + \ldots + ||v_n||_2 \right)
\]

\[
= \frac{1}{n} \left( \sqrt{s_{11}^2 + s_{12}^2 + \ldots + s_{1m}^2} + \sqrt{s_{21}^2 + s_{22}^2 + \ldots + s_{2m}^2} + \ldots + \sqrt{s_{n1}^2 + s_{n2}^2 + \ldots + s_{nm}^2} \right)
\]  

(9)

As shown in figure 8. The original seed filtering strategy of AFL:

1) Ensure that the current coverage rate will not decrease
2) In the case of guaranteed condition \( \square \) select the seed with a smaller “execution time * length” value.

As shown in figure 9. The seed filtering strategy of FunAFL is:

1) Ensure that the current coverage rate will not decrease
2) In the case of guaranteed condition \( \square \) select the seed with a higher score.
3) If the condition \( \square \) is not met, the seed with a smaller “execution time * length” is selected according to the original AFL strategy.

In this way, on the one hand, the maximum coverage rate can be ensured. On the other hand, the function score of each seed hit is considered. The score is a comprehensive judgment on the discovery of new paths and vulnerabilities of a seed. The seeds were further filtered from the fine-grained.
Because the test object of the fuzzing is a program with file input, we select a series of third-party libraries and software such as image processing and audio processing for testing. The crash of the fuzzing is to judge whether it is a uniq crash through the coverage rate and it is easy to produce false positives. What’s more, there are many programs that did not crash during the long-term test, which brought difficulties to our evaluation. While there is a direct positive correlation between the coverage of fuzzing and the discovery of vulnerabilities and coverage can also explain the degree of exploration of the program by fuzzing, so we use the coverage here to evaluate these programs.

The purpose of our fuzzing research is to discover security issues and fix them, so we also counted the vulnerabilities discovered by our FunAFL in the read world program.

B. Experimental Setup

We used a server of NaviData 5200 G3 for experiments. The server has 2 Intel(R) Xeon(R) Gold 6130 CPUs, clocked at 2.10GHz and a total of 32 cores and 64 threads. We experiment and compare AFL, AFLFast and our fuzzer under the same conditions.

C. Experimental Results

We evaluated AFL, AFLFast and FunAFL on the LAVA-M dataset. As shown in the table II, the experimental results show that the number of bugs found by AFL, AFLFast, and FunAFL on the LAVA-M dataset are 2, 0, and 18, respectively. The experimental result of our FunAFL is far better than that of AFL and AFLFast. The reason is that FunAFL can filter out those seeds with low scores as early as possible, that is, filter out seeds with little potential for path and vulnerability discovery, and retain seeds with high comprehensive potential. This experimental result shows that our characterization of the program is meaningful, and the seed filtering strategy based on ACG is effective.

| Fuzzer   | No. of Bugs Found | Bugs ID                        |
|----------|-------------------|--------------------------------|
| AFL      | 2                 | 293 321                        |
| AFLFast  | 0                 | 112 130 169 170                |
|          |                   | 215 222 227 293                |
| FunAFL   | 18                | 297 318 321 322                |
|          |                   | 346 347 368 371                |
|          |                   | 372 443 227                    |

We select programs such as GraphicsMagick, libpng, libtiff, jhead, ffmpeg and libelfin for actual testing. The figure 10 is a comparison image of the path found during the fuzzing. You can see that in all programs, our FunAFL finally found the number of paths are more than those found by AFL and AFLFast. The number of paths discovered by our program is more than that of other fuzzers, which shows that our seed filtering strategy can guide the fuzzing to test more paths of the program without consuming resources on seeds that are meaningless to the results. This also proves our method is effective.

During the experiment, we found some vulnerabilities in the software. As shown in the table III, we have reported these bugs to the software maintainers. Among these bugs, we have obtained 3 CVE numbers: CVE-2020-13438, CVE-2020-13439 and CVE-2020-13440.

VI. CONCLUSION

We put forward the new data structure of ACG on the basis of ACFG, and combined with PageRank algorithm to characterize the importance of instruction and position of each function in the fuzzing process. In the process of fuzzing, we score the seeds according to the importance of the function...
represented by ACG and use the score to adjust seed filtering strategy of the fuzzing. Since fuzzing is a dynamic process, we use the Weisfeiler-Lehman algorithm to dynamically adjust the ACG feature vector data range according to the number of function hits. We have implemented such a dynamic and static fuzzing system and achieved good results in both the LAVA-M data set and the actual softwares.

Compared with AFL, AFLFast, etc., our FunAFL will bring some performance loss, mainly reflected in: FunAFL needs a monitoring process to adjust the ACG data range regularly. FunAFL periodically read the adjusted ACG after attributes propagation. However, since the dynamic adjustment process and the Fuzz process of FunAFL are executed asynchronously, the file reading and writing only occurs once every 25 minutes, without reducing the efficiency of the fuzzing too much. Therefore, the performance loss of FunAFL compared to AFL is acceptable.

TABLE III
NO. OF INJECTED BUGS IN REAL WORLD SOFTWARE

| Software     | No. of Bugs Found |
|--------------|-------------------|
| binutils     | 2                 |
| fjpeg        | 3                 |
| jhead        | 2                 |
| xpdf         | 1                 |
| libellin     | 1                 |
| libtiff      | 1                 |

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