

Context-Sensitive and Directional Concurrency Fuzzing for Data-Race Detection

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Abstract—Fuzzing is popular for bug detection and vulnerability discovery nowadays. To adopt fuzzing for concurrency problems like data races, several recent concurrency fuzzing approaches consider concurrency information of program execution, and explore thread interleavings by affecting thread scheduling at runtime. However, these approaches are still limited in data-race detection. On the one hand, they fail to consider the execution contexts of thread interleavings, which can miss real data races in specific runtime contexts. On the other hand, they perform random thread-interleaving exploration, which frequently repeats already covered thread interleavings and misses many infrequent thread interleavings.

In this paper, we develop a novel concurrency fuzzing framework named CONZZER, to effectively explore thread interleavings and detect hard-to-find data races. The core of CONZZER is a context-sensitive and directional concurrency fuzzing approach for thread-interleaving exploration, with two new techniques. First, to ensure context sensitivity, we propose a new concurrency-coverage metric, *concurrent call pair*, to describe thread interleavings with runtime calling contexts. Second, to directionally explore thread interleavings, we propose an adjacency-directed mutation to generate new possible thread interleavings with already covered thread interleavings and then use a breakpoint-control method to attempt to actually cover them at runtime. With these two techniques, this concurrency fuzzing approach can effectively cover infrequent thread interleavings with concrete context information, to help discover hard-to-find data races. We have evaluated CONZZER on 8 user-level applications and 4 kernel-level filesystems, and found 95 real data races. We identify 75 of these data races to be harmful and send them to related developers, and 44 have been confirmed. We also compare CONZZER to existing fuzzing tools, and CONZZER continuously explores more thread interleavings and finds many real data races missed by these tools.

I. INTRODUCTION

Data race is a common class of concurrency problems. It occurs when two concurrently executed threads access a shared variable, and at least one of them writes the variable without proper synchronization operations. If the racy data influences critical data flow or control flow of the program, serious bugs such as memory corruption and permission bypass can occur. Some works [7], [55], [64], [73] have shown that data races have become a main source of runtime problems in both user-level applications and kernel-level programs. As an

example, “Dirty COW” [20] launches a privilege-escalation attack against the Linux kernel by exploiting a data race in the memory management subsystem of the Linux kernel. Furthermore, many recent CVE-assigned vulnerabilities (e.g., CVE-2020-1667 [16], CVE-2020-9990 [17] and CVE-2020-11173 [18]) also stem from data races.

As data races can be harmful, many detection approaches have been proposed. Some approaches [22], [25], [26], [42], [77], [78] use static analysis, but they suffer from many false positives, due to lacking exact runtime information and inaccuracy of dataflow analysis. To reduce false positives, some other approaches use dynamic analysis based on lockset analysis [10], [19], [21], [66], [68], happens-before relation [27], [51], [56], [62] or sampling [5], [23]. But these approaches require substantial test cases to cover concurrently-executed code and different thread interleavings at runtime.

To automatically generate effective test cases, many recent approaches [1], [4], [9], [15], [30], [45], [50], [60], [61], [70], [72], [79], [80], [82] use fuzzing to cover infrequently-executed code and thus to discover hard-to-find bugs. Encouraged by the promising results of fuzzing, many developers have used existing fuzzing tools (such as AFL [1] and Syzkaller [70]) with third-party data-race checkers (such as TSan [75] and KCSAN [44]) to detect data races [41], [71]. However, general-purpose fuzzing tools are limited in exploring thread interleavings, due to using *sequential* code coverage as program feedback and neglecting *thread interleavings*.

To improve fuzzing in finding concurrency problems like data races, several recent concurrency fuzzing approaches [8], [37], [53], [76], [81] use concurrent-execution information to perform thread-interleaving exploration. However, these approaches still have two major limitations in testing concurrent programs. First, existing concurrency fuzzing approaches use a *context-insensitive* coverage metric as fuzzing feedback without considering runtime contexts, and thus they can miss many deep-hidden data races that occur only in specific runtime contexts. Second, existing concurrency fuzzing approaches perform *random thread-interleaving exploration* (e.g., injecting random delay or randomly adjusting thread priorities), but recent works [12], [74] reveal that such exploration is often inefficient, namely it frequently repeats already covered thread interleavings and misses many infrequent ones.

To solve these two limitations, we develop a novel concurrency fuzzing framework named CONZZER, which can effectively explore thread interleavings and detect hard-to-find data races. The core of CONZZER is a context-sensitive and directional concurrency fuzzing approach containing two

new techniques. First, this approach uses a new concurrency-coverage metric, *concurrent call pair*, to describe thread interleavings with their runtime calling contexts as fuzzing feedback. Each concurrent call pair represents a pair of two concurrently-executed functions augmented with their calling contexts. Second, by using an *adjacency-directed mutation* and a *breakpoint control method*, this approach can directionally explore thread interleavings as many as possible. Specifically, the adjacency-directed mutation infers new possible thread interleavings according to already covered thread interleavings, so as to provide a promising direction for thread-interleaving exploration. Then, the breakpoint-control method deterministically attempts to actually cover these new possible thread interleavings at runtime, by adaptively affecting thread scheduling with breakpoints. This method can increase the possibility of covering infrequent thread interleavings generated by the mutation. With the two techniques, this fuzzing approach can effectively cover different thread interleavings with concrete context information, helping discover hard-to-find data races.

Based on this concurrency fuzzing approach, we implement a customized race checker in CONZZER, by using dynamic lockset analysis [66], and it can achieve higher accuracy than existing race checkers like TSan [75]. Benefiting from different thread interleavings and related context information identified by the fuzzing approach, this race checker can effectively and precisely detect data races in real-world programs. We have implemented CONZZER with LLVM [54] to automatically test both user-level applications and kernel-level programs. Besides, to be compatible with traditional input-driven fuzzing process, CONZZER can mutate concurrent call pairs and program inputs together.

Overall, we make the following main contributions:

- We first reveal the major limitations of existing concurrency fuzzing. Then, to solve these limitations, we propose a novel context-sensitive and directional concurrency fuzzing approach, with two new techniques. First, this approach uses a new context-sensitive concurrency-coverage metric *concurrent call pair* as program feedback, to describe thread interleavings with runtime calling contexts. Second, this approach performs directional thread-interleaving exploration, to smartly infer and deterministically cover new possible thread interleavings. With the two techniques, this fuzzing approach can help to discover hard-to-find data races.
- Based on this fuzzing approach, we develop a new concurrency fuzzing framework named CONZZER, to effectively explore thread interleavings and detect data races. To our knowledge, CONZZER is the first systematic concurrency fuzzing framework to directionally explore thread interleavings in different runtime contexts for data-race detection.
- We evaluate CONZZER on 8 user-level applications of the latest versions and 4 kernel-level filesystems in Linux 5.4. It in total reports 95 real data races with no false positive. All these data races are actually triggered in real execution. We identify 75 of these data races to be harmful and send them to related developers, and 44 have been confirmed. We also experimentally compare CONZZER to existing fuzzing tools (such as AFL++, Syzkaller, Razzer and KRACE) with existing race checkers (such as TSan and KCSAN), and CONZZER continuously explores more thread interleavings and finds more real data races missed by these tools.

II. BACKGROUND AND MOTIVATION

A. Data Race

The execution of two threads can be interleaved, and thus they can concurrently access the same shared variable. In this case, if at least one thread writes to the variable, its value can be uncertain or even corrupted. To solve this problem, synchronization operations are required to protect the memory accesses to the shared variables in concurrently-executed code. Common synchronization operations are acquiring/releasing locks, setting memory barriers, counting semaphores and so on. Since these synchronization operations reduce program concurrency and decrease program performance, they are supposed to be used in only the code where necessary, e.g., minimizing critical sections. But doing so is difficult for developers in practice, because concurrent situations at runtime can be quite complex and unpredictable. Thus, developers sometimes miss necessary synchronization operations or perform them at incorrect code places, which leads to data races. Data races can cause the program to run abnormally or crash directly. Furthermore, some data races can be even exploited by malicious attackers to cause serious security problems such as privilege escalation [20].

B. Motivating Example

Figure 1 shows a harmful data race found by CONZZER in the *jfs* filesystem in Linux 5.4. Once this data race is triggered, it can cause a null-pointer dereference that crashes the Linux kernel. As shown in Figure 1(a), in the function *txEnd*, the variable *JFS_SBI*(*tblk->sb*)*->log* is read and assigned to a local variable *log* on line 501. In the function *ImLogClose*, the variable *sbi->log* is assigned to *NULL* on line 1455. In our testing, the read operation of *JFS_SBI*(*tblk->sb*)*->log* in *txEnd* and the write operation of *sbi->log* in *ImLogClose* are concurrently executed, and the two operations access the same memory area, causing a data race to occur. When the data race is triggered, the read operation can be executed after the write operation, and thus *log* can be *NULL*, causing a null-pointer dereference when *log->active* is accessed on line 534.

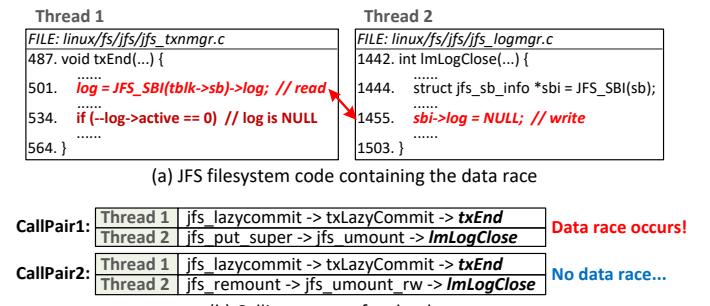


Fig. 1. A harmful data race in *jfs* filesystem.

This data race was first introduced in Linux 2.6.12 (June 2005) and had existed for about 15 years until CONZZER found it, indicating the difficulty of discovering it. In general, detecting data races is quite challenging, as they often occur in infrequent thread interleavings with specific runtime contexts, which are difficult to trigger, due to non-determinism of thread scheduling. For example, in our testing, the data

race in Figure 1 occurs only when the functions `txEnd` and `ImLogClose` are concurrently executed with the calling context `CallPair1` shown in Figure 1(b). When the two functions are concurrently executed with other calling contexts (such as `CallPair2` shown in Figure 1(b)), the data race never occurs. Moreover, the thread interleaving with the calling context `CallPair1` is just infrequently executed in real execution, and thus this data race is hard to trigger at runtime, causing it had existed for a long time, missed by existing race-detection tools though the Linux kernel has been extensively tested. But occurring in an infrequent execution situation does not mean that the data race is less critical. Once knowing the data race, an attacker can transform it into a deterministic vulnerability by intentionally preparing related concurrency workloads [83], [86]. In summary, how to effectively cover infrequent thread interleavings with specific runtime contexts is an important but difficult problem for data-race detection.

C. State of the Art of Concurrency Fuzzing

Nowadays, fuzzing has shown promising results in bug detection and vulnerability discovery for sequential programs. To fuzzing concurrent programs, many developers have used existing fuzzing tools (such as AFL [1], and Syzkaller [70]) with third-party data-race checkers (such as TSan [75] and KCSAN [44]) to detect data races [41], [71]. However, general-purpose fuzzing tools is limited in exploring thread interleavings, due to using *sequential* code coverage as program feedback and neglecting *thread interleavings*.

To improve fuzzing in testing concurrent programs, several recent concurrency fuzzing approaches [8], [37], [53], [76], [81] have been proposed. To perform thread-interleaving exploration, they use several techniques, such as using new concurrency-coverage metrics (e.g., alias instruction pair [81]) as program feedback and randomly adjusting thread priorities [8], [53]. However, these approaches still have two major limitations in testing concurrent programs:

1) Using context-insensitive concurrency-coverage metric. These approaches tune traditional code coverage [8], [37], [53], [76] or use new concurrency-coverage metrics [81] as program feedback. However, they miss the runtime contexts of thread interleavings. On one hand, code coverage only describes sequential-execution situation, and thus it cannot effectively describe thread interleavings though being tuned. On the other hand, as the sole new concurrency-coverage metric of these approaches, the alias instruction pair proposed by KRACE [81] only describes the locations of two concurrently-executed instructions, but neglects their calling contexts, and thus this metric cannot differentiate concurrent-execution situations in different calling contexts. For example in Figure 1, with a context-insensitive concurrency-coverage metric, the pairs of two racy instructions executed in `CallPair1` and `CallPair2` are considered identical. But the data race occurs only when the two racy instructions executed in `CallPair1`. Thus, the data race can be missed by concurrency fuzzing in this case.

2) Performing random thread-interleaving exploration. These approaches inject random delays at memory access points [81] or randomly adjust thread priorities at runtime [8], [53], to cover different thread interleavings. However, recent works [12], [74] reveal that such exploration is often inefficient, namely it frequently repeats already covered thread

interleavings and misses many infrequent ones. For example in Figure 1, the functions `txEnd` and `ImLogClose` are executed quickly with different calling contexts at runtime, and thus their executions actually have little chance to interleave with the calling contexts `CallPair1`. For this reason, to detect the data race, it is important to delicately schedule *Thread 1* and *Thread 2* during testing. In the evaluation (Section V-D), we try random delay injection in concurrency fuzzing for 24 hours, but the data race is missed.

Due to lacking concrete runtime contexts and missing many infrequent thread interleavings, existing concurrency fuzzing approaches are still limited in discovering hard-to-find data races. Thus, solving these limitations is important to improving concurrency fuzzing in data-race detection.

III. CONTEXT-SENSITIVE AND DIRECTIONAL FUZZING

To address the limitations of existing concurrency fuzzing, we propose a context-sensitive and directional concurrency fuzzing approach to effectively explore thread interleavings:

- 1) To ensure context sensitivity, this approach uses a new concurrency-coverage metric, *concurrent call pair*, to describe thread interleavings with their runtime calling contexts as fuzzing feedback.
- 2) To reduce the inefficiency caused by randomness and cover infrequent thread interleavings, this approach performs directional thread-interleaving exploration, which first uses an *adjacency-directed mutation* to infer new possible thread interleavings with already covered thread interleavings and then uses a *breakpoint-control method* to attempt to actually cover these new ones at runtime.

A. Context-Sensitive Concurrent Call Pair

Inspired by existing function-level concurrency-coverage metrics (e.g., concurrent function pair [19] and concurrent method pair [12]), which are context-insensitive, we propose a new metric *concurrent call pair* that considers the calling contexts of concurrently-executed functions:

$$ConCallPair = [CallCtx_a, CallCtx_b] \quad (1)$$

We describe the calling context of a function using its runtime call stack (`CallCtx`), which contains the information of each function call (`CallInfo`) at the call stack (from caller to callee), including the location of this function call (`CallLoc`) and the location of the called function (`FuncLoc`). Specifically, we describe a calling context as:

$$CallCtx = \{CallInfo_1, CallInfo_2, \dots, CallInfo_n\} \quad (2)$$

$$CallInfo = [CallLoc, FuncLoc] \quad (3)$$

Based on the above description, the information about each concurrent call pair can be hashed as a key for storage, and the number of times that each pair is covered can be represented as a hash value. In this way, similar to the code coverage stored in AFL [1], concurrent call pairs can be stored as key-value pairs in a hash table:

KEY	Hash(ConCallPair ₁)	Hash(ConCallPair ₂)	Hash(ConCallPair _x)
VALUE	0 - 255	0 - 255	0 - 255

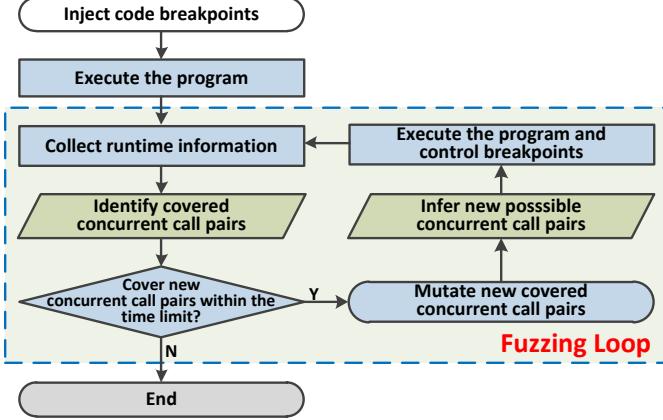


Fig. 2. Process of context-sensitive and directional fuzzing.

In fact, concurrently-executed functions and their runtime call stacks are actually decided by program execution, and thus statically determining them is quite difficult. For this reason, concurrent call pairs should be dynamically identified and collected during program execution.

According to our metric, when two functions are concurrently executed in N different calling contexts, there will be N concurrent call pairs. In this way, $CallPair_1$ and $CallPair_2$ in Figure 1(b) can be differentiated. Thus, concurrent call pair is helpful to performing finer-grained concurrency fuzzing and detecting data races in specific runtime contexts.

B. Directional Thread-Interleaving Exploration

We believe that the already covered thread interleavings provide a reasonable direction to infer other possible and infrequent thread interleavings. For example, if the function $Func_A$ is concurrently executed with the function $Func_B$, we can infer that the callees and callers of $Func_A$ are possible to be concurrently executed with $Func_B$. Then, we can deterministically affect thread scheduling to check whether the inferred possible thread interleavings are realistic at runtime.

Based on this basic idea and concurrent call pair, we propose a new directional thread-interleaving exploration method, which contains two parts: an *adjacency-directed mutation* (Section III-B1) to generate new possible thread interleavings with already covered thread interleavings; and a *breakpoint-control method* (Section III-B2) to attempt to actually cover these new possible thread interleavings at runtime.

Figure 2 shows the process of our context-sensitive and directional concurrency fuzzing, which has six basic steps:

(S1) At compile time, it injects a code breakpoint containing time delay at the entry of each function;

(S2) It executes the tested program without enabling any breakpoint, and collects covered concurrent call pairs and thread-execution information;

(S3) After program execution, it adds these covered concurrent call pairs into a global set $pair_set$ that records all distinct covered concurrent call pairs;

(S4) It performs the adjacency-directed mutation for these covered concurrent call pairs with thread-execution information, to generate new possible concurrent call pairs;

(S5) It executes the tested program, uses the breakpoint-control method to deterministically and adaptively cover the possible concurrent call pairs, and collects covered concurrent call pairs and thread-execution information;

(S6) After program execution, it identifies new covered concurrent call pairs from these covered concurrent call pairs by comparing with $pair_set$, and iteratively mutates these new ones using thread-execution information again as (S4) does, which constructs a fuzzing loop.

1) Adjacency-Directed Mutation: Our mutation is inspired by an insight that *if two functions are concurrently executed, the functions executed adjacently to them are probably concurrently executed as well*. Based on this insight and concurrent call pair, we propose an inference where new possible thread interleavings can be identified in promising directions, according to the already covered concurrent call pairs:

Inference: if $Func_A$ and $Func_B$ are concurrently executed with the calling contexts $CallCtx_a$ and $CallCtx_b$, and $Func_B$ and $Func_C$ are executed adjacently with the calling context $CallCtx_b$ and $CallCtx_c$, so $Func_A$ and $Func_C$ are possible to be concurrently executed with the calling contexts $CallCtx_a$ and $CallCtx_c$.

Algorithm 1: Adjacency-Directed Mutation

```

Input: covered_pair_set
Output: possible_pair_set
1 possible_pair_set  $\leftarrow \emptyset$ 
2 for covered_pair  $\in$  covered_pair_set do
3    $[CallCtx_1, CallCtx_2] \leftarrow GetCallCtx(covered\_pair)$ 
4   for AdjCallCtx1  $\in$  GetAdjCallCtx(CallCtx1) do
5     ConCallPair  $\leftarrow$  GenNewPair(AdjCallCtx1, CallCtx2)
6     if ConCallPair  $\notin$  covered_pair_set then
7       AddConCallPair(possible_pair_set, ConCallPair)
8
8   for AdjCallCtx2  $\in$  GetAdjCallCtx(CallCtx2) do
9     ConCallPair  $\leftarrow$  GenNewPair(CallCtx1, AdjCallCtx2)
10    if ConCallPair  $\notin$  covered_pair_set then
11      AddConCallPair(possible_pair_set, ConCallPair)

```

Our adjacency-directed mutation is shown in Algorithm 1. The mutation takes the set of covered concurrent call pairs, namely $covered_pair_set$ as input, and outputs the set of new possible concurrent call pairs, namely $possible_pair_set$. For each covered concurrent call pair, the mutation gets its two corresponding calling context $CallCtx_1$ and $CallCtx_2$ (lines 2-3). Then, each adjacent calling context $AdjCallCtx_1$ of $CallCtx_1$ is combined with $CallCtx_2$ to generate a new possible concurrent call pair $ConCallPair$ (lines 4-5). If $ConCallPair$ does not repeat with existing concurrent call pairs, it will be added into $possible_pair_set$ (lines 6-7). Similarly, $CallCtx_2$ is also handled in this way (lines 8-11) to generate new possible concurrent call pairs. Note that $AdjCallCtx$ is regarded as the adjacent calling context of $CallCtx$ if their corresponding functions can be executed adjacently in these calling contexts.

Example. Figure 3 presents an example of our adjacency-directed mutation, which generates four new possible concurrent call pairs and drops two repeated ones. For a given covered concurrent call pair $[CallCtx_a, CallCtx_b]$, the mutation

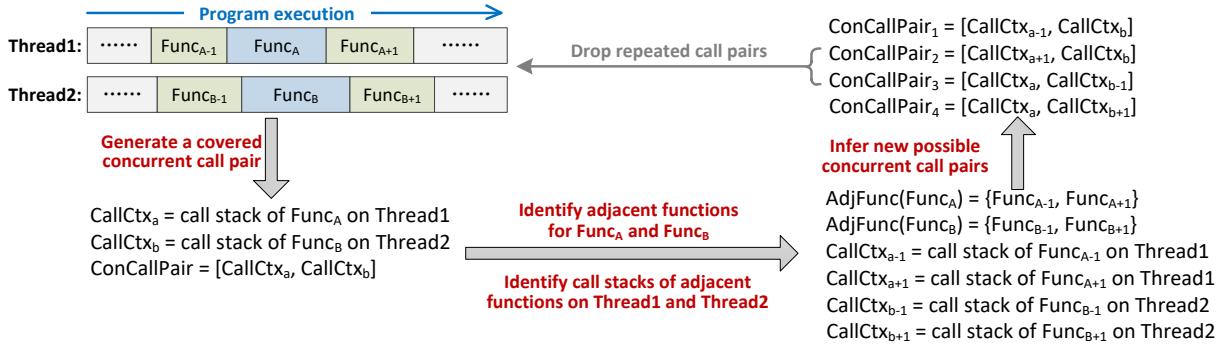


Fig. 3. Example of mutating concurrent call pairs.

first selects their concurrently-executed functions Func_A and Func_B , and identifies the runtime information about their threads Thread1 and Thread2 . Then, the mutation checks the information about Thread1 and identifies the two functions Func_{A-1} and Func_{A+1} that are executed adjacently to Func_A . The mutation infers that Func_{A-1} and Func_{A+1} would be also likely concurrent with Func_B when they are executed in specific calling contexts. Based on this inference, from the collected information about Thread1 , the mutation identifies the corresponding call stacks of Func_{A-1} and Func_{A+1} , namely CallCtx_{a-1} and CallCtx_{a+1} , and then combines each of them with CallCtx_b to generate two new possible concurrent call pairs $[\text{CallCtx}_{a-1}, \text{CallCtx}_b]$ and $[\text{CallCtx}_{a+1}, \text{CallCtx}_b]$. Similarly, the mutation also handles Func_B and the runtime information about Thread2 , to generate another two new possible concurrent call pairs $[\text{CallCtx}_a, \text{CallCtx}_{b-1}]$ and $[\text{CallCtx}_a, \text{CallCtx}_{b+1}]$. In total, four new possible concurrent call pairs are generated from the given pair, and two of them are dropped in the comparison with existing covered ones.

2) *Breakpoint-Control Method*: Because thread scheduling is often non-deterministic during concurrent execution, it is difficult to actually cover specific possible concurrent call pairs (generated by our adjacency-directed mutation) at runtime. To solve this problem, our breakpoint-control method works from two aspects: 1) for each possible concurrent call pair, the method performs deterministic breakpoint control to attempt to cover it; 2) for the whole set of possible concurrent call pairs, the method performs adaptive breakpoint control to attempt to effectively cover them as many as possible.

Deterministic breakpoint control. For a possible concurrent call pair $[\text{CallCtx}_p, \text{CallCtx}_q]$, the method aims to cover this pair if the involved functions Func_P and Func_Q can be concurrently executed in related calling contexts, by deterministically controlling the breakpoints. Figure 4 shows the main procedure of deterministic breakpoint control. During program execution, suppose that Func_P is executed and its calling context matches CallCtx_p , the method enables the breakpoint of Func_P to perform time delay on the running thread, to wait another function Func_Q to be executed. During time delay, if Func_Q is executed and its calling context matches CallCtx_q , indicating the possible concurrent call pair is actually covered at runtime, the breakpoint ends delay and becomes disabled. Otherwise, when the time delay reaches the time limit, indicating the possible concurrent call pair may never be covered in the current running, the breakpoint ends delay and becomes disabled.

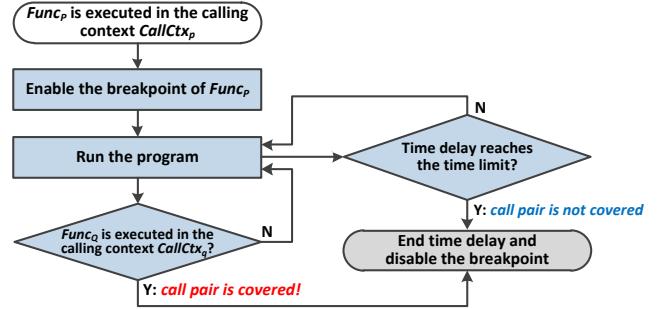


Fig. 4. Deterministic breakpoint control.

Indeed, the uncovered case can occur due to two possible reasons. First, the possible concurrent call pair is unrealistic because the involved functions are synchronized. Second, the possible concurrent call pair is indeed realistic but not actually covered in the current running, due to the non-determinism of thread scheduling. For the second reason, the method provides additional chance for the call pair, by running the program several times. The number of running times is decided when performing the adaptive breakpoint control for multiple possible concurrent call pairs, which is introduced as follow.

Adaptive breakpoint control. Our adjacency-directed generates multiple possible concurrent call pairs, and each of them should be properly handled with breakpoint control. If each of these call pairs is handled in each run, the whole running time would be too long; if all of these call pairs are handled in just one run, the possibility of covering one call pair is increased, but too much overhead may be introduced, making the program run abnormally. Thus, it is important to properly select possible concurrent call pairs in each run.

To solve this problem, the method performs adaptive breakpoint control, presented in Algorithm 2. It is analogous to the slow start of TCP congestion control [69] by exponentially increasing the number of possible concurrent call pairs.

The method takes the set of possible concurrent call pairs possible_pair_set as input. This method first initializes the number of handling call pairs in each run (select_num) to be one (line 1). Then the method enters the main loop which ends when possible_pair_set is empty or select_num is larger than the number of call pairs in possible_pair_set (line 2). In the loop, the method first randomly selects select_num call pairs from possible_pair_set , and stores them in a set try_pair_set (line 3). Then, the method runs the program and perform deterministic breakpoint control for each call pair

Algorithm 2: Adaptive Breakpoint Control

```

Input: possible_pair_set
1   select_num  $\leftarrow 1$ 
2   while possible_pair_set  $\neq \emptyset$  and
3       select_num  $\leq \text{Size}(\text{possible\_pair\_set}) do
4           try_pair_set  $\leftarrow \text{RandSelect}(\text{possible\_pair\_set}, \text{select\_num})$ 
5           RunProgramWithBreakpointControl(try_pair_set)
6           covered_pair_set  $\leftarrow \text{GetCoveredPair}()$ 
7           common_pair_set  $\leftarrow \text{try\_pair\_set} \cap \text{covered\_pair\_set}$ 
8           if common_pair_set  $\neq \emptyset$  then
9               DeletePair(possible_pair_set, common_pair_set)
10            else
11                select_num  $\leftarrow \text{select\_num} \times 2$$ 
```

stored in *try_pair_set*, to attempt to actually cover them (line 4). During program execution, the method collects covered concurrent call pairs in a set *covered_pair_set* (line 5). After program execution, the method compares *try_pair_set* and *covered_pair_set* to get their intersection set *common_pair_set*, which stores the actually covered possible concurrent call pairs in the latest running (line 6). If *common_pair_set* is not empty, the method deletes the call pairs existing in *common_pair_set* from *possible_pair_set* (line 8), indicating that these call pairs are not required to be handled any more. If *common_pair_set* is empty, it indicates that none of the selected call pairs is actually covered, and thus the method doubles *select_num* to provide more chance of covering one call pair in the next running (line 10). Finally, the method checks back the loop condition and prepare to enter the next iteration.

C. Discussion on Alternative Design Choices

When designing our fuzzing approaches, we considered and tried some alternative choices for specific techniques. When selecting the feedback granularity of concurrency fuzzing, we also considered and tried to use concurrent instruction pairs or concurrent basic-block pairs. However, performing instruction-level or basic-block-level dynamic analysis introduces too much runtime overhead in program execution, which greatly degrades the performance of overall fuzzing process. Besides, we observed that enabling context sensitivity on instruction pairs or basic-block pairs causes over-sensitive problems of fuzzing, namely too many test cases are labeled as interesting seeds. To further confirm it, in Section VI-A, we implement an alternative tool named *inst-fuzzer* that uses concurrent instruction pairs as feedback for random thread-interleaving exploration without considering the runtime contexts of instruction pairs, and experimentally compare to it. For these reasons, we finally chose to perform function-level analysis and use concurrent call pairs as program feedback in our concurrency fuzzing approach.

Moreover, when performing adaptive breakpoint control in Algorithm 2, we also considered and tried two possible strategies. First, we tried to enable all possible concurrent call pairs for deterministic breakpoint control in program execution (namely dropping line 3 and replacing *try_pair_set* with *possible_pair_set* on line 4). Second, we tried to linearly increase *select_num* if no expected concurrent pair is covered at runtime (namely using “*select_num*+” on line 10). However, these two possible strategies heavily degrade the performance of fuzzing process. For the first strategy, enabling all possible

concurrent call pairs introduces too much runtime overhead of program execution; for the second strategy, linearly increasing the number of possible concurrent call pairs reduces the runtime overhead of program execution, but largely increases the execution number of the tested program, which heavily decreases fuzzing efficiency.

D. Beneficial Effect in Data-Race Detection

Our context-sensitive and directional concurrency fuzzing approach can help to discover hard-to-find data races, from two aspects. On the one hand, with a new context-sensitive concurrency metric, namely concurrent call pair, our approach can effectively explore thread interleavings in different runtime contexts, to help find data races only triggered in specific runtime contexts. On the other hand, with a new adjacency-directed mutation and breakpoint-control method, our approach can efficiently explore infrequent thread interleavings, to help find data races only triggered in infrequent execution situations. To our knowledge, our approach is the first concurrency fuzzing approach to perform context-sensitive and directional thread-interleaving exploration, and it can help to discover many hard-to-find data races missed by existing concurrency fuzzing approaches [8], [37], [53], [76], [81] that use context-insensitive and random thread-interleaving exploration.

IV. CONZZER FRAMEWORK AND IMPLEMENTATION

Based on our context-sensitive and directional concurrency fuzzing approach, we develop a new fuzzing framework named CONZZER, to effectively explore thread interleavings and detect data races. We implement CONZZER with Clang 9.0 [13] and perform analysis on the LLVM bytecode. To be compatible with traditional input-driven fuzzing process, CONZZER is able to mutate concurrent call pairs and program inputs together. Figure 5 shows its architecture that has five parts:

- **Code analyzer.** It compiles and instruments the program code, and finally generates an executable tested program.
- **Runtime analyzer.** It executes the tested program with the generated program inputs, records runtime information of the program, and performs breakpoint control according to generated possible concurrent call pairs.
- **Call-pair generator.** It mutates covered concurrent call pairs to generate new possible concurrent call pairs, according to thread-execution information.
- **Input generator.** It exploits input-driven fuzzing process to mutate and generate new inputs, according to code coverage.
- **Race checker.** It analyzes the runtime information of thread interleavings covered by our concurrency fuzzing approach to detect data races.

A. Customized Race Checker

The race checker heavily affects race-detection accuracy, so selecting a precise race checker is important to CONZZER. We intended to use a third-party data-race checker like TSan [75], which is used by many existing fuzzing approaches [8], [76]. However, when testing real-world programs, we find that TSan report many false positives (as shown in our comparison experiments in Section VI-A and Table VI), due to neglecting special synchronization primitives such as message queue and condition variable [67]. Thus, to improve race-detection

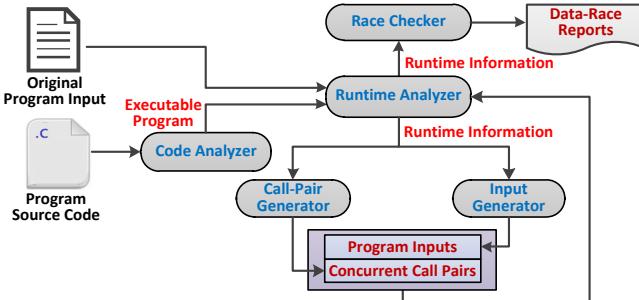


Fig. 5. Overall architecture of CONZZER.

accuracy, we implement a customized race checker based on our concurrency fuzzing approach, instead of using TSan.

Overall, this checker performs two steps: (S1) using dynamic lockset analysis [66] to detect possible data races during fuzzing, and (S2) performing validation of these possible data races to detect real ones after fuzzing.

(S1) During program execution, our checker maintains a lockset for each running thread, and records the runtime information about shared-variables accesses and related context information. Once our checker identifies two functions are concurrently executed at runtime, it dynamically performs lockset analysis for the memory accesses in these two functions to detect possible data races. For each possible data race, our checker records its racy instructions and related concurrency call pairs identified by our concurrency fuzzing approach.

(S2) For each reported possible data race, our checker injects breakpoints at its racy instructions and executes the program again. During program execution, our checker maintains the calling context of each thread, and dynamically controls the breakpoints to attempt to concurrently execute racy instructions accessing to the same variable with the recorded concurrency call pairs. If the attempt succeeds, this possible data race is identified to be real, as it is actually triggered.

The primary advantage of our checker is no false positive, because all the reported data race can be actually triggered in the runtime validation. But it can introduce false negatives for two main reasons. First, the online lockset analysis only detects possible data races in functions that are actually concurrently-executed. If two functions containing real data races are not concurrently-executed in testing, it will miss these data races. To reduce such false negatives, our concurrency fuzzing approach can efficiently cover different thread interleavings. Second, due to non-determinism of thread interleaving, the runtime validation may fail to trigger some real data races during execution. To reduce such false negatives, we suggest to perform the runtime validation multiple times.

Note that besides our customized race checker, other third-party data-race checkers can be also used in CONZZER. For example in Section VI-A, we have used TSan in CONZZER to test user-level applications, without any change of TSan and our fuzzing approach.

B. Phases of CONZZER

P1: Code instrumentation. In this phase, the code analyzer identifies and instruments three kinds of places in the program's LLVM bytecode files:

- *Calls to lock-acquiring/-release functions.* They are instrumented to maintain the locksets of memory accesses for each running thread.
- *Function definitions and calls.* The entry and exit of each function and each function call are instrumented, to collect concurrent call pairs and calling-context information.
- *Memory accesses to possible shared variables.* They are instrumented by our customized race checker for runtime monitoring and data-race detection. For identifying these accesses before fuzzing, we implement a static analysis referring to [11], to automatically analyze program code.

Through compiling the instrumented LLVM bytecode files, CONZZER generates the executable tested program for runtime fuzzing in the next phase.

P2: Runtime fuzzing. In this phase, through the instrumented code, CONZZER performs our context-sensitive and directional concurrency fuzzing approach to effectively explore thread interleavings by identifying and covering concurrent call pairs. During fuzzing, CONZZER uses dynamic lockset analysis to detect possible data races. After fuzzing, our customized race checker performs runtime validation of all possible data races, and finally reports real ones. The fuzzing process and data-race detection are automated.

Note that though our concurrency fuzzing explores concurrent call pairs not concurrent instruction pairs, the race detection of CONZZER is performed at instruction level for high accuracy. On one hand, if two instructions are concurrently executed, their caller functions should be concurrently executed. Thus, identifying concurrent call pairs is important to identifying concurrent instruction pairs. On the other hand, our customized race checker performs dynamic lockset analysis of each instruction in the identified concurrent call pairs. Besides, CONZZER uses common lock-acquiring/-release functions (like `pthread_mutex_lock`) described in POSIX thread libraries and Linux official documents. Missing some customized lock-acquiring/-release functions would only cause false positives in dynamic lockset analysis, which are however dropped in runtime validation of our customized race checker.

C. Compatibility with Input-Driven Fuzzing

CONZZER is able to collaborate with traditional input-driven fuzzing, because concurrent call pairs explored by our concurrency fuzzing approach are orthogonal to program inputs from files and system calls. Specifically, for CONZZER, a test case consists of two parts, namely covered concurrent call pairs and program inputs. In seed identification, CONZZER considers a test case as an interesting seed when new concurrent call pairs or new branches are covered at runtime. In seed selection, CONZZER gives more priority to the seeds that cover more new concurrent call pairs, to preferentially explore new thread interleavings. In seed mutation, CONZZER mutates and generates concurrent call pairs and program inputs together. At runtime, CONZZER collects and tries to cover concurrent call pairs via concurrency fuzzing, and collects code coverage via input-driven fuzzing. We have implemented input-driven fuzzing process in CONZZER, by referring to AFL [1] and Syzkaller [70]. We believe that recent input-driven fuzzing approaches (such as AFLFast [4] and Angora [9]) can also collaborate with CONZZER to improve fuzzing performance.

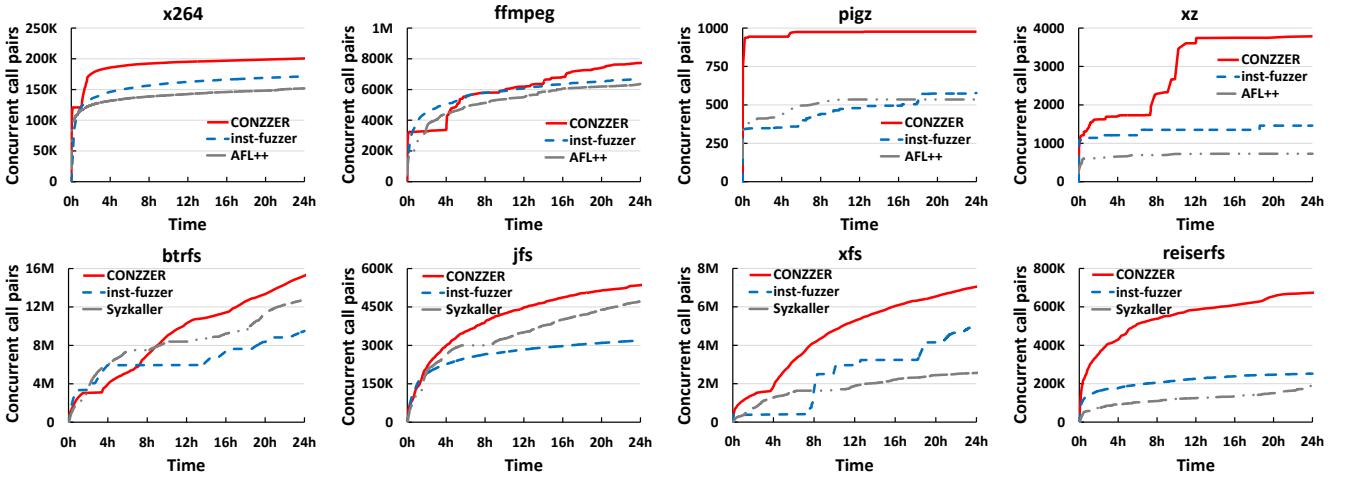


Fig. 10. Growth of covered concurrent call pairs in comparison.

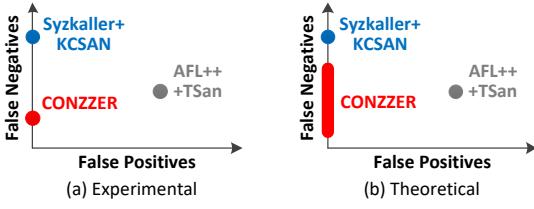


Fig. 11. Precision of data-race detection in comparison.

random delay in the watchpoint of each monitored instruction, but catching two concurrently-executed instructions that have race conditions is still difficult in this way. By contrast, our customized checker extends the detection scope to all the memory accesses in concurrently-executed functions, which can find many data races missed by KCSAN. Moreover, our concurrency fuzzing approach covers more thread interleavings than Syzkaller, which can help find more data races.

Indeed, TSan just reports possible data races using lockset analysis and happens-before relation, without validating these data races at runtime; while our customized race checker performs runtime validation of possible data races, and thus it may miss some real data races when they are not triggered in runtime validation, due to the non-determinism of thread scheduling. As a result, in some cases, TSan is able to find real data races missed by our customized checker. For this reason, and considering that our concurrency fuzzing approach can explore more thread interleavings than AFL++, it is difficult to determine whether CONZZER have less or more false negatives than AFL++ with TSan in theory, as shown in Figure 11(b).

B. Concurrency Fuzzing Approaches

Razzer [37]. It first uses static analysis to identify possible racy instructions, and then injects code breakpoints at possible racy instructions to try to trigger related race bugs at runtime. CONZZER has three significant differences from Razzer:

1) The static analysis of Razzer is not accurate enough and fails to identify real racy instructions involving complex cases (such as alias relationships and function-pointer calls), causing its dynamic analysis to miss many real data races. By contrast, CONZZER uses a context-sensitive and directional concurrency fuzzing approach to effectively explore infrequent thread interleavings, helping discover hard-to-find data races.

2) Razzer finds only memory bugs and warnings caused by race conditions, and it does not use any race checker. However, many harmful data races never cause memory bugs. The harmful data race shown in Figure 7 is such an example, and it can cause malfunction not memory bug. By contrast, CONZZER focuses on detecting data races, without checking whether they can cause memory bugs or not.

3) Razzer can test only OS kernels with a modified virtual machine. By contrast, CONZZER can test both kernel-level programs and user-level applications on a physical machine, which is more convenient to deploy.

We successfully run Razzer with its source code [63], to test 4 kernel-level filesystems in Table I. Each filesystem is tested for 24 hours. The static analysis of Razzer identifies 1503 pairs of possible racy instructions in the four filesystems, but its dynamic analysis finds no race bug in the four filesystems with these pairs. By contrast, CONZZER finds 59 data races (including 2 data races triggering null-pointer dereferences) in these four filesystems.

KRACE [81]. It exploits a new concurrency-coverage metric, alias instruction pair, to describe thread interleavings. This metric is identical to concurrent call pair that used by inst-fuzzer in Section VI-A. It also injects random delays to cover different thread interleavings. To cover more concurrency code, it uses an evolution algorithm to mutate and generate multi-threaded syscall sequences as inputs for concurrency fuzzing. We find a KRACE repository in the Github [47]. Unfortunately, after much manual effort, we were still not able to run it due to various runtime errors and the lack of its documentation. We also compare CONZZER to KRACE in methodology:

1) The alias instruction pair used by KRACE is a *context-insensitive* metric, namely it only describes the locations of two concurrently-executed instructions without considering their execution contexts. By contrast, CONZZER uses a new context-sensitive metric, concurrent call pair, which considers both the locations and calling contexts of two concurrently-executed functions. Thus, CONZZER is more effective in finding data races that occur only in specific runtime contexts.

2) The random delay injection used by KRACE is inefficient in thread-interleaving exploration, namely it frequently repeats already covered thread interleavings and misses many

infrequent thread interleavings. By contrast, CONZZER uses a directional fuzzing approach to infer and cover new possible thread interleavings, which can more efficiently cover infrequent thread interleavings. The results in Table IV show that this fuzzing approach indeed covers many infrequent thread interleavings missed by random delay injection, which can help discover hard-to-find data races.

According to the KRACE paper, three filesystems (*btrfs*, *ext4* and *vfs*) in Linux 5.4-rc5 are tested, and the found data races are listed in the paper. Accordingly, we select *btrfs* and *ext4* in this kernel version and use CONZZER to test them. We also intended to test *vfs* with CONZZER, but at present CONZZER can only test filesystems running as loadable kernel modules and *vfs* cannot run in this mode. The KRACE paper presents that it finds 15 real data races in the two filesystems (11 in *btrfs* and 4 in *ext4*). In our evaluation, CONZZER finds 39 real data races in the two filesystems (34 in *btrfs* and 5 in *ext4*). By comparing to the race reports in the KRACE paper, we find that: (1) CONZZER and KRACE both finds 4 identical data races; (2) CONZZER finds 35 data races missed by KRACE, because our context-sensitive and directional concurrency fuzzing approach actually covers the related infrequent thread interleavings in specific runtime contexts; (3) KRACE finds 11 data races missed by CONZZER, as its evolution algorithm optimizes syscall-sequence generation and covers more concurrency code than Syzkaller-like input-driven fuzzing used by CONZZER. We believe that by using KRACE's evolution algorithm to generate syscall sequences, CONZZER can also find these missed data races.

MUZZ [8]. It uses thread-aware instrumentation to collect the changes of code coverage caused by thread interleavings, in order to improve seed selection of concurrency fuzzing. Moreover, it randomly adjusts thread priorities of the tested program at runtime, to try to cover different thread interleavings during fuzzing. Because MUZZ is not open-source, we focus on making a methodological comparison. CONZZER has two significant differences from MUZZ:

- 1) Although being enhanced with the changes caused by thread interleavings, code coverage still mainly describes sequential-execution situations, and thus it is limited in describing concurrent-execution situations and guiding concurrency fuzzing. To thoroughly replace code coverage, CONZZER exploits a new concurrency-coverage metric, concurrent call pair, which can effectively describe thread interleavings with different calling contexts.
- 2) Similar to random delay injection, randomly adjusting thread priorities is also inefficient in covering infrequent thread interleavings. To solve this problem, CONZZER uses a directional fuzzing approach to perform more effective and efficient thread-interleaving exploration.

VII. DISCUSSION

Feasibility of found data races. To affect thread scheduling of the program, CONZZER injects and controls breakpoints containing time delays during fuzzing. These time delays just slightly increase the running time of related threads, and have no effect on synchronization and concurrency logic. Moreover, our customized race checker guarantees that all found races are triggerable with specific inputs and thread interleavings.

Besides, the program is actually tested on a physical machine instead of a tuned virtual machine. For these reasons, the data races found by CONZZER are all realistic and feasible.

Identifying harmful data races. In the current evaluation, we manually check the found data races to estimate their harmfulness. In fact, some existing approaches [43], [59], [85] can automatically classify data races by analyzing the runtime information about concurrent execution or statically analyzing source code. Thus, these approaches can help CONZZER to reduce the manual work of identifying harmful data races.

Supporting other concurrency checkers. CONZZER is able to conveniently support other concurrency checkers (such as atomicity-violation checkers and other data-race checkers) to detect hard-to-find concurrency problems, by covering infrequent thread interleavings. For example in Section VI-A, we have used TSan in CONZZER to test user-level applications, without any change of TSan and our concurrency fuzzing approach. With CONZZER, TSan finds many data races missed by using AFL++ in our experiments.

Limitations and future works. First, in the current evaluation, CONZZER still misses much error handling code and thus cannot find related data races. We plan to introduce fault injection [3], [40] in CONZZER to strengthen data-race detection in error handling code. Second, CONZZER does not specially handle atomic instructions, which are mostly used in low-level libraries and kernel core parts. We plan to statically identify all atomic instructions in LLVM bytecode and neglect these instructions in dynamic lockset analysis. Third, as shown in Section VI-A, CONZZER has a lower fuzzing throughput than AFL++, which limits testing efficiency. Thus, we plan to improve CONZZER fuzzing performance, by optimizing code instrumentation to reduce runtime overhead [33], [87] and using parallel systems to speed up fuzzing [49], [52]. Finally, besides data races, we plan to extend CONZZER to detect other concurrency problems, such as atomicity violations.

VIII. RELATED WORK

A. Coverage-Guided Fuzzing

Coverage-guided fuzzing evolutionally mutates and generates program inputs to increase testing coverage, guided by the code-coverage metric. Compared to traditional mutation testing [38], [39], coverage-guided fuzzing can more efficiently generate useful program inputs.

Code-coverage-guide fuzzing. AFL [1] and Syzkaller [70] are two well-known scalable coverage-guided fuzzing frameworks that integrate many practical mutation strategies and engineering techniques. AFL tests user-level applications through program inputs, while Syzkaller tests kernel-level programs through system calls. These two frameworks have found thousands of bugs and vulnerabilities in common applications and OS kernels. Based on AFL and Syzkaller, many approaches [4], [15], [30], [45], [50], [60], [61], [72], [79], [80], [82] have been proposed to further improve fuzzing effectiveness for code coverage and bug detection.

Concurrency fuzzing. To fill the gaps between coverage-guided fuzzing and concurrent program testing, several recent concurrency fuzzing approaches [8], [37], [53], [76], [81] have

been proposed. As for fuzzing feedback, except KRACE [81] using a concurrency-coverage metric, the other approaches tune traditional code coverage. In fact, these approaches are still limited in finding concurrency issues like data races, due to lacking effective concurrency-coverage metric and using random thread-interleaving exploration. To solve this problem, CONZZER uses a new context-sensitive concurrency-coverage metric and a new directional concurrency fuzzing approach, to discover hard-to-find data races that occur only in specific runtime contexts and infrequent thread interleavings.

B. Data-Race Detection

Static analysis. Many approaches [22], [42], [77], [78] are based on flow-sensitive static lockset analysis. RacerX [22] uses inter-procedural and context-sensitive analysis to maintain and check locksets of memory accesses in each code path. To speed up static analysis, it creates a summary cache for each analyzed function to store the information about inside memory accesses and related locksets. Some approaches [25], [65] are based on flow-insensitive type-based analysis. Flanagan et al. [25] propose a type-based approach that uses formal type annotations to capture synchronization patterns from program code, and detects data races based on these patterns.

Static analysis approaches can achieve high coverage of data-race detection without running the tested program. But they suffer from overwhelming false positives, without exact runtime information about concurrent memory accesses.

Dynamic analysis. Some approaches [10], [19], [21], [66] are based on lockset analysis. They maintain a lockset for each running thread, and compute the intersection between the locksets of shared-variable accesses to detect data races. But due to neglecting concurrent contexts of memory accesses and non-lock synchronization primitives, these approaches often have many false positives. To reduce false positives, some approaches [27], [51], [56], [62], [84] perform happens-before-relation inference. They track memory accesses and synchronization events to infer happens-before relation between these events. But they have many false negatives and introduce much runtime overhead caused by tracking memory accesses and inferring happens-before relation. Some approaches [5], [23] are based on sampling, and they monitor memory accesses at intervals to reduce runtime overhead. But they may miss many real races when the sampling frequency is low and have much runtime overhead when the sampling frequency is high.

Dynamic analysis approaches need to cover different thread interleavings for race detection. For this purpose, they often perform random delays to cover more thread interleavings, but this method frequently repeats already covered thread interleavings and miss many infrequent ones [12], [74]. To solve this problem, CONZZER uses a new context-sensitive and directional concurrency fuzzing approach to efficiently explore thread interleavings, helping discover hard-to-find data races.

C. Thread-Interleaving Exploration

To find more concurrency problems during runtime testing, some approaches [6], [28], [29], [31], [58] use randomized thread scheduling to explore thread interleavings. PCT [6] is an effective priority-based and randomized scheduler that can

increase the probability of finding concurrency bugs when the program is repeatedly executed. When a thread is created, PCT assigns it a random scheduling priority, and dynamically changes this priority at some randomly chosen steps.

Similar to random delay injection, the efficiency of thread-interleaving exploration for these approaches is also limited, as they frequently repeat already covered thread interleavings and miss many infrequent ones [12], [74]. To solve this problem, CONZZER uses a new context-sensitive and directional concurrency fuzzing approach to deterministically infer and cover new possible thread interleavings, according to already covered thread interleavings.

IX. CONCLUSION

In this paper, we design CONZZER, a novel and practical concurrency fuzzing framework for data-race detection. It uses a new context-sensitive and directional concurrency fuzzing approach to perform thread-interleaving exploration, with a new concurrency-coverage metric, concurrent call pair, as program feedback. This approach can effectively cover infrequent thread interleavings with concrete context information, to help discover hard-to-find data races. We have evaluated CONZZER on 8 user-level applications and 4 kernel-level filesystems, and found 95 real data races. CONZZER is available at <https://oslabs.cs.tsinghua.edu.cn/CONZZER/>.

ACKNOWLEDGMENT

This work was mainly supported by the National Natural Science Foundation of China under Project 62002195. Kangjie Lu was supported in part by the NSF awards CNS-1931208 and CNS-2045478. Jia-Ju Bai is the corresponding author.

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Appendix II

Figure 12 shows the completed sensitivity results about the growth of covered concurrent call pairs for all the 12 tested program in Section V-D. CONZZER covers more concurrent call pairs than other alternative methods, which proves the effectiveness of CONZZER in thread-interleaving exploration.

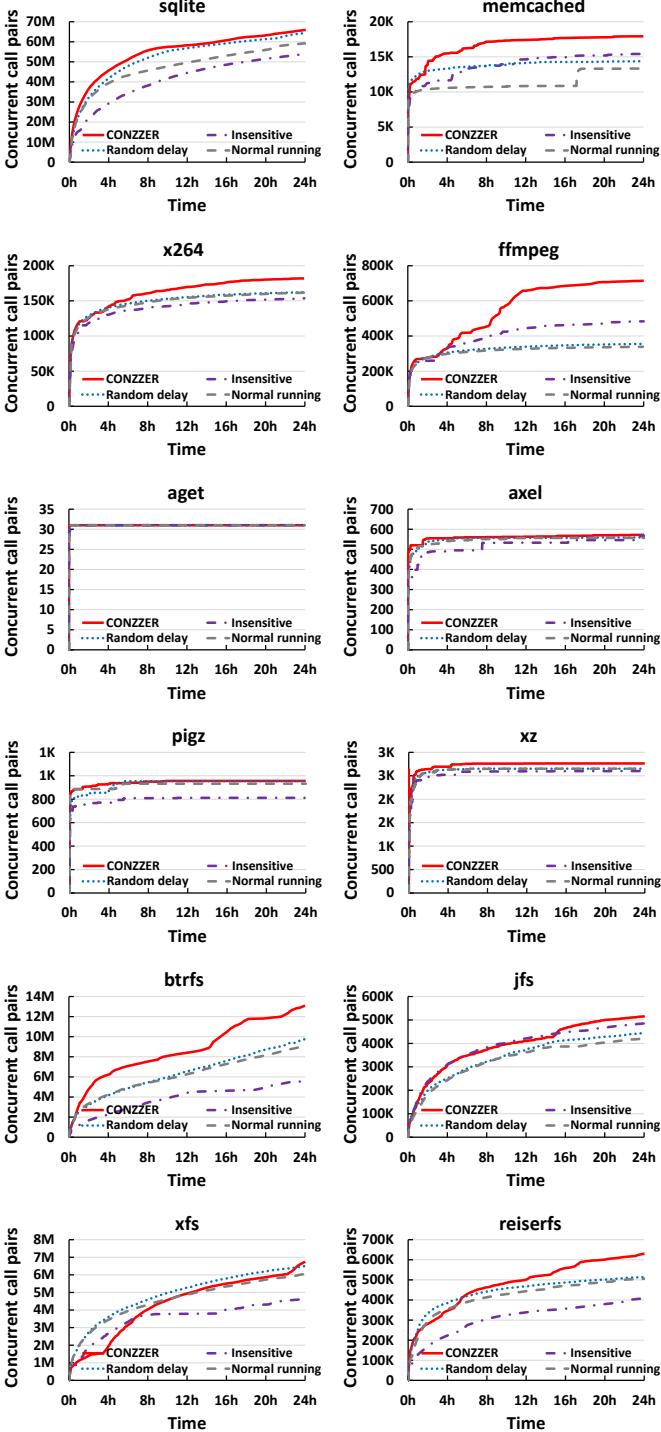


Fig. 12. Complete results about the growth of concurrent call pairs in sensitivity analysis.

Figure 13 shows the completed comparison results about the growth of covered concurrent call pairs for all the 12 tested program in Section VI-A. CONZZER covers more concurrent call pairs than other fuzzing tools, which proves the effectiveness of CONZZER in thread-interleaving exploration.

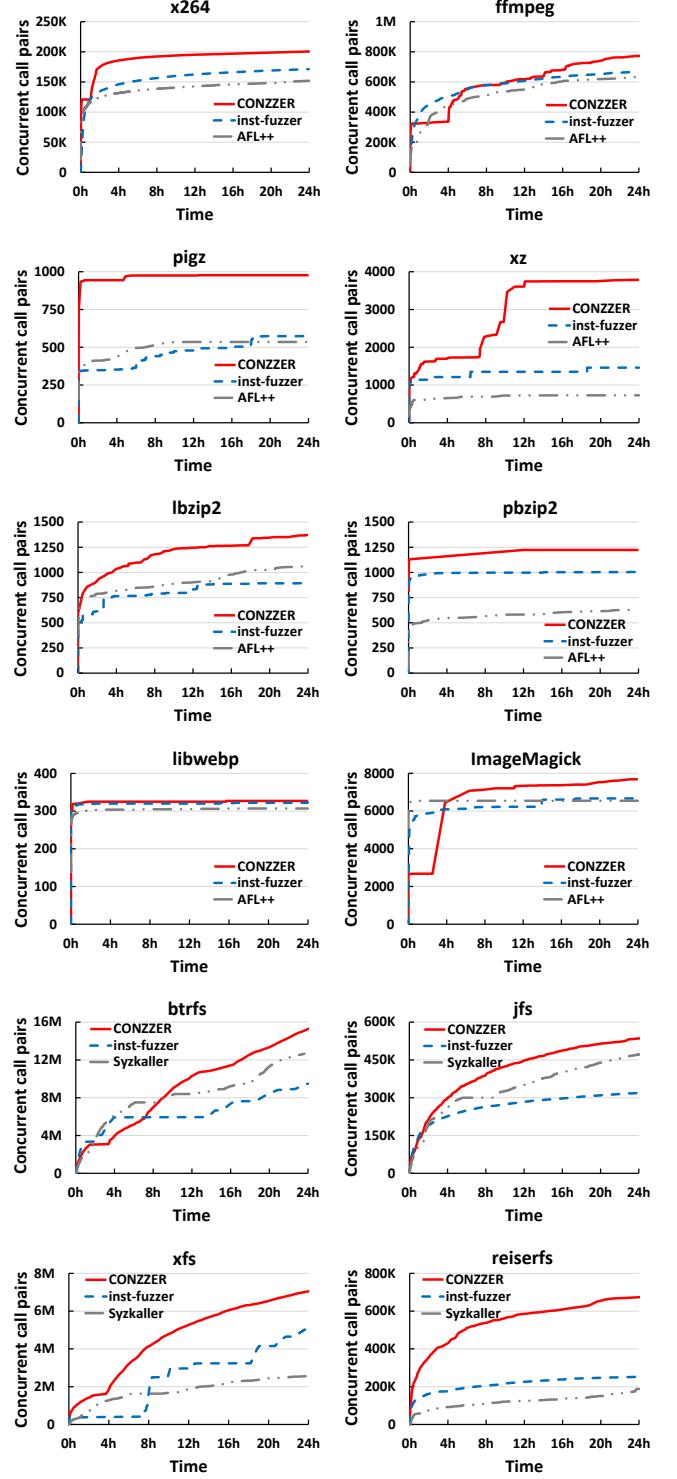


Fig. 13. Complete results about the growth of concurrent call pairs in comparison experiment.