BinCC: Scalable Function Similarity Detection in Multiple Cross-Architectural Binaries

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ABSTRACT With the undeniable increase in popularity of open source software, also the availability and reuse of source code have increased. While the detection of code clones helps tracking reuse and evolution while dealing with source code, little prior work exists that can be used in binary code. This is complicated by the increased difficulty posed by the compilation transformations.

In this paper, we present a CFG refinement useful to find function-level clones in a fast and scalable way by comparing the high-level structure of multiple disassembled binaries altogether. We are capable of determining if functions belonging to other programs have been copied or reused, even when the processor architecture is different. Specifically, our algorithm consists in the extraction of the various functions flows and the reconstruction of a higher level structure, leveraging architectural differences and allowing efficient comparison in linear time with structural hashing.

We implemented our idea in a tool called BinCC, and analyzed 24 million functions spanning different architectures and optimization levels. Results show that our approach can achieve precision between 91% and 99% within the same architecture and 75% in detecting clones among different architectures, and can also detect the presence of specific library functions inside an executable. Our approach can reach comparable precision of current state-of-the-art learning approaches while being three order of magnitude faster.

INDEX TERMS Code clones, static code analysis, reverse engineering, compilers.

I. INTRODUCTION

Free software has grown in popularity in recent years, and with that also the adoption of this kind of software by companies and its integration inside closed source projects. This popularity is mainly driven by the ease of customization and flexibility rather than economic reasons [1]: code is usually modified, adapted or simply reused and then re-released with a compatible license. With a higher availability of code, another common practice has become copy-pasting and reusing source code in form of small code snippets from online discussion platforms such as Stack Overflow. Aside from the potential license violation, reused code snippets have been proven to be usually harmful [2] or with security flaws that in the original repository have long been patched [3]. Although code cloning has been successful at determining copied function reuse both for legal implications [4] and plagiarism detection [5], its main scope is usually code evolution and vulnerability propagation [6], [7], [8].

Nonetheless, in recent years, several clone detection tools targeting lower-than-source-code have been developed. These are mainly driven by a normalization step performed by the compiler, rather than the lack of availability of the source code. These works have been targeting Java Bytecode [9], [10] or LLVM IR [11].

Different motivations can be found when working exclusively with binary code: we already cited the license violation in closed source software [12], [13]. Additional scenarios may involve detecting the presence of a vulnerable function in proprietary software [14], [15], analyzing the evolution of
closed source software or the evolution of compiler transformations, and even aiding the disassembly when a known function snippet is detected.

While existing works in the field are mainly focused in malware detection, the main motivation for our work is software evolution and propagation in binary files, even in case of security-related issues (e.g. bug propagation in release of proprietary software). For this reason, the focus points of our research are the ability to analyze multiple executables at the same time and detect the propagation of a given function, the ability to perform such analysis in a reasonable time for any amount of given executables, and the ability to work amongst different architectures, even lesser known.

In order to address these problems, our approach is based on the idea of generating a common structure between the compiled code in different architectures in order to leverage compilation differences, similar to how decompilation helps normalize source code differences [16]. In particular, starting from a Control Flow Graph (CFG), we generate a higher level structure using structural analysis. This structure allows efficient comparison in linear time, as opposed to the exponential time required by a subgraph comparison. This structure has the additional property of normalizing the various architectural differences, allowing cross-architectural comparison. Thanks to its linear time scalability, our approach can be used to efficiently analyze multiple binaries altogether, outlining the evolution and propagation of code among huge codebases such as the LLVM project or the GNU toolchain, while existing works are usually limited to a pairwise comparison [17], [18].

The main novelty of our work is the following:

- A novel structural analysis designed specifically for clone detection.
- Unlike previous work in decompilation (e.g. [19]), our analysis can not emit go to and thus must sacrifice some correctness. For this reason, we had to develop a novel analysis with different detection rules for converting a CFG. This new analysis is described in detail in Section III-D.
- A novel comparison method to efficiently detect structural clones among multiple binaries.
- Comparing two CFGs requires an exponential algorithm [20] and even the average function length of 40 nodes is intractable. While previous works have based their comparisons on statistical properties [14] or dominator trees [21] we based our comparison on tree hashing, allowed by our structural analysis.
- An evaluation of clone detection across different CPU architectures.

Previous work using structural or semantic analysis always targeted trivial binaries such as Java Bytecode [16], [21] or has been limited to the same architecture [22]. Whereas cross-architecture clones have been researched with deep learning methods, we propose a structural analysis algorithm that works in binary code and does not require a training step.

The paper is structured as follows: Section II presents the State of the Art in code cloning for binaries and binary analysis. Section III explains in detail how the entire analysis is done, including the structural analysis algorithm and the final comparison. Section IV evaluates our approach across varying architectures. Section V describes some limitations and threats to the validity of our work, and finally Section VI closes the paper.

II. RELATED WORKS

Given the intrinsic difficulty at analyzing binary files and the high amount of information lost during the compilation process, the literature in clone detection dealing with compiled executables is more scarce compared to the one dealing with plain source code. The most complete and, to our knowledge, only existing analysis aimed at finding clones in binary files is the one performed by Sæbjørnsen et al. which uses a semantic approach based on vectors containing the instruction sequences [22]. This analysis is itself an extension of the one developed by A. Schulman [23].

In the matter of license violation, on the other hand, Hemel et al. performed three different types of analyses based on string, data compression and binary deltas analysis [24]. Both these approaches have been tested only on executables or libraries within the same architecture, although the string analysis of Hemel et al. could technically be applied also to different architectures.

The structural reconstruction, instead, has been studied in-depth by Engel et al. [25] and later refined by Brumley et al. [26] and Yakdan et al. [27]. The latter two, however, studied an approach more akin to decompilation and semantic preservation while we care more about having the same reconstruction in different binaries or architectures rather than a correct reconstruction.

In the software security field, several tools are available to check for similarities between binaries. In particular, BinDiff [17] and DarunGrim [18] present a structural analysis that use CFG isomorphism and basic block matching. BinSlayer [28] and discoverE [14] improve the existing work by providing faster CFG matching. However, these studies are aimed at finding bugs by analyzing CFG properties, while we refined even further the analysis in order to transform the CFG into a tree and have linear time comparison. This allows us to process thousands of functions in seconds. In contrast to structural analysis, some tools present a detection based on semantic properties. It is the case of BinHunt [29] using symbolic execution and BinJuice [30] that extracts the semantic representation of basic blocks. While all these works are essentially single-architecture, Pewny et al. provided a cross-architectural one by using a semantic representation of basic blocks [15], while, in contrast, our tool uses structural similarity. In addition to these tools, BinSim [31] can support obfuscated binaries.

In recent years, with the prevalence of IoT devices, cross-architectural analysis of binary files has been the scope of work such as BinGo [32] and CACompare [33] that use the
signature of a function to perform comparisons. Hu et al., in particular, investigates also the impact of different compilers and optimization levels [34].

Recent works have also started introducing Deep Learning approaches in order to detect similarities between binaries [35], [36]. While some of these were focused just on graph properties [37], recent approaches are more similar to Natural Language Processing [38], [39], [40], [41].

The main difference between our approach and Machine Learning-based ones is the lack of requirement of a training step: building and retrieving a training dataset is already challenging for some dominant CPU architectures [38], [41], and it may be almost impossible in case of obscure or proprietary architectures. Our approach implementation, instead, currently supports 20 architectures, and additional ones can be added by writing a few lines of code, provided a disassembler is available. An additional downside of the learning based approaches is the runtime: several works such as InnerEye [38] and DeepBinDiff [39] can reach high precision, but require an enormous amount of time to run, that usually hampers scalability. In our approach, instead, the runtime is completely dominated by the disassembly time and is orders of magnitude faster than the aforementioned approaches.

III. APPROACH

This section presents our approach for detecting function clones in a binary file. Our idea consist of generating a tree-like representation of each function, starting from a CFG, that may represent the original source code structure. Then, efficiently checking for clones in the subtrees of these representations. This come from the idea that, even for different architectures, the duplicated code once compiled should retain the same structure in both architectures.

However, directly comparing a graph as the CFG is not trivial, as it is known to be a NP-complete problem [20]. Comparing two CFGs with an exponential algorithm, for every pair of function we want to process, is thus unfeasible.

For this reason we use a structural analysis step, to reduce a CFG into a tree, more suitable for analysis. This step is akin to a decompilation, but it differs from it in the sense that semantic correctness is secondary as opposed to reconstruction completeness, allowing us to remove CFG edges.

A. OVERVIEW

The overview of our approach can be seen in Figure 1. In this figure, several binaries labeled as Binary 1, Binary 2 and Binary 3 are analyzed in order to find cloned functions between them. We can see from the figure that our approach requires one or more binary files as input, and produces a single output: this output contains clone classes (clone sets) [42] which indicate cloned functions. Each clone class represents functions implementing the same behavior: two or more functions are reported as belonging to a clone class along with their name, original binary name and cloned basic blocks. Our approach compares all functions of all binaries together and is based on three main steps namely Structural Analysis, Comparison and Semantic Analysis.

Structural Analysis is used to retrieve a structural representation of every binary function. With those representations, the Comparison step generates the clone classes, and the Semantic Analysis further filters those clone classes from false positives. A detailed description of the various steps in Figure 1 is the following:

Disasm

In this step, the original binary code is disassembled and, for every function, a list of tuples \(<offset, mnemonic, arguments>\) is obtained. This step is performed once for every binary.

CFG

In this step, the CFG of each function is retrieved, starting from the list of statements. Additionally, these CFGs are refined and slightly modified as explained in Section III-C. This step is performed for every function retrieved during disassembly.

Reconstruction

This step is the core of our approach: here each CFG is transformed into a representation of the original function using nested high-level structures (e.g. If, While, Do-While). These nested structures can represent the function in the form of a tree thus allowing constant time comparison, unlike a CFG. Our analysis, however, does not completely preserve the program structure. In fact, our approach modifies the CFG in case the analyzed function does not have structured control flow (e.g. loops with break and continue statements). For this reason, the algorithm is explained in detail in Section III-D along with reconstruction rules for each CFG pattern.

Comparison

The results of the reconstruction are compared altogether and if any duplication or match is found it is reported as output. Comparison is done using an hash-based approach, by searching for hash collisions while linearly processing all functions. Further details on this step are explained in Section III-E.

Semantic Analysis

Finally, in this step potential clones reported by the comparison step are checked for semantic consistency. A different approach is used based on whether the potential clones belong to the same
architecture or not. This step is described in detail in Section III-F.

B. DISASSEMBLY

The first step of the entire analysis is the disassembly, requiring as input the original binary file, either as executable, library, or object code. Given that a binary file is just a collection of bytes interpretable as machine code, data, or comments, the purpose of this step is taking as input the aforementioned binary file and providing as output assembly instructions required by the subsequent steps. An assembly instruction is a pair \(\text{<mnemonic, arguments>}\) where \text{mnemonic} represents a particular instruction to be executed by a CPU, taken from a set of instructions composing the CPU Instruction Set Architecture (ISA), and \text{arguments} is a sequence of elements passed as arguments to the \text{mnemonic}. Additionally, ensuing steps of our analysis require assigning a unique \text{offset} to each instruction. This \text{offset} is generally calculated as the number of bytes from the beginning of the file until the instruction, and must be coherent with the jump targets: if an instruction performs a jump to another one, the argument of the jump must be the offset of the target instruction.

We can thus say that, for the purpose of our analysis, an assembly instruction is a tuple \(<\text{offset, mnemonic, arguments}>\), and an example of this can be seen in the following code:

```plaintext
0x601 cmp dword [var_4h], 0
0x605 je 0x60e
0x607 mov eax, 0
0x60c jmp 0x613
0x60e mov eax, 1
0x613 pop rbp
0x614 ret
```

In this code, each line represents an instruction. The first number of each line is the offset, followed by a space and the mnemonic. Everything else on each line are the mnemonic arguments.

The expected output from this step is a list of function names, and for each function a list of assembly instructions. In our implementation we relied on external tools in order to perform the disassembly, as such, in order to keep generality, subsequent steps in our analysis assumes this list of assembly statements as plain strings in Intel syntax, as presented in the previous example.

C. CONTROL FLOW GRAPH

The purpose of this step is the transformation of the list of instructions obtained in the Disasm step into a suitable representation in form of a CFG, required for the structural analysis. This step is performed for every function obtained in the disassembly step. A CFG is a directed graph \(G = (V, E)\) where every node \(v_i \in V\) represents a basic block and every edge \(e_{i,j} = (v_i, v_j) \in E \land v_i, v_j \in V^2\) represents a possible movement from the basic block \(v_i\) to the basic block \(v_j\). This kind of graph is effective at presenting the flow of the program and is the starting point for our structural analysis.

Given the relatively easy task of transforming a list of statements into a CFG, we are not going to present its implementation here. The only requirement is to have the list of conditional and unconditional mnemonics for each ISA.

Additionally, after retrieving the CFG, a refinement step is performed, consisting of the following actions:

- **Single exit**
  - If multiple exits for the analyzed function are found, a new single exit is created. This step is required to preserve consistency with some patterns defined later in Section III-D.

- **Dead nodes removal**
  - Dead basic blocks, unreachable from the root, are removed from the resulting CFG. These basic blocks are resulting from indirect jumps, i.e., jumps to a dynamically known address which are unsolvable at static time and thus ignored during the CFG reconstruction [43, 44].

D. RECONSTRUCTION

The refined CFG with a single entry and a single exit obtained in the previous step is refined in this step. In particular, we aim at iteratively reducing CFG portions into high-level structures until a single node is left. This node will represent the entire function, and recursively contains the various structures composing it. This representation two major advantages over a plain CFG:

- Loops are removed, and the resulting output is a rooted tree. The resulting tree nodes are labeled by type, allowing faster comparison through hashing. Comparing a CFG instead requires exponential time [20].
- Minor differences between the x86_64 and aarch64 CFGs are leveraged.

![Figure 2](image-url)

**Figure 2.** Example of the Reconstruction step. The nodes 0, 1 and 2 of the CFG are removed and replaced with a node labeled as If-else structure. The new If-else structure and node 3 can then be replaced with a Sequence structure. When only one node is left the algorithm terminates.

An example of the reconstruction can be seen in Figure 2, with its interpretation in tree form on Figure 3. On the left of the Figure, the basic blocks 0, 1 and 2 forming an If-else
structure have been reduced. Then, in the center, the newly created If-else structure and basic block 3 are reduced into a Sequence, thus terminating the algorithm, as shown on the right. This analysis reduces CFG portions to the following structural types: Sequence, Self-loop, If-then, If-else, While, Do-While, Switch, and Optimized If.

Algorithm 1 Reconstruction Main Loop

inputs: A CFG $G = (V, E)$  
output: A single node representing the nested structures. Nil if the procedure failed

Function Reconstruction($G$):

```
sccs ← FindStronglyConnectedComponent($G$)  
foreach scc ∈ sccs do
  TransformNaturalLoop($G$, scc)  
while $|G| > 1$ do
  list ← postorderDFS($G$) while list ≠ ∅ do
    node ← pop(list)  
    $R ← reduce(node)$ if $\lvert R\rvert > 0$ then
      Let $r$ be a single node containing $R$ $G ← (G \setminus R) \cup r$  
      foreach $(v_i, v_j) \in E \land v_j \notin R$ do
        if $v_j \in R$ then
          $v_j ← r$
        break
      if not modified $G$ then
        return nil
  return $G$
```

Algorithm 1 presents the reconstruction procedure. In the Reconstruction function, the first three lines are used to modify Natural Loops, loops with more than one exit, and are explained in Section III-D6. In the remaining part, we can see that the outer while is the iterative step, running until the graph is composed solely by one node. For each iterative step, a post-order depth-first visit is performed. The reason for the post-order visit lies in the fact that while processing a node, every possible descendant of it has already been given the possibility to be reduced beforehand. Then, the inner while attempts to reduce each node of the post-order visit to a known structure by calling the reduce function on each node.

The reduce function takes a node as input and returns a set, called $R$, containing the original nodes composing a particular structure. Reductions are tried in the following order: Self loop, While and Do-While altogether, If-then, If-else, Sequence, Switch and Optimized If. If the reduction succeeds, firstly every node composing the region is removed from the CFG and a new structural node named $r$ is added. Then, for each edge $e_{i,j} = (v_i, v_j)$ where $v_j$ does not belong to the reduced region, the target $v_j$ mapping to a component of the region itself is remapped to $r$. The edge becomes $e = (v_j, r)$, effectively replacing a region with a single node.

Lastly, the inner loop is terminated, given that the post-order visit is now invalidated having the CFG been modified. The outer while generates a new post order visit and the process is repeated until a single node is left. If, instead, the list is processed in its entirety without any modification to the CFG the procedure terminates with a failure state. We now explain how every region has been reduced, excluding self-loops which are trivial.

1) IF-THEN RESOLUTION

We can see in Figure 4, on the left, the representation of a minimal If-then structure as it would appear on a CFG. Solid lines represent the nodes that will be reduced. Note that in case an If-then structure has more complex logic in the then node, this has already been reduced in previous iterations. In order to reduce a node as an If-then region, the following conditions must hold:

1) The current node has two children, the then node and the next node.
2) The then node is a node with a single predecessor and a single successor.
3) The successor of the then node is the next node.

If all these conditions are satisfied, the current node and the then node are transformed into an If-then region, with the next node as its successor. In Figure 4, on the right, we can instead see the CFG for an If-then with a short-circuit evaluation. Recall that short-circuit evaluation is the semantic

![Figure 3. The CFG of Figure 2 represented as tree after reconstruction.](image)

![Figure 4. If-then and Short circuit If-then. A sequence of nodes composed of conditional jumps with the target being fixed (2) can be considered as if-then structure.](image)
of a boolean expression where some arguments are not evaluated if the truth value of the expression has already been established, represented in this example by the edge $e_{0,3}$. This kind of If-then is automatically resolved iteratively using the previously defined rules, generating a nested If-then region where the then node is another If-then region. In our implementation we flattened these nested nodes into a single If-then keeping the first $n-1$ nodes as the various conditions and the last node as the actual then. Moreover, the number of conditions are not considered in the comparison phase, so a short circuit If-then is reconstructed identical to a normal one.

2) IF-ELSE RESOLUTION

In Figure 5 on the left, the minimal structure of an If-else is presented. Exactly like the If-then resolution, the following set of conditions must be verified in order to reduce a node as an If-else node:

1) The current node has two children, the then node and the else node.
2) The then node has a single predecessor and a single successor.
3) The else node has a single predecessor and a single successor.
4) The successor of the then node is the same of the else node.

If all these conditions are satisfied, the current node, then, and the else node are merged into an If-else region with the successor of then as successor. It is important to note that deciding which node is then and which node is else is not trivial and has some consequences, however, this will be discussed in Section III-E when dealing with the comparison. Additionally, unlike the If-then structure, the short-circuit version of the If-else presented on the right in Figure 5 is not resolved automatically using the previous rules, given that the rule number 3 is violated by the short-circuit. It is thus required to implement a routine that tries to descend into the then subtree, asserting that every successor is either another then node or the else node. The new rule 3 instead will ensure that every predecessor of the else node is either the current node or one of the then nodes. Also in this case, short-circuit version and normal one are treated equally in the comparison phase.

![Figure 5. If-else and Short circuit If-else. Two different paths sharing a node (0) and a sink (3) can be reduced as an If-else structure. In principle, the two paths must be disjoint, except in the case where every node of a path connects to the same node of the other, indicating a short circuit If-else.](image)

![Figure 6. Optimized if structure. This structure is similar to an If-else, but the two paths are not disjoint.](image)

![Figure 7. Switch structure. Any sequence of disjoint paths from a node (0) to a sink (4) with more than two paths can be reduced to a Switch structure.](image)

3) SWITCH RESOLUTION

A more complex variant of the If-else is the Switch. These structures, after compilation, are usually implemented with a jump table and thus require particular care to be detected statically. Fortunately, several algorithms for recovering statically these tables exist in literature, and the task is thus delegated to the disassembler [45].

![Figure 9. Switch structure. Any sequence of disjoint paths from a node (0) to a sink (4) with more than two paths can be reduced to a Switch structure.](image)

In the CFG, switch thus appear as in Figure 7 and can be easily detected as its root node has a number of edges higher than 2. If all these nodes point to the same successor, they are
reduced as *Switch*, otherwise the successors should be refined first.

4) **SEQUENCE RESOLUTION**

Sequences do not present particular cases, so it is sufficient that the current node and its successor satisfy these conditions to merge them into a 2-nodes sequence:

1) current node has a single exit
2) successor has a single entry and a single exit

Additionally, if the current node or the successor is already a sequence, the newly created one is not nested but appended to the existing ones.

5) **WHILE AND DO-WHILE RESOLUTION**

![FIGURE 8. While and Do-While loops structures. A path of length 2 starting from and ending in the same node can be considered a loop. If the loop entry and exit are from the same node, this loop can be reduced as a while structure, otherwise as a Do-While structure.](image)

*While* and *Do-While* loops are conceptually similar, as can be seen in Figure 8 with the former on the left and the latter on the right, the only difference being the exit node. While these loops can be found quite easily using the Tarjan’s Strongly Connected Component (SCC) algorithm, particular care must be taken when dealing with nested loops, where the head of a loop is also the tail of the other one, as shown in Figure 9 on the left. Specifically, the SCC cannot be blindly used to determine the exit of a loop, given that in case of nested loops both the inner and outer loop have the same SCC. Additionally, unlike *While* loops, *Do-While* constructs can have a minimal form composed of three nodes that can not be reduced to two nodes using *Sequence* rules, and requires an ad-hoc reduction. This form is shown in Figure 9 on the right.

![FIGURE 9. Nested Do-While and minimal 3-nodes Do-While. These are two particular cases of Do-While structure that require additional care: (a) for the correct identification of loop entry and exit and (b) because the combination of Sequence and Do-While detection rules can not detect this particular case.](image)

6) **TRANSFORM NATURAL LOOP**

In case the original source code had a loop with *break* or *return* statements, in the CFG this loop could potentially have multiple exits. In order to effectively reduce a loop to a minimal 2-nodes variant, a single exit is required and the first three lines in Algorithm 1 are used to detect and remove these edges from the CFG. In fact, our analysis aims at reconstructing only the original structure and thus these loop-breaking statements are redundant. Given a CFG $G = (V, E)$ and a particular set of exit edges $EX(k)$ from a SCC $k$ as

$$EX(k) = \{\forall e_{ij} \in E \mid v_i \in V \land v_j \in V \land SCC(v_i) = k \land SCC(v_j) \neq k\}$$

where $SCC(k)$ is the SCC index, the natural loop resolution is run for the SCC if $|EX(k)| > 1$, meaning that more than one exit exists for that SCC. From here on, given $e_{ij} = (v_i, v_j)$ such that $v_i \in EX(k)$ is an exit edge, we call exit node the node $v_j$ and target the node $v_i$. Asserted that the number of exit nodes is always greater than one, two possible types of natural loop exist:

**Single Target**

This type of natural loop is generated by *break* statements without any kind of cleanup, like `if(condition)break;`. If an exit node has a higher number of predecessors than the others it is kept as the real exit, with the assumption that this loop would be a *While* loop. Otherwise, the first exit node encountered in a Depth-First Search (DFS) is kept. Although this could be the wrong one, recall that we are focusing on consistency between different programs rather than decompilation correctness. Every edge not belonging to this exit is removed from the CFG.

**Multiple Targets**

In addition to the single target, *if* constructs with additional logic before the *break* keyword generate a different exit target. Moreover, also *return* statements generate an additional target. While the latter can be easily spotted by searching a jump directly to the function exit, we decided to keep only the target having the longest path $d(v_j, v_k)$ where $v_j$ is the target, $v_k$ the function return node and $d(v_j, v_k)$ the minimum distance between the two nodes. Every edge pointing to the wrong target is removed, then the natural loop is resolved in the same way as the Single Target one. Note that unlike the Single Target, this approach could generate orphan nodes.

After the removal of these edges from the CFG, the loop can be reduced to the minimal form of the *While* or the *Do-While* presented in Section III-D5 with the iterative step of Algorithm 1.
E. COMPARISON

After completing the reconstruction step, the output graph can be represented as a tree of structures, similar to the example shown in Figure 10. In order to efficiently compare all the possible subtrees generated by the reconstruction of every function, we use Locality-Sensitive Hashing (LSH). Specifically, we choose a hash function such that the collisions between trees with the same structure are maximized. It is of vital importance to carefully design this function: we want to ensure an hash collision for structures that are similar, not identical. In fact, the functionality and high level structure of two functions may be the same, but they may use basic blocks or jumps with different offsets. For this reason we hash only the node type, avoiding the basic block offsets, recursively.

In our implementation we used as hashing function \( f_h \) the public domain FNV-1a [46] and implemented the function \( h(t) \), in order to hash a subtree, shown in Equation 1.

\[
h(t) = f_h(\text{type}(t)) \circ h(c_0) \circ h(c_1) \ldots \circ h(c_n) \\
\forall c_i \in C_t
\]

where \( C_t \) is the set containing the children of \( t \) (1)

We can see that the hash of a node \( t \) is calculated by composing the hash of the current node type with the hash of all its children. The node type is a unique value assigned to each structure type. If two nodes \( t_1 \) and \( t_2 \) are both the same structure (e.g. Sequence, If-Else, etc.) \( \text{type}(t_1) \) and \( \text{type}(t_2) \) have the same value.

We apply this function to every reconstructed function of each binary. If the tree depth of the current node is higher than a threshold \( \theta \), it is written into a hash table data structure, with \( h(t) \) as key and \( t \) as value. Upon iterating all the keys of this hash table, if a key contains more than one value, the key itself represents a clone class and all its values represent the various clone snippets belonging to this class.

Considering that \( f_h \) is a constant time operation, the complexity of \( h(\text{root}) \), where \( \text{root} \) is the root of each reconstructed tree, is linear in the number of tree nodes. According to our reconstruction rules, a reconstructed tree can not have more nodes than basic blocks, implying that our approach has a comparison step with linear complexity in the total number of basic blocks retrieved from all functions.

We can see that hashing is not based on the statements contained inside a specific structure, but only on the structural shape itself. This enables the comparison between different architectures at the cost of increased false positives ratio, in case two pieces of code are structurally similar but perform different actions. Being thus the hashing distance based solely on the structural shape, we use the threshold \( \theta \) as variable to control the ratio between false positives and negatives: a lower \( \theta \) will match structures with few nested nodes that may be shared by code performing different operations, while a higher \( \theta \) will require a more unique structure but may miss some matches.

We do, however, account for children’s order when calculating the hash; it is thus easy to see why in Section III-D2 it was important to clearly determine the then node and else node deterministically.

F. SEMANTIC ANALYSIS

The comparison presented in Section III-E is sufficient for finding clones, however, its calculations are entirely based on the structure of binary code. This can present a situation where two binary functions are reported as clones because they share the same structure, albeit having different opcodes thus resulting in different functionality. For this reason, in this section we present an additional refinement step to our approach, that should run on the comparison results, in order to filter some false positives that happen to have the same structure, but different opcodes.

This refinement is based on the idea that to every instruction we can assign a number, representing the amount of times that particular opcode appears in the function over the total number of opcodes in the function, thus creating a frequency vector. Then, a function to measure the similarity between two vectors, can be used to measure the degree of similarity between two frequency vectors. If this value is greater than a threshold, the two basic blocks can be considered the same. We run this comparison on the (unordered) list of opcodes composing the basic blocks of two matching reconstructed tree, similar to the one in Figure 10. Moreover we do not consider the opcode parameters: doing so would overspecialize our comparison and match only identical functions. In our implementation we used cosine similarity as similarity function: given two frequency vectors \( A \) and \( B \), their similarity is given by \( S_{AB} = \frac{A \cdot B}{||A|| \cdot ||B||} \).

Naturally, if the architecture between the potential clones is different, their opcodes would not match and their similarity will always be zero. For this reason, in case of different architectures, instead of using the opcodes directly we assign them to a “family of operation” and determine the frequency of each opcode family instead of the opcode itself. For example, the jmp opcode for \( \text{x86}_64 \) and b opcode for \( \text{aarch64} \) are both assigned to the JUMP family, and the similarity calculated on the frequency of the JUMP family, instead of the frequency of jmp or b. In total we divided opcodes into
different architectures. Additionally, the threshold parameter checking for clones in binaries within the same architecture or not be compared with hashing. The second research question, is meant to measure the precision of our detection when not known. This means that, to compare functions, operations have to be performed, compared to the \( O(n) \) required by the structural analysis. This explains why, in our approach, the semantic analysis is used only after gathering a list of potential clones from the structural one, and its higher run time is confirmed by the experimental results we provide in Section IV.

**IV. EVALUATION**

We implemented our analysis in Rust under Linux, however, we are able to analyze the binaries for multiple operating systems and 20 different architectures. The implementation of our approach is named BinCC, and is openly available on GitHub.\(^1\) In this evaluation, we target mainly the x86_64 and aarch64 architectures, being the dominant architecture for the Desktop and Mobile market respectively.

As mentioned in Section III-B we depend on an external disassembler to retrieve the list of functions and statements. In our implementation we used the open source tool radare2\(^2\), version 5.7.4, whereas every other step is independent of external tools. Despite using radare2, we do not depend exclusively on it: in fact any disassembler could be used, provided that a list of statements like the one in Section III-B is returned as a string.

In order to evaluate the effectiveness of our approach, we want to address the following research questions:

- **RQ1 completeness**: How many functions are successfully converted to a single node representation?
- **RQ2 correctness**: How precise is our tool at detecting function clones across different architectures?
- **RQ3 use-case**: Is our tool able to find function reuse from libraries in a real-case application?
- **RQ4 performance**: How performant is our tool, varying the input executable size?

The first research question, **RQ1**, is meant to determine the amount of functions that can actually be reconstructed, across different architectures and optimization levels. This can be seen as a measure of the goodness of our structural analysis algorithm, given that functions that are not reconstructed can not be compared with hashing. The second research question, **RQ2**, is meant to measure the precision of our detection when checking for clones in binaries within the same architecture or different architectures. Additionally, the threshold parameter \( \theta \) for the LSH function defined in Section III-E is evaluated here and our approach is compared against existing state-of-the-art works. The third research question, **RQ3**, is meant to be a use-case evaluation, measuring the precision at detecting function reuse with binaries and libraries resembling more a real-case scenario. Finally, the last research question, **RQ4**, is used to measure the time required by the analysis and the scalability of our approach.

In order to ensure an evaluation as close as possible to the final use-case, while still guaranteeing a correct evaluation, in this study a different dataset was used for each research question. A summary of the various datasets can be found in Table 1, while details on their creation are listed in the respective Research Questions.

| RQ | Binaries | Functions | Stripped | Optimization |
|----|----------|-----------|----------|--------------|
| RQ1 | 11211 | 23953469 | yes | O0, O2, Os |
| RQ2 | 216 | 40907 | no | O2 |
| RQ3 | 800 | 276485 | Unknown | Unknown |
| RQ4 | 1934 | 1434790 | yes | O2 |

A. **RQ1: COMPLETENESS**

In order to answer RQ1 we used as dataset a collection of binaries publicly available on Zenodo [47]. These binaries come from multiple open source projects of different scopes and are compiled using different optimization levels. As reported in Table 1, these binaries are stripped. We used binaries compiled using GCC for the x86_64 and aarch64 architectures, divided into O0, O2, Os optimization levels.

For the evaluation, we ran the reconstruction on every function and checked if the output was effectively a single node. Input functions already composed of a single node are not considered in this evaluation.

**FIGURE 11.** Perfectly reconstructed functions on stripped binaries, excluding trivial ones.

Figure 11 shows the percentage of correctly reconstructed functions over the total, for a given CFG input size. The immediate result we can note is that the higher the

\(^1\) https://github.com/davidepi/bincc

\(^2\) https://rada.re/r/
optimization level, the lower the chance our algorithm is able to correctly perform the reconstruction. This is somewhat expected, as higher optimization levels introduce additional compilation patterns that are more difficult to map to the structures we defined in Section III-D. In particular, we analyzed the failed reconstructions and determined that most failures are due to variations of the Optimized If defined in Section III-D2. With high optimization levels, the compiler enables jumps between the various if-else branches, generating complex branching structures that cannot be easily categorized.

Differences between the two architectures instead are minor: the reconstruction in aarch64 is slightly less precise compared to x86_64 in both O0 and Os, but not in O2. We could not determine the reason of this difference by looking at the functions, and we can only assume it is due to the disassembler being more proficient with x86_64.

In fact, the maximum amount of nodes we found is 4202 for the aarch64 architecture and 9424 for x86_64 with an average of 40 nodes per function. In these cases, the CFG analysis without our reconstruction is absolutely intractable with an \( \mathcal{O}(2^n) \) algorithm. However, as we can see from Figure 13 even in case of failed reconstructions our analysis reduces the number of nodes by 30-40% in any optimization level, and may allow tractability in the average case, going from \( 2^{40} \) comparisons to less than \( 2^{30} \).

Given the results, we can answer RQ1 as follows:

The average percentage of correctly reconstructed functions is around 90% for the O0 optimization level, 70% for Os and 45% for O2. Even in the case of failed reconstructions, the number of nodes is reduced by 35-45%, and enables tractability in the average case.

### B. RQ2: CORRECTNESS

For the second research question, we want to analyze how accurate is the detection rate of cloned functions in our approach, while also estimating the change in accuracy varying the approach parameters. Specifically, we first analyze the clone detection using structural analysis only, then semantic analysis only and, finally, a combination of the two. We close this analysis by comparing our tool with two existing state-of-the-art products: BinDiff [17] and DeepBinDiff [39].

For this Research Question we compiled GNU coreutils\(^3\) tagged v.9.31 on Linux for the x86_64 and aarch64 architectures with optimization level O2. We chose coreutils for the reason that, being composed by several programs in a single codebase, we expect to find more clones than by choosing two completely random binaries. In the “same architecture” analysis we ran our tool comparing all functions belonging to the 108 coreutils binaries built for x86_64, reporting both intra-project and inter-project clones. Similarly for the “cross architecture” analysis we added also the functions belonging to the same binaries built for aarch64. As highlighted in Table 1, this time we did not strip the binaries: in fact, using non-stripped binaries allows us to investigate false negatives by matching the various function names. Note that our approach supports also sub-function granularity, as presented in Section III-E, however, to reduce the amount of manual analysis to be done, we limit the study to function granularity.

Unlike most tools in literature [17], [18], [31], ours compares not only pairs, but entire sets of similar functions. For this reason, the metrics were defined as follows: for each reported clone class \( A \), the most similar clone class \( B \) was retrieved from the ground truth using Jaccard Similarity. With

\(^3\)https://www.gnu.org/software/coreutils/
TABLE 2. True positives, False Positives, False Negatives, Precision and Recall in clone detection using structural analysis alone, varying the minimum tree depth threshold $\theta$. Results obtained comparing all the coreutils binaries together.

| $\theta$ | TP | FP | FN | Precision | Recall |
|----------|----|----|----|-----------|--------|
| 2        | 3337 | 3774 | 48 | 0.4693 | 0.9858 |
| 3        | 2150 | 581 | 309 | 0.7873 | 0.8743 |
| 4        | 1540 | 291 | 162 | 0.8411 | 0.9048 |
| 5        | 687 | 68 | 129 | 0.9099 | 0.8419 |
| 6        | 375 | 34 | 91 | 0.9169 | 0.8047 |

TABLE 3. True positives, False Positives, False Negatives, Precision and Recall in clone detection using semantic analysis alone, varying the minimum cosine similarity threshold. Results obtained comparing all the coreutils binaries together.

| Min.Cosine Sim. | TP | FP | FN | Precision | Recall |
|-----------------|----|----|----|-----------|--------|
| 0.95            | 93287 | 252978 | 7360 | 0.2694 | 0.9269 |
| 0.98            | 12256 | 14220 | 2090 | 0.4612 | 0.8543 |
| 0.99            | 7928 | 2648 | 307 | 0.7496 | 0.9627 |
| 0.999           | 9222 | 1163 | 3724 | 0.8487 | 0.7055 |

TABLE 4. Precision and Recall in clone detection within the same architecture, using structural analysis and semantic analysis combined, varying their input thresholds.

| $\theta$ | Same architecture (x86_64) | Cross architecture (x86_64, arch64) |
|----------|----------------------------|-----------------------------------|
|          | Min. Cosine Sim. | TP | FP | FN | Precision | Recall | TP | FP | FN | Precision | Recall |
| 2        | 0.8494 / 0.9746 | 0.8702 / 0.9708 | 0.8752 / 0.7690 |
| 3        | 0.9148 / 0.9114 | 0.9280 / 0.9084 | 0.9306 / 0.9235 |
| 4        | 0.9178 / 0.9143 | 0.9345 / 0.9145 | 0.9363 / 0.9039 |
| 5        | 0.9627 / 0.8953 | 0.9876 / 0.8646 | 0.9901 / 0.7964 |
| 6        | 0.9658 / 0.8905 | 0.9888 / 0.7599 | 0.9907 / 0.8004 |

While discussing Table 2 we explained how most of the False Positives in the structural analysis are determined by clones with the same structure but different opcodes. For this reason, by using the results of the structural analysis and applying semantic analysis on them, we overcome this problem and obtain the results shown in Table 4. The Table reports only precision and recall, but we can clearly see how dramatic the improvement in precision is: even for simpler functions composed of three nested structures both precision and recall are now above 91%. For complex functions the precision can reach up to 99% with our best result being 474 True Positives and only 4 False Positives in one configuration. The remaining false positives are due to the granularity of our approach returning block-level clones but being treated such as x86_64 that potentially can use thousands of opcodes, in practice most functions use a small subset of common opcodes. This problem is exacerbated in the cross architectural detection by our “opcode family” described in Section III-F that further reduces variance between functions, resulting in 80% precision with functions that have a similarity higher than 0.999. In addition to this problem, the semantic analysis has complexity $O(n^2)$ in the number of functions, compared to the $O(n)$ of the structural analysis, limiting its scalability.
as function-level clones by our experimental settings, in particular for $\theta = 2$.

**TABLE 5.** Precision and Recall in clone detection across different architectures, using structural analysis and semantic analysis combined, varying their input thresholds.

| $\theta$ | Cross architecture (x86_64, aarch64) | Min. Cosine Sim. |
|----------|-------------------------------------|------------------|
| 2        | 0.7311 / 0.5071                     | 0.7334 / 0.5087  |
| 3        | 0.7241 / 0.5402                     | 0.7368 / 0.5476  |
| 4        | 0.7691 / 0.5504                     | 0.7679 / 0.5647  |
| 5        | 0.7204 / 0.5398                     | 0.7240 / 0.5145  |
| 6        | 0.7410 / 0.4922                     | 0.7430 / 0.4908  |

This solution, however, does not work for cross architectural clones, as can be seen in Table 5. Here the main problem lies in the structural analysis not correctly mixing the various clone classes and this problem can not be fixed by the semantic analysis.

**TABLE 6.** Time required to perform the structural analysis, semantic analysis and combined analysis in both same architecture and cross architecture using $\theta = 3$ and min similarity of 0.99. Results obtained analyzing all coreutils binaries together.

| Analysis          | Time same arch. (us) | Time cross arch. (us) |
|-------------------|----------------------|-----------------------|
| Structural only   | 5066                 | 8922                  |
| Semantic only     | 16111921             | 46399417              |
| Combined          | 543672               | 497643                |

Finally, Table 6 shows the time required for each approach. We can clearly see how the semantic analysis is 1000 times slower than the structural one, while the combination of the two still manages to reach an acceptable time, due to the initial filtering performed by the structural analysis.

**TABLE 7.** Precision and number of detected clones in pairwise function detection of several state-of-the-art approaches. The listed programs have been compared against du.

| bin   | BinCC (ours) | BinDiff | DeepBinDiff |
|-------|--------------|---------|-------------|
| dir   | 0.9593 (172) | 0.9333 (105) | 0.9368 (95) |
| ls    | 0.9593 (172) | 0.9333 (105) | 0.9167 (96) |
| mv    | 0.9704 (169) | 0.9739 (115) | 0.9245 (106) |
| cp    | 0.9652 (144) | 0.9783 (92)  | 0.8295 (88)  |
| sort  | 0.9923 (131) | 0.9670 (91)  | 0.9157 (83)  |
| du    | 0.9574 (188) | 0.9937 (159) | 0.9933 (150) |
| csplit| 0.9574 (94)  | 0.9254 (67)  | 0.9194 (62)  |
| expr  | 0.9489 (98)  | 0.9677 (62)  | 0.9062 (64)  |
| nl    | 0.9444 (90)  | 0.9672 (61)  | 0.9828 (58)  |
| ptx   | 0.9266 (109) | 0.9444 (72)  | 0.9234 (67)  |
| split | 0.9375 (96)  | 0.9538 (65)  | 0.9831 (59)  |
| mean  | 0.9562       | 0.9580       | 0.9303       |

In Table 7 we compare our approach against BinDiff [17], a commercial tool for binary diffing, and DeepBinDiff [39], a research tool performing the same task using deep learning. Given that both BinDiff and DeepBinDiff support only pairwise comparison, and none of them support cross-architectural comparison, we compared eleven binaries in the coreutils package of different size against du. In particular we used our tool combining structural and semantic analysis with a low threshold in order to match as many clones as possible ($\theta = 2$). For BinDiff and DeepBinDiff, instead, we report as clone a pair of functions having at least half their basic blocks matching. Using higher threshold for all tools would result in perfect precision, but would miss most function pairs.

We can see that BinCC, our tool, even with low thresholds, can emit more clones compared to the state-of-the-art. This is due to our tool being capable of emitting intra-project clones that, depending on the use case, may be desirable or not. The precision of the detected clones is similar with respect to the other state-of-the-art tools. We determined that our tool, similarly to DeepBinDiff, fails in cases where functions have identical implementation modulo a different function call. For example, they both detect `xcalloc` and `xmalloc` as clones, being these two functions different only in the allocation function used. The results obtained from DeepBinDiff are comparable with the results presented in its original paper [39], while for BinDiff we obtained slightly more accurate results compared to previous experiments [31].

A huge difference instead, can be noted in the speed. Table 8 shows a comparison between our tool and DeepBinDiff. BinDiff using Ghidra requires to manually disassemble the file, and for this reason it is not listed. The Table clearly shows that our tool is order of magnitudes faster than the competition, in some cases reaching difference of a factor $10^3$ (e.g. the comparison `du-du`). In addition, DeepBinDiff can compare only two binaries together, requiring to perform the analysis for any combination of executables, whereas our tool can report the clones for all 108 coreutils binaries together in less than a minute.

For RQ2 we can thus conclude:

**TABLE 8. Use-Case**

After performing the evaluation on a controlled case with unstripped binaries in our possession, in this section we want to simulate a use-case by checking the detection rate on stripped-only, real-case binaries.

Given that after the strip phase every information about the function name is lost, building a ground truth set requires manually checking every function. For this reason, we adopted an approach similar to the one of Hemel et al. [24]: we compiled several binaries with the default options and static linking. After that, we ran the comparison between the binary itself and the libraries reported to be used at link time. Additionally, we performed the check
for a limited set of extra libraries unrelated to the project. In this case, being more of a use-case, we wanted to check more consistent functions and thus used higher thresholds. In the dataset summary of Table 1, we reported the optimization for this Research Question as “unknown”: being this a real-case scenario, we used binaries without knowing the original compilation options. We used a value $\theta$ of 7 and a minimum number of nodes of 7 for the reconstruction and 15 for the CFG.

### TABLE 8. Time required to compare du with the binary listed in the column bin, in seconds. The size column contains the combined size of du and the target binary. Times have been counted from program invocation until program termination.

| bin  | size (KiB) | BinCC (ours) | DeepBinDiff |
|------|------------|--------------|-------------|
| dir  | 1081       | 3.40s        | 1409s       |
| ls   | 1081       | 3.18s        | 1432s       |
| mv   | 1045       | 3.43s        | 1999s       |
| cp   | 978        | 3.22s        | 1740s       |
| sort | 952        | 2.90s        | 1216s       |
| du   | 921        | 2.80s        | 2043s       |
| csplt| 682        | 2.55s        | 659s        |
| expr | 673        | 2.44s        | 652s        |
| nl   | 642        | 2.43s        | 527s        |
| ptx  | 749        | 2.58s        | 771s        |
| split| 701        | 2.43s        | 702s        |

Table 9 shows the results for busybox tag 1_31_0 which uses libm and libresolv. Our tool correctly reported function reuse only in the libraries statically linked with the binary. We then ran the same analysis against those libraries compiled for aarch64 and obtained similar results except for libm that was not detected: of the 40 functions checked in x86_64, 0 were analyzed in aarch64. The reason for this is that multiple functions were under the threshold and thus not analyzed, probably due to the smaller CFG in the second architecture. The number of analyzed functions for the other libraries were similar instead.

However, in order to not bias the evaluation given that we purposely used libraries unrelated to the project, we also reran the evaluation with 800 libraries usually present in an Ubuntu Linux install. In this specific case, we found 407 libraries that had function reuse and 393 that did not. We did not check if all the reports were false positives or negatives, because this would require a prohibitively high amount of time having to manually understand and analyze over 8000 functions in assembly. However, we found that most of the reported libraries are dependent upon libc, that is statically linked with the executable we analyzed.

For this reason, we plan to conduct a more controlled test, analyzing also the dependencies between the various libraries.

We can then answer RQ3 as follows:

By analyzing a stripped real-case binary executable our approach detects the libraries statically linked with it and also the dependencies of those libraries. Libraries unrelated with them are not detected.
We experimented with the disassembler, and managed to perform a faster disassembly by analyzing only the function calls instead of performing a full binary analysis. However, the reconstruction accuracy suffered greatly: the fast disassembly took around the same time as our structural analysis, but the reconstruction accuracy presented in RQ1 dropped by a flat 20% in every optimization level. For this reason, we decided not to report this analysis with the fast disassembly option.

For RQ4 we can thus conclude:

Our analysis scales linearly and is completely dominated by the time required to perform the disassembly.

V. LIMITATIONS AND THREATS TO VALIDITY

A. PREDICATION

In some architectures, such as ARM, predication is used as an alternative to branching by converting flow dependency to data dependency. Predication works by associating instructions with a predicate, a boolean value, usually a CPU flag, used to indicate if the instruction is allowed to execute. If this boolean value does not hold at the time the instruction should be executed, that instruction does not modify the architectural state, with the advantage of not breaking the CPU pipeline. As an example, consider the following code:

```assembly
0x410 cmp r0, 0
0x414 cmpne r1, 0
0x41c movne r0, 5
0x420 moveq r0, 6
0x424 bx lr
```

The first instruction executes a comparison and sets the CPU flags according to the result. If the flags are set as true, the second and third instructions do nothing, and the fourth is executed, otherwise the second is executed which changes the flags values again for when the third will be executed. The problem with predication thus lies in the fact that a CFG reconstructed just by looking at jumps will miss the flow hidden beneath these instructions. In our implementation we decided to ignore predication given that only two mnemonics, namely CMOV and SETcc, supports these operations in x86_64, while in aarch64 these are mostly deprecated given the recent advancements with branch predictors [49].

B. MISMATCHED COMPILER CONFIGURATIONS

In addition to the results showed in Section IV-B, we briefly analyzed potential clones between binaries compiled with different compilers or optimization settings.

Results show that our algorithm fails at finding potential clones when the compiler or the optimization flags are different: these results are due to the fact that code is rearranged during the data flow analysis performed by the compiler, and thus the output dramatically changes depending on the analyses performed at compilation time.

This was originally highlighted by Sæbjørnsen et al. [22] and we can confirm that not only the compiled binary is semantically different at various optimization levels but also structurally different, and we expect every CFG-based approach to suffer from this limitation. In order to overcome this problem, however, a previous work of us was focused on determining automatically the compiler and optimization level used in a binary, in order to mitigate failed analyses due to mismatched compiler configurations [50].

C. DISASSEMBLER DEPENDENCY

In this work, the starting point of our analysis is the disassembler. We relied on an external tool as there is no novelty in implementing our own and deemed the process as out-of-scope for this work. However, this means the goodness of our structural analysis is dependent on the disassembly quality: using a different disassembler may result in a different qualitative result in terms of structural analysis ability and clone
VI. CONCLUSION
In this paper, we presented our approach for finding function reuse and clones using a high-level refined CFG. We implemented this analysis and conducted several tests in 24 million functions in the x86_64 and aarch64 architectures.

Results show that our analysis is faster than existing approaches, and the time required is dominated by the disassembly step on which it depends. Our technique can be applied without any training step in 20 different architectures, analyzing any given number of executables at the same time.

When performing the comparison, our work showed to be capable of detecting function clones with precision ranging from 91% to 99% when comparing binaries from the same architecture and 75% when comparing binaries in different architectures. In addition, we showed that our approach can detect the presence of functions coming from a particular library.

VII. REPLICATION
The dataset used in our study can be found on Zenodo at the following URL [47], while source code can be found publicly on GitHub. On GitHub, the branch experiments contains all the experimental data and results used in this paper.

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