Automatic Library Version Identification, an Exploration of Techniques

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Abstract—This paper is the result of a two month research internship on the topic of library version identification. In this paper, ideas and techniques from literature in the area of binary comparison and fingerprinting are outlined and applied to the problem of (version) identification of shared libraries and of libraries within statically linked binary executables. Six comparison techniques are chosen and implemented in an open-source tool which in turn makes use of the open-source radare2 framework for signature generation. The effectiveness of these techniques is empirically analyzed by comparing both artificial and real sample files against a reference dataset of multiple versions of dozens of libraries. The results show that out of these techniques, readable string-based techniques perform the best and that one of these techniques correctly identifies multiple libraries contained in a stripped statically linked executable file.

I. INTRODUCTION

When scrutinizing the security of an embedded device, one of the things an analyst looks for are vulnerabilities in the collection of executables and shared libraries contained in the device’s firmware image. Often, these shared libraries are common, non-proprietary utility libraries and the executables will have often been statically linked against such libraries. A vulnerability in one of these libraries could lead to exploitation of the device, especially when considering that these libraries often process user controlled data (e.g. for multimedia decoding or compression). Some of these libraries have a history of vulnerable versions for which there are known exploits. The task of exploitation could therefore be as simple as determining the exact version or variant of each library and – if a vulnerable version is found – using public vulnerability information to devise an exploit for an executable file that makes use of the vulnerable library.

This paper focuses on a specific aspect of this process: the problem of automatically identifying the version of a given shared library file. Six techniques of three different signature types have are implemented in an experimental open-source tool in order to evaluate their effectiveness. Preliminary experiments are also performed on the applicability of these techniques on the harder problem of identifying libraries in statically linked executables. Samples and corresponding reference libraries of both ARM and MIPS architectures are used for these experiments.

II. RELATED WORK

Intuitively, the identification problem as described above – at least the shared library identification variant – comes down to the problem of determining executable object similarity. After all, in order to identify the best matching library version to some sample file, one has to calculate some metric of similarity between the sample file and each version of each reference library. In the case of statically linked executables, this will not result in matches of (close to) 100% similarity, but it will give an indication of the amount of overlap between a library version and the sample file, which might be an indicator for the probability that that library (version) is actually contained inside the sample file.

A structural way to perform such an executable object comparison was laid out by Dullien and Rolles in [4]. They reduce it to the problem of creating a (fuzzy) graph isomorphism between control-flow graphs (CFGs) of both executable objects. Specifically, they treat an executable object as a graph of graphs, i.e. a function callgraph where each of the nodes – i.e. each function – contains that function’s control-flow graph which in turn has basic-blocks as its nodes. Metrics are defined to determine basic-block and function similarity, allowing a full isomorphism to be created.

Building on these techniques and specifically focusing on polymorphic worm detection, the authors in [8] apply a fingerprinting technique on a canonical representation of k-subgraphs of a CFG, allowing quick (partial) matching of a sample file. Following up on this, Cesare and Xiang [2] implement a complete malware classification system which among other things translates full CFGs into strings based on a specific grammar, allowing them to be compared quickly using Levenshtein distance (i.e. edit distance). Similarly, Koret’s open source malware clustering toolkit Cosa Nostra represents CFGs as prime products determined by the cyclomatic complexity values of functions, allowing for permutation-independent fuzzy comparisons [7].

Doing away with graph-theoretic techniques, Gheorghescu proposes three classification methods on the flat list of basic-blocks of an executable object, the most innovative of which uses Bloom filters (see section IV-B) to achieve a fixed small signature size [5].
Taking an entirely different approach, Tian et al. propose a system for malware classification that achieves high accuracy by using the printable strings from a sample as an input for several classification algorithms including Bayesian and K-nearest neighbour [9].

The work presented in this paper is a preliminary exploration of the effectiveness of applying variants of the above-mentioned techniques to the problem of library version identification.

III. CFG GENERATION TOOLS

To perform the non-string based comparison techniques mentioned in section II (i.e. all but the system by Tian et al.), we first need to construct the CFGs of all of the functions in the executable objects in question. This requires disassembling the objects and using knowledge of the instruction set and calling conventions in order to build a directed graph of the control flow between basic-blocks. Several pieces of software can perform this task, the most popular of which is the proprietary IDA Pro, which is easily scriptable and is often used for similar purposes. An interesting alternative for our purpose however is the open source binary analysis framework angr [7]. Like IDA Pro, it supports many architectures and formats and in addition to its ability to generate accurate CFGs using symbolic execution, it has built-in binary comparison functionality based on [4] (see section IV-A). Another alternative is the radare2 reverse engineering framework. It too has built-in support for (static) CFG generation and binary comparison (see section IV-A). Additionally, it supports even more architectures than angr and has bindings for almost any language. In practice, it also turns out to be faster than angr in static analysis tasks. For this reason radare2 was used in lieu of angr for the final iteration of this project as is explained in more detail in section IV-A.

IV. TECHNIQUES

From the related work discussed in section II we can distill multiple techniques of creating executable object signatures (i.e. fingerprints) and multiple techniques of comparing those signatures. Three of these combinations are detailed in this section: basic block hash comparison using Bloom filters (section IV-B), several cyclomatic complexity–based techniques (section IV-C) and several string-based techniques (section IV-D). Before discussing these techniques, we must however understand why they are useful, especially when compared with graph isomorphism-based techniques. This is explained in section IV-A.

A. Graph isomorphisms

While angr has the ability to perform several static analysis techniques, its main purpose is symbolic execution. For generating the CFG of an executable object, it offers two methods: CFGAccurate and CFGFast. The former uses symbolic execution of basic-blocks to accurately determine all of the possible control-flow paths, while the latter uses a more traditional heuristics-based approach. The result of either can be passed to angr’s BinDiff analysis method which is named after commercial software of the same name by Zynamics [10]. Just like its namesake, it implements the graph isomorphism technique from [4].

For our purposes, we can use these methods to create a graph isomorphism between two potentially similar libraries. A similarity measure can then be derived from the number of identical or almost identical functions and basic-blocks.

However, such an isomorphism has to be created for every reference file (i.e. every library version to compare against). Ideally we would want to compare a sample against every version of every library in our reference set, and possibly even against compilations of the same version by different compilers, or with varying optimization levels or other compiler flags. This means that the number of isomorphism calculations that needs to be done for one sample is really high and will grow quickly (but linearly) with added reference libraries. Additionally, the CFG information (i.e. the whole graph and associated data) needed by angr’s BinDiff needs to be pre-calculated and stored for each one of these reference files and loaded into memory when the comparison is performed.

As it turns out, both of these factors make angr a less than ideal framework for our purpose. The data structure produced by its CFG generation methods is large and contains data unnecessarily for the BinDiff method. Additionally, the BinDiff method makes heavy use of angr’s lifting functionality to lift machine code to an intermediate representation (using PyVEX), which takes up most of the method’s long execution time. An attempt was made to mitigate these problems by stripping down both the CFG datastructure and simplifying BinDiff by performing the lifting at CFG generation time. This resulted in a small improvement but the core problems of heavy memory usage and long computation times remain.

Both of these are however not necessarily a problem of angr but of the graph isomorphism-based algorithm in general. The radiff2 tool of radare2 also implements the algorithm from Dullien and Rolles [4] and achieves similar performance. It becomes clear why [2] and [8] implement more efficient CFG fingerprinting techniques: graph isomorphisms are generally too slow for a one-to-many comparison. This is especially true for angr’s implementation which is slowed down by operations like the lifting described above. This is not surprising however, because angr is mainly intended to be used interactively on very small (and often artificial) samples.

For these reasons, both the original and the optimized version of angr’s BinDiff were not integrated into the library identification tool. They are not practically usable with a reference database of a few hundred samples and will therefore not scale to much larger databases that could be used in practice.

1Optimistically, such compiler and flag differences would be abstracted away by techniques such as [4] but as those authors themselves note, modern optimizing compilers can make drastic changes to assembly output depending on compiler flags and other variables.

2A single comparison with angr’s BinDiff can take up to a minute for large reference libraries and a lot longer for even larger samples.
B. Basic-block matching using Bloom filters

Clearly we need signatures that are both quicker to compare against and have a smaller footprint than a full CFG. Gheorghescu’s Bloom filter approach [5] satisfies these requirements. The technique consists of creating a fixed size Bloom filter3 for each reference object and inserting into it the hashes of all of that file’s basic-blocks. It is not specified exactly what the input to the filter’s hash function is, but presumably the raw byte code of a basic-block is used. We can now obtain a similarity ratio between files by calculating the Jaccard index (or similarity coefficient) of the sets of bits in their Bloom filters, i.e. for filters \( x \) and \( y \), calculate
\[
d(x, y) = \frac{\sum_{i} (x_i \land y_i)}{\sum_{i} (x_i \lor y_i)}.
\]
Because the run time of element insertion and look-up in a Bloom filter are both \( O(1) \), this makes the time complexity of signature generation linear in file size. More importantly, signature comparison is constant in the size of the Bloom filter.

We can implement this technique by using radare2 to obtain basic-block information. Specifically, we can use the type label it gives to every instruction in place of the instruction byte code itself. This way, we abstract away differences in register allocation and constants. The hash of basic-block \( B \) consisting of instructions \( \{b_1, ..., b_n\} \) is then constructed as follows:
\[
h(B) = \text{crc32}(\text{type}(b_1) \ || \ \text{type}(b_2) \ || \ ... \ || \ \text{type}(b_n))
\]
For a Bloom filter of size \( m \) bits, the \( \log_2(m) \) least significant bits of the hash output are used as an index. A value of \( m = 2^{15} \) is used in this implementation.

C. Function matching using cyclomatic complexity

Another way to create really small signatures (i.e. in the order of \( O(\log n) \) in the file-size) of executable objects is by calculating and comparing the cyclomatic complexity values of their containing functions. The cyclomatic complexity \( M_f \) of a function \( f \) whose CFG contains \( N_f \) nodes (i.e. basic-blocks) and \( E_f \) edges is usually defined as: \( M_f = E_f - N_f + 2 \). In the implementation of this technique by Koret in the Cosa Nostra framework, the signature of an executable object is then calculated by taking the product of primes, indexed by the cyclomatic complexity of each function [7]. In other words, if \( p_n \) denotes the \( n \)th prime, the file signature is calculated by:
\[
\text{sig(file)} = \prod_{f \in \text{file}} p_{x_f}
\]
Two of these signatures or fuzzy hashes can then be compared by factoring them and counting the number of differing factors between them. This concept of using small primes products to determine if one feature-set is (almost) a permutation of another was introduced by Dullien and Rolles [4]. In their algorithm it is instead used on sets of instructions for determining code similarity as a step in finding a graph isomorphism.

Retrieving the needed information to generate such signatures is trivial when using radare2. After analysing a file it provides the cyclomatic complexity value as the \( cc \) attribute of every function in the output of the aflj command. Storing not only the prime product but also the list of \( cc \) values (or the list of prime factors, as used for technique \( cc3 \) in our tool) for every reference file saves a factoring step and allows us to perform additional types of comparison on them. For this project, two additional comparison techniques were implemented on the list of \( cc \) values: Levenshtein distance (permutation-sensitive) as technique \( ccl \) and set similarity (permutation-insensitive) as technique \( cc2 \).

D. Printable strings matching

Every non-trivial executable object contains a set of printable strings. These sets often consist of error messages, copyright or usage information, but also of strings for internal use like file content in media parsing or generation libraries. Additionally, symbol tables can be present, containing function or object names. Tian et al. show that such a list of strings can be an accurate signature of an executable object when used for malware classification using various machine learning algorithms [9]. However, one wonders if it is possible to forgo such algorithms and instead perform a fuzzy comparison using Levenshtein distance, or even more trivial, a simple set difference calculation.

Retrieving the printable strings from an executable object is a trivial operation. The basic functionality of the Unix strings command can be replicated in less than 50 lines of code. As a trade-off, the resulting signature (i.e. the list of strings) is not as small as those in the previous two techniques, nor is it constant in size. It is however never bigger than the executable object itself (which can be the case when using angr’s BinDiff comparison method). On these signatures, two comparison techniques are implemented and tested:

- **Fuzzy** string matching by calculating the Levenshtein distance on two sorted and concatenated lists of strings. In other words, calculate \( a_{\text{cat}} \) and \( b_{\text{cat}} \) as the concatenations of all of the strings from the sample and the reference file respectively, before calculating the similarity ratio as follows:
\[
r = 1 - \frac{\text{Levenshtein}(a_{\text{cat}}, b_{\text{cat}})}{\max(|a_{\text{cat}}|, |b_{\text{cat}}|)}
\]
This metric handles both differences within strings and differences between the lists of strings, i.e. added or removed strings. In the tool, this is implemented as technique \text{str1}.

- **Exact** position-sensitive string matching using the similarity between two sets of strings. Specifically, the similarity ratio between two string sets \( A \) and \( B \) is calculated as:
\[
r = \frac{|A \cup B|}{|A \cap B|}
\]
This will give the Jaccard index of the sets, indicating the ratio of strings that occur in both the sample and the reference file versus all of the strings that occur in either file. This is implemented as technique \text{str2}.
V. THE LIBRARY IDENTIFICATION TOOL

The aforementioned techniques (sections IV-B - IV-D) have been implemented into an experimental open-source library identification tool\(^4\). It is written in Python, making use of several open-source packages including the r2pipe package for communicating with a radare2 instance during signature generation. Architecturally, the tool is composed of a main file, library_identification.py, which contains the LibraryFile and ReferenceDb classes which respectively implement an abstraction for shared library files, and a manager for library signature databases. These classes are used by the tool’s two front-end scripts: identify.py and generate_db.py.

Six signature comparison techniques are implemented in identify.py as functions with a standardised interface, allowing them to be passed as function pointers to helper functions. Table 1 shows all of these comparison functions with descriptions of what they do.

VI. REFERENCE DATASET

The implemented techniques have been tested on both types of samples: shared library files and statically linked executables. For the latter category, both real and semi-artificial samples were picked. Information about these samples and the results obtained from them can be found in section VII.

To provide the best testing scenario, a database of many library version signatures is needed. For the experiments in this paper, a database was constructed using a custom tool that downloads and cross-compiles as many versions as possible of a given open-source library. This was done by making use of the build instructions in PKGBUILD files provided for each package in the Arch Linux repositories\(^5\). The result after applying this tool to a selection of common libraries and other packages starting with lib is a set of more than 60 libraries for ARM and MIPS, each with anywhere between 1 and 40 versions, but with an average of about 5. The full dataset used in the experiments is provided in appendix A.

VII. RESULTS

In the sections below, the results of several experiments are shown. Section VII-A details the results of several experiments related to the identification of shared libraries, while section VII-B deals with the secondary goal of version identification of libraries contained within statically linked binaries.

A. Identifying shared libraries

This section contains explanations and the results of several experiments with shared libraries as the sample files.

1) Speed: After running the tool on various samples, the first thing that stands out is the major difference in speed between the techniques. Table II shows the duration of using each technique to compare a sample to 188 references (the total amount of library versions in the dataset for the MIPS architecture). We can see that str1 — the fuzzy string matching technique — performs the slowest, while cc1 and cc2 perform the fastest. In fact, for all of the samples tested, fuzzy string matching is slower than cc1 and cc2 by a factor of more than a thousand. The third cyclomatic complexity-based technique — cc3 — is much slower than the other two. This is to be expected because it employs a prime factorisation algorithm which is relatively computationally expensive. Lastly, we observe that the Bloom filter comparison algorithm takes more time than cc1 and cc2, but still finishes in well under a second on our database of 188 references. More importantly, its running time varies very little between the different samples and does not depend on their size.

2) Version identification: When the identification tool is applied to a sample library version of which the signature is present in the reference database, all six techniques produce the same version as a match with 100% similarity, as would be expected. More interestingly, when comparing a sample library version to other versions of the same library, we see that with most techniques, the versions with the highest similarity scores are closest in version to the sample. An example of this is shown in table III. Here, libjpeg version 9.2.0 is compared to all libjpeg versions in the database. We see that the nearest version — 9.1.0 — is given the second-highest similarity score by all the techniques. In fact, for all techniques except for cc2, the sorted list of versions by similarity score is in perfect chronological order. Assuming that each version is based on the previous version and no major rewrites were performed, this result is entirely as expected. The fact that in this case, all techniques give a similarity score of 93+% to the version nearest to the sample, means that even if the exact version of the sample is not in the reference database, a good approximation of its version will still be returned.

3) False positives: While a good comparison technique for our purpose should give a high similarity score to close versions of the same library, this is not the only metric of effectiveness. In table IV, another metric is shown: the similarity score of the highest rating library version that is not a version of the same library as the sample. In other words, all results of the correct library are ignored, and the highest remaining similarity score is recorded. Since these results are by definition not matches or near-matches\(^6\), the recorded scores should be low. In practice, str2 performs really well in this regard: for all samples in table IV, the highest “false positive” similarity score is below 9%, which is low compared to the 20+% values returned by other techniques. The cyclomatic complexity–based techniques perform badly because the probability that functions from unrelated libraries have the same cyclomatic complexity value is high, especially for large libraries. This is an expected trade-off of the small

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\(^4\)https://github.com/Riscure/Library-Identification/

\(^5\)This approach was preferred over a binary source (e.g. Debian package archives) because it allows us to create binaries of old library versions without future security patches being applied.

\(^6\)This is assumed to be true in this dataset. In general, libraries could share code or be forked from each other, in which case high similarity ratings could be legitimate.
## Implemented comparison techniques

| Function name | Short name | Description |
|---------------|------------|-------------|
| compare_bb_hash_bloomfilter | bloom | Compares the sample and the reference by comparing the Bloom filter signatures of each using the Jaccard index. |
| compare_cc_list_levensteiin | cc1 | Compares the cyclomatic complexity values of all functions in the sample with those of all functions in the reference by taking the Levenshtein distance between these lists. |
| compare_cc_list_set_union | cc2 | Performs a permutation-independent comparison between the lists of cyclomatic complexity values of both the sample and the reference by treating both as sets and calculating the overlap between these sets using the Jaccard index. |
| compare_cc_spp | cc3 | Compares the cyclomatic complexity values of the functions in the sample and the reference by factoring the small prime products of each and determining the number of matching factors. |
| compare_strings_concat_levensteiin | str1 | Performs a fuzzy string and string list comparison by taking the Levenshtein distance between the concatenations of the lists of strings in both the sample and the reference. |
| compare_strings_set_union | str2 | Performs an exact, permutation-independent string list comparison by treating the lists of strings in both the sample and the reference as sets and calculating the overlap between these sets using the Jaccard index. |

### Table I: Implemented comparison techniques

| Sample library | str1 | str2 | cc1 | cc2 | cc3 | bloom |
|----------------|------|------|-----|-----|-----|------|
| libpng 1.6.15 | 91903 ms | 47 ms | 9 ms | 15 ms | 13095 ms | 304 ms |
| libz 1.1.3 | 16257 ms | 28 ms | 5 ms | 9 ms | 13210 ms | 364 ms |
| curl 7.43.0 | 146191 ms | 80 ms | 66 ms | 19 ms | 13437 ms | 309 ms |
| bzip2 1.0.6-5 | 18625 ms | 28 ms | 5 ms | 10 ms | 13152 ms | 348 ms |

Table II: Averaged duration of the comparison of each sample against 188 MIPS library versions on a Core i7 laptop.

| Reference library | str1 | str2 | cc1 | cc2 | cc3 | bloom |
|-------------------|------|------|-----|-----|-----|------|
| libjpeg 9.2.0 | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% | 100.00% |
| libjpeg 9.1.0 | 99.97% | 99.35% | 98.75% | 93.62% | 97.49% | 97.19% |
| libjpeg 9.0.0 | 99.87% | 94.62% | 91.41% | 84.00% | 90.48% | 88.38% |
| libjpeg 8.4.0 | 99.39% | 92.91% | 89.66% | 70.37% | 88.09% | 84.64% |
| libjpeg 8.3.0 | 99.25% | 92.77% | 86.83% | 70.37% | 86.52% | 78.78% |
| libjpeg 8.0.2 | 99.24% | 92.77% | 86.83% | 73.58% | 86.52% | 78.42% |
| libjpeg 8.0.1 | 99.22% | 92.77% | 86.21% | 73.58% | 86.52% | 78.06% |
| libjpeg 8.0.0 | 99.20% | 92.61% | 86.21% | 73.58% | 86.52% | 77.34% |
| libjpeg 7.0.0 | 95.14% | 88.85% | 78.37% | 65.45% | 78.37% | 77.12% |

Table III: Similarity of libjpeg.so.9.2.0 (MIPS) to other libjpeg versions.

The bloom technique performs similarly, largely because of a similar reason: unrelated libraries share basic-blocks that produce the same hash. Considering the fact that the hash is made from the list of instruction types, and that these references contain many small basic-blocks, this was to be expected.

An outlier here is the result of bloom on libz version 1.1.3. In this case, all non-libz library versions are given similarity scores of less than 1%, a much better result than the others in its column. Why only this specific library shares so little basic-block hashes with others is unknown. One possible cause of this could be that instructions in versions of this library are consistently different or ordered differently from those in other libraries, which could be explained by a different compiler or different compiler flags being used.

### B. Identifying libraries within statically linked executables

All six techniques perform well at the task of identifying the most likely version of a shared library file. We would, however, also like to know how well these techniques apply to the problem of identifying libraries inside statically linked executables. In order to evaluate this, the tool was run on both artificial and real-world statically linked executables. The results of which are detailed here.

Firstly, the sample code provided by libjpeg in example.c was used to create a dummy program that calls the
read JPEG_file and write JPEG_file functions. Nine samples were created by statically linking this program with nine different versions of libjpeg. Each sample was stripped of symbols before performing the experiments. Table V shows for each combination of sample and technique, whether the correct libjpeg version (the one that the sample was linked with) is the top result (i.e. whether it has the highest similarity score out of all the references).

In the table, we can see that str2 is the only technique that consistently gives the highest similarity score to the correct library version. The fuzzy string comparison technique, str1, performs almost as well but strangely produces version 7.0.0 for the sample which was linked to libjpeg version 8.0.0.

Of course, when interpreting the program output in this manner, we assume that the sample file is statically linked to exactly one library and that this library is contained in the reference database. A more complex scenario would be a sample that is statically linked against multiple libraries. One such a sample is the statically linked version of the castget program, an open source podcast downloader\(^7\). Three libraries are statically linked into this relatively large (1.7MB) binary: curl (7.50.0), libxml2 (2.8.0) and id3lib (3.8.3). Because two out of three of these libraries are in the reference database – curl and id3lib – it makes for a good real-world test case.

Looking at the results, we see that str2 is the only technique where the two correct matches have the highest similarity scores, with a significant percentage drop afterwards (i.e. from 11.13% for id3lib to 2.51% for libmp4v2). The str2 technique has matched the correct version of curl but not of id3lib, where it matched version 3.8.0 instead of 3.8.3, the actual version contained in the sample. This was however entirely expected, because version 3.8.0 is the only reference version for id3lib in the database.

### VIII. Robustness against Obfuscation

While some of the techniques are clearly more effective than others when applied to the samples above, it is also good to consider their robustness against intentional and unintentional obfuscation in more obscure scenarios. The authors of firmware images containing shared libraries or statically linked executables might exploit weaknesses of the identification techniques in order to make it as difficult as possible for an analyst to determine the version of these libraries. A clear example of such a countermeasure is string obfuscation. There exists a wide range of techniques for string obfuscation – ranging from trivial transformations to cryptographic techniques – but even the simplest of these will render str1 and str2 fruitless. On the other hand, the cyclomatic complexity and basic-block–based techniques are sensitive to changes to the CFG structure or individual instructions which can be caused by (heavy) compile-time optimization or intentional code obfuscation. In such situations, the string-based techniques are the most robust.

While such countermeasures are important to keep in mind, the best-case scenario of a non-optimized and non-obfuscated sample was assumed during this project. Certainly, it is much more straightforward for a firmware-creator to keep their included open-source libraries up to date than to attempt to obfuscate them to hide the fact that they are out of date. Therefore one would not expect to come across many intentionally obfuscated open-source libraries in practice.

Another factor that could cause the string-based techniques to perform less well is the fact that the number of strings in libraries is not necessarily related to their size, i.e. there could be low-level libraries that barely contain any (unique) strings, causing low similarity scores and relatively high false-positive scores.

### IX. Future Work

The work presented in this paper only scratches the surface of what could be possible in terms of library version identification using existing fingerprinting and binary comparison techniques. The six implemented techniques represent several combinations of fingerprint creation and fingerprint comparison techniques, but more combinations and variations are possible. Specifically, more advanced approaches like the use of machine learning algorithms \(^9\) could yield better results.

The biggest problem with the current approach is that all techniques compare the entire contents of the sample file to the entire contents of reference files, resulting in absolute rather than relative similarity scores. These are useful when the sample is a shared library file but less so for statically linked executables, especially when these contain multiple linked libraries, as seen in table VI. In such cases, one might want to first identify which parts of the executable file are library code at all and possibly even apply fingerprinting techniques on a per-function basis\(^9\). Research is required to determine whether or not such solutions are feasible and more effective.

More generally, other approaches to this problem could be the use of symbolic execution (i.e. comparing functions or basic-blocks by their constraints) or visualisation \(^3\) using image processing techniques.

\(^7\)From http://castget.johndal.com/

\(^9\)IDA's F.L.I.R.T.[6] provides library function identification using small fingerprints, but it is rather fragile, and geared more towards manual reverse-engineering and small sets of libraries.

| Sample library | str1 | str2 | cc1 | cc2 | cc3 | bloom |
|----------------|------|------|-----|-----|-----|-------|
| libpng 1.6.15 | 23.16% | 3.96% | 30.00% | 54.29% | 64.15% | 27.78% |
| libx 1.1.3    | 20.19% | 7.71% | 29.01% | 69.57% | 46.15% | 0.97%  |
| curl 7.43.0   | 22.28% | 2.89% | 37.30% | 62.12% | 73.40% | 38.89% |
| bzip2 1.0.6-5 | 20.17% | 8.27% | 29.63% | 57.58% | 33.93% | 31.82% |

Table IV: Similarity of the highest matching version of an incorrect library.
### Table V: Does the correct libjpeg version have the highest similarity rating when comparing a statically linked executable against 188 references? “yes”: the correct libjpeg version has the highest similarity score; “no”: a different library has the highest similarity score; “(n)”: version n of libjpeg has the highest similarity score; “(multiple)”: several versions of libjpeg have a shared highest similarity score.

| Sample file                      | str1 | str2 | cc1  | cc2  | cc3  | bloom |
|----------------------------------|------|------|------|------|------|-------|
| jpeg_7.0.0_example_static        | yes  | yes  | yes  | yes  | yes  | yes   |
| jpeg_8.0.0_example_static        | (7.0.0) | yes  | (8.0.1) | no  | (multiple) | (multiple) |
| jpeg_8.0.1_example_static        | yes  | yes  | yes  | no   | yes  | yes   |
| jpeg_8.0.2_example_static        | yes  | yes  | (multiple) | no  | (multiple) | (multiple) |
| jpeg_8.3.0_example_static        | yes  | yes  | yes  | no   | (8.0.1) | (8.0.1) |
| jpeg_8.4.0_example_static        | yes  | yes  | (8.3.0) | no  | (multiple) | (multiple) |
| jpeg_9.0.0_example_static        | yes  | yes  | yes  | yes  | yes  | yes   |
| jpeg_9.1.0_example_static        | yes  | yes  | (multiple) | yes | yes  | yes   |
| jpeg_9.2.0_example_static        | yes  | yes  | (multiple) | yes | yes  | yes   |

### Table VI: Top 5 distinct matched libraries for the castget ARM sample. Each table shows the result for a single technique.

| Library   | Version | Similarity |
|-----------|---------|------------|
| libisoburn | 1.4.0   | 18.03%     |
| curl      | 7.50.0  | 18.91%     |
| libisofs  | 1.4.6   | 17.85%     |
| libarchive| 3.2.2   | 16.95%     |
| libexif   | 0.6.21  | 14.93%     |
| curl      | 7.50.0  | 18.91%     |
| id3lib    | 3.8.0   | 11.13%     |
| libmp4v2  | 2.0.0   | 2.51%      |
| libburn   | 1.2.2   | 1.37%      |
| libisoburn| 1.3.6   | 1.37%      |
| libburn   | 1.2.2   | 1.37%      |
| libisoburn| 1.3.6   | 1.37%      |
| libburn   | 1.2.2   | 1.37%      |

### X. Conclusions

In this project, six comparison techniques were detailed and implemented, inspired by existing research in the areas of executable file comparison and fingerprinting. Out of these techniques, the exact set-based readable string comparison technique, str2, performed the best. In terms of effectiveness it (empirically) outperforms all others, most notably by correctly assigning relatively high similarity scores to libraries contained inside a statically linked executable, and low scores to others. Using the output of this technique – given an exhaustive reference database – an analyst is able to more quickly determine (the versions of) libraries contained in statically linked executables.

While str2 performs well in the tested scenarios, it is acknowledged that the kind of signature it uses to recognize a library (i.e. the list of printable strings in the file’s data) is fragile in the sense that it can easily be obfuscated. This is however true for all techniques, to a lesser degree.

### XI. Acknowledgements

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APPENDIX

This appendix shows the contents of the reference database used for the experiments in this paper. Library versions were compiled for one of three architectures: X86, MIPS or ARM. As can be seen below, not all versions of every library were obtained for every architecture. Unless stated otherwise, the set of reference library versions used for each experiment is a subset of this database, as obtained by filtering this list by the architecture of the sample file.

- attr:
  - MIPS: 2.4.47-2
  - ARM: 1.0.4 1.0.5 1.0.6
  - MIPS: 1.0.5 1.0.6-5
- curl:
  - ARM: 7.21.4 7.21.5 7.21.6 7.21.7 7.22.0 7.23.0 7.23.1 7.24.0 7.25.0 7.26.0 7.27.0 7.28.0 7.28.1 7.29.0 7.30.0 7.31.0 7.32.0 7.33.0 7.34.0 7.35.0 7.36.0 7.37.0 7.37.1 7.38.0 7.39.0 7.40.0 7.41.0 7.42.0 7.43.0 7.44.0 7.45.0 7.46.0 7.47.0 7.47.1 7.48.0 7.49.0 7.50.0 7.50.1
- MUPS: 7.21.4 7.21.5 7.21.6 7.21.7 7.22.0 7.23.0 7.23.1 7.24.0 7.25.0 7.26.0 7.27.0 7.28.0 7.28.1 7.29.0 7.30.0 7.31.0 7.32.0 7.33.0 7.34.0 7.35.0 7.36.0 7.37.0 7.37.1 7.38.0 7.39.0 7.40.0 7.41.0 7.42.0 7.43.0 7.44.0 7.45.0 7.46.0 7.47.0 7.47.1 7.48.0 7.49.0 7.50.0 7.50.1 7.50.2 7.50.3
- flac:
  - MIPS: 1.21 1.3.0 1.3.1
  - ARM: 3.8.0
- lame:
  - MIPS: 3.98.4 3.99.1 3.99.2 3.99.3 3.99.4 3.99.5 3.99
- libao:
  - ARM: 0.8.8 1.0.0 1.1.0 1.2.0
- libarchive:
  - ARM: 3.0.4 3.1.2 3.2.0 3.2.1 3.2.2
- libart-lpql:
  - ARM: 2.3.21
- libburn:
  - ARM: 0.6.0 p01 0.6.2 p01 0.6.4.p01 0.6.6.p00 0.7.0.p00 0.7.2.p00 0.7.2.p01 0.7.4.p00 0.7.6.p00 0.8.p00 0.8.2.p00 0.8.4.p00 0.8.6.p00 0.8.8.p00 0.9.0.p00 1.0.0.p00 1.0.2.p00 1.0.4.p00 1.0.6.p00
- libblurnddio:
  - ARM: 0.30.12.0 3 0.99 12
  - MIPS: 0.99.12-4 0.99.12-7 0.99.12
- libcrypto:
  - ARM: 1.3.0 1.3.2
- libcss:
  - ARM: 0.82 0.83 0.90 0.92 0.93
- libcrypto:
  - ARM: 0.86 0.97 0.98
- libgssglue:
  - ARM: 1.0.0
- libidn:
  - ARM: 0.12 0.1 0.2 0.1 0.2 1 0.2 2 0.2 3 0.2 4 0.2 5 0.2 6 0.2 8 0.2 9
  - libs: 1.94:
  - ARM: 2.1 0.2 1.2 2.1 2.2 2.2 2.2 2.4
- libdaa:
  - ARM: 0.5
- libdiscal:
  - ARM: 0.30 0.5 0.41 0.5 0.51 0.5 0.5 0.61
- libdmux:
  - ARM: 0.7 4
- libdy:
  - ARM: 1.0
- libdvlpma:
  - ARM: 0.16 0.1 0.1 0.2 0.2 0.2 1 0.0 1.1 0.1 1.1 0.1 1.3 0.3
- libdvdcss:
  - ARM: 1.26 1.1 1.1 1.2 1.2 3.2 1.2 3.0 1.4 0
- libebml:
  - ARM: 0.7 8 0.8 0.1 0.0 1.2 1.2 1.2 3.1 3.1 1.3 1.3 1.4
  - MIPS: 0.7 8 0.8 0.4 1.0 0.4 1.2 0.4 1.2 1.1 1.2 2.2 1 3.0 1.3 1.1 1.3 3.2 1.3 4 1.3 4
- libreif:
  - ARM: 0.6 1.6 0.1 6.0 16.0 16.2 0.2 0.2 0.6 2.1
- libfd:
  - ARM: 3.0 10.0 3.1 11 3.1 12 3.0 13 3.0 8.0 3.0 7.1 3.2 1
- libgssglue:
