OCELOT: A Search-Based Test-Data Generation Tool for C

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ABSTRACT

Automatically generating test cases plays an important role to reduce the time spent by developers during the testing phase. In last years, several approaches have been proposed to tackle such a problem: amongst others, search-based techniques have been shown to be particularly promising. In this paper we describe OCELOT, a search-based tool for the automatic generation of test cases in C. OCELOT allows practitioners to write skeletons of test cases for their programs and researchers to easily implement and experiment new approaches for automatic test-data generation. We show that OCELOT achieves a higher coverage compared to a competitive tool in 81% of the cases. OCELOT is publicly available to support both researchers and practitioners.

CCS CONCEPTS

• **Software and its engineering → Maintaining software**; **Search-based software engineering**;

KEYWORDS

Automated Testing, Test Case Generation, Search-Based Software Engineering

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1 INTRODUCTION

Software testing —and, in particular, test case writing— is one of the most human-intensive and time-consuming activities in software development life-cycle [1]. Therefore, noticeable effort has been devoted toward automated test-data generation, applying and possibly combining approaches like random testing, symbolic, and concolic execution [3, 7, 10, 16, 20]. Search-based approaches have also been proved to be particularly well-suited [8, 13].

While many search-based tools are nowadays available for Java, some of which very mature and used in practice (*e.g.*, EvoSuite [6]), the same is not true for C. Indeed, the tools developed in the past, like TESTGEN [5], QUEST [2], and GADGET [15], are quite dated and not available (neither as executable binaries). To the best of our knowledge, the most recent search-based tools for test-data generation in C are: i) IGUANA, proposed by McMinn [14], developed in Java and relying on JNI to interface with C; ii) Austin, introduced by Lakhotia *et al.* [12], developed in OCaml and based on the CIL framework[1]; iii) CAVM, recently proposed by Kim *et al.* [9], developed in C, C++, and Python and based on CLang and gcc for source code instrumentation. Considering that both IGUANA and CAVM are not publicly released, the only available tool for test-data generation in C is Austin. However, despite being open source[2], this project is not active anymore. In summary, C remains a widely used language (ranked 2nd in the TIOBE Index for May 2018[3]) and, for this reason, we believe that the search-based research community should put some effort into actively developing test-data generation tool for this programming language.

In this paper, we take a step in such a direction and we present OCELOT, a search-based test-data generation tool for C that provides an extensible framework to quickly implement different types of search-based approaches. OCELOT is also able to automatically write test suites, relying on the LibCheck framework[4]. We empirically evaluate OCELOT with respect to Austin on 26 functions from 3 open-source C programs, and we show that OCELOT achieves a higher branch coverage in 81% of the cases. OCELOT is publicly available[5] along with its documentation[6].

2 BACKGROUND

In the context of white-box coverage-driven testing, the automatic test-data generation consists of the generation of a (possibly minimal) set of inputs (TD) for a given target program P to reach a desired amount of code coverage (*e.g.*, branch coverage). To achieve this goal, a search-based test-data generator (TDG) uses a search algorithm, calling P with many combinations of inputs (test data),

[1] http://www.cs.berkeley.edu/~necula/cil/ [2] https://github.com/kiranlak/austin-sbst
[3] https://www.tiobe.com/tiobe-index/ [4] https://libcheck.github.io/check
[5] https://ocelot.science/ [6] https://ocelot.gitbook.io/manual/

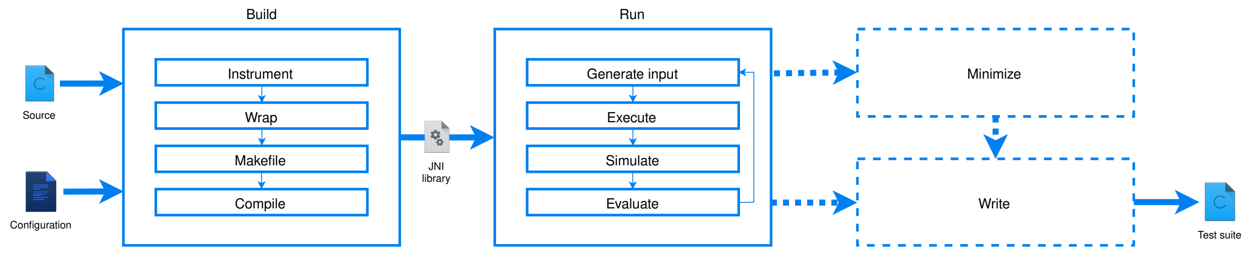


Figure 1: The Workflow of Ocelot

with the aim of maximizing the total achieved coverage. This process continues until the specified search-budget (*e.g.*, number of iterations) is over. Therefore, generating test data requires a continuous interaction between the target program and the test-data generator. When TDG calls P with a given input, P has to provide feedback about the branches covered with that input to TDG.

Since C is a procedural programming language, it is possible to consider functions as the units to test (P). This makes test generation conceptually different compared to object-oriented languages (*e.g.*, Java), where the units to test are classes with a state [21]. Furthermore, automatically generating test data for C presents unique technical challenges. The main technical challenge (C_1) is the *instrumentation* of P, necessary to register what happens in P when TDG tests a specific input. Indeed, the object language of C depends on the target architecture and it is necessary to find a way to instrument P, without tying to a specific architecture/operating system, to grant a certain level of portability. A second technical challenge (C_2) regards the *integration* between TDG and P^* (*i.e.*, the instrumented P). It is necessary to devise a mechanism to i) make the input generated by TDG suitable for P^* and ii) to make P^* able to communicate with TDG. A final major research and technical challenge (C_3) regards one of the main peculiarities of C, *i.e.*, pointers. Consider a function that takes as input `(int* a, int b)`. At some point in the function, there is a condition `if (*a == b)`. A test-data generator should be able to generate test data that evaluate such a condition as `true`. While Java has a more rigid and implicit typing rule (*i.e.*, objects are stored as references, primitive types are stores by values), in C it is possible to have mixed situations, that makes handling data types in TDG more difficult.

3 OCELOT

The architecture of Ocelot is inspired by IGUANA [14]: it is developed in Java and uses JNI as interface with the target program to try different combinations of test data. Running Ocelot consists of two distinct macro-phases: *build* and *run*. Figure 1 shows the phases of test-data generation in Ocelot. In the *build* phase, the target program is instrumented, wrapped in a JNI library and then compiled. The output of such a phase is a static library. This library is linked by Ocelot and used in the *run* phase, where a search-based algorithm is exploited to identify a set of inputs that maximize the code coverage. The output of this phase is a set of test data that can be used to test the target program. Ocelot also provides two additional optional phases: *minimize* and *write*. During the *minimize* phase, test data that do not contribute to improve the code coverage are removed, while during the *write* phase, skeletons of actual test cases are written. Such skeletons lack the assertions, that should be manually added, and they are based on the LibCheck framework.

3.1 Build Phase

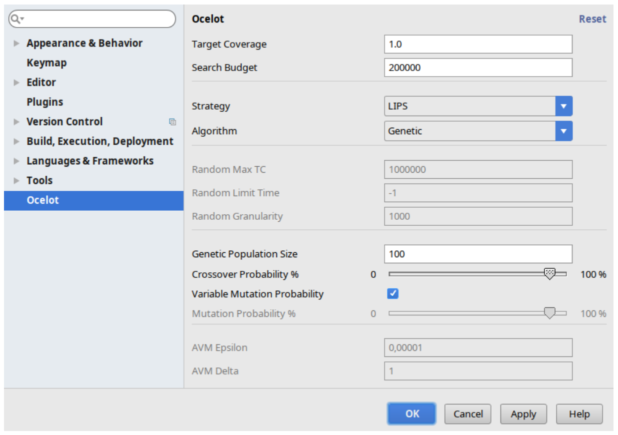
The *build* phase consists of: i) *instrumenting* the target program (*i.e.*, transforming P to P^*), ii) *wrapping* it in the JNI library, iii) generating the *makefile*, and iv) *compiling* the static library. Ocelot directly instruments the C source code, making it able to potentially work regardless of the target architecture. Specifically, it adds probes near the control structures to track the exact steps executed in P. Existent tools (*e.g.*, `gcov` or `lcov`) are not used, since they do not report the runtime values of the variables, needed to compute part of the fitness function for some approaches. During the *wrapping* sub-phase, Ocelot adds to the target function a set of pre-defined C functions to integrate P^* in Ocelot through JNI. Moreover, it adapts some of those files to handle the specific inputs required by P. Indeed, while the static Java interface to call P remains the same, each target function has its own input types. The *wrapping* sub-phase handles the information that will be passed by Ocelot during the *run* phase and translate it into actual C variables that will be passed to P^* for the execution. Finally, Ocelot generates the *makefile* (depending on the operating system and on the special requirements of the target program) and it *compiles* the JNI library.

3.2 Run Phase

The *run* phase consists of: i) *generating* inputs for P, ii) calling the JNI interface to *execute* the code, iii) grabbing the execution events and *simulating* them on the Control Flow Graph of P, and iv) *evaluating* the inputs and giving feedback to generate other inputs. The input generation and the feedback mechanism strongly depend on the specific test-data generation strategy used. For example, a strategy based on random search would randomly generate inputs and ignore the evaluation, adding all the generated test data to the resulting test suite. On the other hand, the *execution* and *simulation* sub-phases are common to all the strategies. After the execution of P^*, a list of events (*i.e.*, the actual evaluations of conditions and fitness function) is generated. Such a list is used to *simulate* the events on the Control Flow Graph of P to easily compute the fitness function necessary to give feedback to the strategy.

3.3 Features

Ocelot provides some additional features compared to the state-of-the-art tools. First of all, it implements different search-based approaches and it is easily extensible. Indeed, Ocelot is not tied to



Ocelot

Target Coverage: 1.0
Search Budget: 200000
Strategy: LIPS
Algorithm: Genetic
Random Max TC: 1000000
Random Limit Time: -1
Random Granularity: 1000
Genetic Population Size: 100
Crossover Probability % 0 – 100 %
Variable Mutation Probability: ✓
Mutation Probability % 0 – 100 %
AVM Epsilon: 0,00001
AVM Delta: 1

Figure 2: The CLion plugin configuration for Ocelot

any specific approach. It implements LIPS [19], MOSA [18], AVM [11], and the random approach [17] while, for instance, CAVM [9] is only based on AVM [11], while Austin implements AVM and AVM+ [12]. Furthermore, it supports different budget-handling and minimization strategies that can be combined together with the aforementioned algorithms. Thus, Ocelot is not designed to work only with a specific type of algorithm and, therefore, it is easily extensible with new test-data generation strategies. With respect to other tools (*e.g.*, Austin), Ocelot is based on Eclipse CDT[7]. Hence, it is able to automatically detect the data types of the parameters and to fully instrument code.

Ocelot strongly relies on a configuration file, in which all the parameters for all the phases have to be specified. For example, this file contains the maximum number of evaluations, the desired target coverage, the name of the target function, the path to the file with the target function, and so on. Since there are many parameters that can be set, we also developed a user interface for Ocelot, implemented in a CLion[8] plugin. This plugin allows developers to easily use Ocelot for their projects. While, as previously stated, the command line allows to make experiments, the CLion plugin is focused on practitioners and, therefore, it supports by default the *write* mode able to generate skeletons of test cases. It adds a configuration page for Ocelot in the general configuration of CLion. Moreover, it introduces an item in the "*Code*" menu (*i.e.*, "*Generate TC*"). When clicking on this item, the plugin shows a window with all the functions of the current files for which the developer could generate test-data. Finally, the plugin automatically recognizes the signature of each function, allowing the users to specify, for each parameter, the ranges of possible values. Figure 2 shows the Ocelot configuration window in CLion.

4 EVALUATION

In this section we report a comparison between Ocelot and Austin, the only available search-based tool for automatically generating test-data in C, to the best of our knowledge. We were not able to compare Ocelot to CAVM or IGUANA, since these tools are not publicly available. Note that our goal was to compare Ocelot with competitive search-based tools, so we did not consider test data generation tools for C based on other approaches, such as CUTE [20] and DART [7]. This comparison will be part of future work.

As previously shown in Section 3, Ocelot provides a broader number of features compared to other state-of-the-art tools . Moreover, it is more flexible and easily extensible. Amongst the others, Ocelot allows to generate tests relying on different meta-heuristics. Being the *goal* of the evaluation to check whether Ocelot is a good alternative to Austin, we set Ocelot to run with AVM, *i.e.*, the search-algorithm employed by Austin.

With our study we aim to compare out-of-the-box the performance of these tools. It is worth noting that Austin requires an explicit pointer constraints in the source code of the target function to instantiate any pointer. Thus, a pointer will not be instantiated if the code does not compare it to `NULL`. We argue that this an important limitation for the usability of the tool. Therefore, as done in previous work [9], we decide to not manually modify the subjects to evaluate the tools in a real-world scenario.

To compare the tools, we run both of them on a subset of 26 functions coming from 3 different C open source projects: `GIMP`, `GLS`, and `SGLIB`. `GIMP` is the open source GNU image manipulation software; `GLS` stands for GNU Scientific Library; `SGLIB` is a library offering generic utilities. It is worth noting that this set of functions has been used both in our previous work and in the paper that introduced Austin [12, 19]. Table 1 lists the set of functions, representing the *context* of the comparison. In total, we take into account 400 branches for 26 functions.

As done in previous work [9], we set 1000 evaluations for each branch of the function under test as search budget. Moreover, for the same reason, we do not impose any time limit constraints.

We run the tools 20 times for each function; we then compare the achieved *branch coverage* relying on the non-parametric Wilcoxon Rank Sum Test [4] with significance level $\alpha = 0.05$. Significant *p-values* allows us to reject the null hypothesis, *i.e.*, that the two tools achieve the same coverage. Moreover, we rely on the Vargha-Delaney ($\hat{A}_{12}$) statistic [22] to estimate the effect size, *i.e.*, the magnitude of the difference between the measured metrics. $\hat{A}_{12} <= 0.5$ means that Ocelot reaches a higher coverage than Austin, while $\hat{A}_{12} > 0.5$ has the opposite meaning. Vargha-Delaney statistics also classifies such effect size into four different levels: *negligible*; *small*; *medium*; *large* [22]. For the experiments, we execute both the tools on a virtual machine with 8 cores and 32GB RAM, running Ubuntu 16.04 LTS. We make available two docker images on DockerHub —one for each tool— to foster the replicability of the results[9,10].

4.1 Results

Table 1 summarizes the branch coverage results with the comparison between Austin and Ocelot. The table shows the average coverage achieved over 20 runs along with the *p-values* obtained with the Wilcoxon test and the Vargha-Delaney statistic. We typeset the statistically significantly results (*i.e.*, p-value$\leq$ 0.05) in bold, highlighting the tool reaching the highest coverage. From Table 1 we notice that Ocelot performs better than Austin in 21 out 26 cases ($\approx$ 81%), while the opposite happens in only one case. In detail, the coverage improvement ranges from a minimum of 43%

[7] https://www.eclipse.org/cdt/ [8] https://www.jetbrains.com/clion/

[9] https://hub.docker.com/r/giograno/austin/
[10] https://hub.docker.com/r/giograno/ocelot/

Table 1: Comparison between Austin and Ocelot

Program	Function	Branches	Austin	Ocelot	p-value	$\hat{A}_{12}$
SGLIB	sglib_int_array_quick_sort	48	0.17	**0.93**	0.00	0.00 (L)
SGLIB	sglib_int_array_heap_sort	44	0.19	**1.00**	0.00	0.00 (L)
SGLIB	sglib_int_array_binary_search	14	0.32	**0.75**	0.00	0.00 (L)
GLS	gsl_poly_eval_derivs	12	0.58	**1.00**	0.00	0.00 (L)
GLS	gsl_poly_solve_cubic	20	0.55	0.55	0.15	0.55 (N)
GLS	gsl_poly_solve_quadratic	14	0.64	0.63	0.07	0.65 (S)
GLS	gsl_poly_complex_solve_quadratic	14	0.64	0.64	0.56	0.55 (N)
GLS	gsl_poly_complex_solve_cubic	22	**0.73**	0.42	0.00	1.00 (L)
GIMP	gimp_cmyk_to_rgb	2	0.00	**1.00**	0.00	0.00 (L)
GIMP	gimp_cmyk_to_rgb_int	2	0.00	**0.68**	0.00	0.00 (L)
GIMP	gimp_hsl_to_rgb	4	0.00	**0.75**	0.00	0.00 (L)
GIMP	gimp_hsl_to_rgb_int	4	0.00	**0.76**	0.00	0.00 (L)
GIMP	gimp_hsv_to_rgb	10	0.00	**0.80**	0.00	0.00 (L)
GIMP	gimp_rgb_to_cmyk	8	1.00	1.00	NaN	0.50 (N)
GIMP	gimp_rgb_to_hsl	14	0.00	**0.17**	0.00	0.00 (L)
GIMP	gimp_rgb_to_hsl_int	28	0.00	**0.85**	0.00	0.00 (L)
GIMP	gimp_rgb_to_hsv4	26	0.00	**0.78**	0.00	0.00 (L)
GIMP	gimp_rgb_to_hsv_int	30	0.00	**0.80**	0.00	0.00 (L)
GIMP	gimp_rgb_to_hwb	10	0.00	**0.50**	0.00	0.00 (L)
GIMP	gradient_calc_square_factor	10	0.50	**0.93**	0.00	0.00 (L)
GIMP	gradient_calc_radial_factor	8	0.50	**0.93**	0.00	0.03 (L)
GIMP	gradient_calc_linear_factor	12	0.09	**0.99**	0.00	0.00 (L)
GIMP	gradient_calc_bilinear_factor	8	0.12	**0.97**	0.00	0.00 (L)
GIMP	gradient_calc_spiral_factor	10	0.30	**0.89**	0.00	0.00 (L)
GIMP	gradient_calc_conical_sym_factor	14	0.21	**0.89**	0.00	0.00 (L)
GIMP	gradient_calc_conical_asym_factor	12	0.25	**0.87**	0.00	0.00 (L)
Total Average			0.26	0.79		

to a maximum of 100% for the function (*e.g.*, `gimp_cmyk_to_rgb`). Indeed, in each of the aforementioned cases, the effect size is *large*.

Qualitatively looking at the results, we can see that Austin stops at 0% of coverage for the subjects having only pointers as arguments (*e.g.*, `gimp_hsl_to_rgb`). Furthermore, even in case of functions with only primitive values as parameters, Ocelot is able to reach a higher coverage than Austin. For example, on `gradient_calc_radial_factor` Austin constantly achieves 50% of coverage, while Ocelot hits ≈ 93% on average with a 0.13 standard deviation.

Even if we do not impose any time limit constraints as search budget, it is still worth to discuss this dimension when it comes to compare the two tools. In particular, during our experiment we noticed that, given the same maximum amount of iterations, Ocelot is way faster than Austin. Just to give an idea, the evolutionary search for the function `sglib_int_array_quick_sort` takes ≈ 6 seconds for Ocelot, while it takes ≈ 4 minutes for Austin.

5 CONCLUSION AND FUTURE WORK

In this paper we presented Ocelot, a search-based tool for automatically generating test-data for C programs. We released the executable of Ocelot, describing the configuration parameters that can be set, to allow both researchers and practitioners to use the tool. Our preliminary study shows that Ocelot is able to achieve higher coverage than Austin. Moreover, Ocelot presents some additional advantages over Austin: i) it is *easier to use*: on the one hand Austin requires manual code-changes to instantiate pointers or to specify input preconditions; on the other hand Ocelot automatically handles those cases; ii) it is written in Java, a more common programming language compared to OCaml, and it is actively maintained; iii) it offers a CLion plugin to help the practitioners to configure the tool; iv) it supports different search algorithms, generation and minimization strategies that can be combined together; v) it is more effective and efficient.

Future work will be aimed at improving Ocelot in several aspects. We plan to implement a different representation for the test input, to support recursive data structures. We also plan to implement a new instrumentation process with of aim of reducing the time needed for the instrumentation of multiple target functions: this step should improve the scalability of the tool. Finally, we plan to release the code of tool as open source in the near future.

REFERENCES

[1] A. Bertolino. Software testing research: Achievements, challenges, dreams. In *2007 Future of Software Engineering*, pages 85–103. IEEE Computer Society, 2007.

[2] K. H. Chang, J. H. CROSS II, W. H. Carlisle, and S.-S. Liao. A performance evaluation of heuristics-based test case generation methods for software branch coverage. *International Journal of Software Engineering and Knowledge Engineering*, 6(04):585–608, 1996.

[3] K. Claessen and J. Hughes. Quickcheck: a lightweight tool for random testing of haskell programs. *Acm sigplan notices*, 46(4):53–64, 2011.

[4] W. J. Conover and W. J. Conover. Practical nonparametric statistics. 1980.

[5] R. Ferguson and B. Korel. The chaining approach for software test data generation. *ACM Transactions on Software Engineering and Methodology*, 5(1):63–86, 1996.

[6] G. Fraser and A. Arcuri. Evosuite: automatic test suite generation for object-oriented software. In *Joint meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on the Foundations of Software Engineering*, pages 416–419. ACM, 2011.

[7] P. Godefroid, N. Klarlund, and K. Sen. Dart: directed automated random testing. In *ACM Sigplan Notices*, volume 40, pages 213–223. ACM, 2005.

[8] M. Harman, Y. Jia, and Y. Zhang. Achievements, open problems and challenges for search based software testing. In *Software Testing, Verification and Validation (ICST), 2015 IEEE 8th International Conference on*, pages 1–12. IEEE, 2015.

[9] J. Kim, B. You, M. Kwon, P. McMinn, and S. Yoo. Evaluating cavm: A new search-based test data generation tool for c. In *International Symposium on Search Based Software Engineering*, pages 143–149. Springer, 2017.

[10] J. C. King. Symbolic execution and program testing. *Communications of the ACM*, 19(7):385–394, 1976.

[11] B. Korel. Automated software test data generation. *IEEE Transactions on software engineering*, 16(8):870–879, 1990.

[12] K. Lakhotia, M. Harman, and H. Gross. Austin: An open source tool for search based software testing of c programs. *Information and Software Technology*, 55(1):112–125, 2013.

[13] P. McMinn. Search-based software test data generation: a survey. *Software Testing, Verification and Reliability*, 14(2):105–156, 2004.

[14] P. McMinn. Iguana: Input generation using automated novel algorithms. a plug and play research tool. *Department of Computer Science, University of Sheffield, Tech. Rep. CS-07-14*, 2007.

[15] C. C. Michael, G. E. McGraw, M. A. Schatz, and C. C. Walton. Genetic algorithms for dynamic test data generation. In *International Conference Automated Software Engineering*, pages 307–308. IEEE, 1997.

[16] C. Pacheco and M. D. Ernst. Randoop: feedback-directed random testing for java. In *Companion to the 22nd ACM SIGPLAN conference on Object-oriented programming systems and applications companion*, pages 815–816. ACM, 2007.

[17] C. Pacheco, S. K. Lahiri, M. D. Ernst, and T. Ball. Feedback-directed random test generation. In *Proceedings of the 29th international conference on Software Engineering*, pages 75–84. IEEE Computer Society, 2007.

[18] A. Panichella, F. M. Kifetew, and P. Tonella. Automated test case generation as a many-objective optimisation problem with dynamic selection of the targets. *IEEE Transactions on Software Engineering*, 44(2):122–158, 2018.

[19] S. Scalabrino, G. Grano, D. Di Nucci, R. Oliveto, and A. De Lucia. Search-based testing of procedural programs: Iterative single-target or multi-target approach? In *International Symposium on Search Based Software Engineering*, pages 64–79. Springer, 2016.

[20] K. Sen, D. Marinov, and G. Agha. Cute: a concolic unit testing engine for c. In *ACM SIGSOFT Software Engineering Notes*, volume 30, pages 263–272. ACM, 2005.

[21] P. Tonella. Evolutionary testing of classes. In *ACM SIGSOFT Software Engineering Notes*, volume 29, pages 119–128. ACM, 2004.

[22] A. Vargha and H. D. Delaney. A critique and improvement of the cl common language effect size statistics of mcgraw and wong. *Journal of Educational and Behavioral Statistics*, 25(2):101–132, 2000.