

Towards Counterexample-guided *k*-Induction for Fast Bug Detection Mikhail R. Gadelha Felipe R. Monteiro Lucas C. Cordeiro Denis A. Nicole 26th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering

Towards Counterexample-guided *k*-Induction for Fast Bug Detection

Mikhail R. Gadelha, Felipe R. Monteiro, Lucas C. Cordeiro, and Denis A. Nicole





Motivation

Why should we invest in software reliability?







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 The ubiquity of embedded systems drives a need to test and validate a system before releasing it to the market, in order to protect against system failures.



"Formal automated reasoning is one of the investments that AWS is making in order to facilitate continued simultaneous growth in both functionality and security."

- Byron Cook, FLoC, 2018.

Why should we invest in software reliability?

- Embedded software must be as robust and bug-free as possible, given that even subtle system bugs can have drastic consequences:
 - In April 2014, the **Heartbleed** was publicly disclosed, a security bug in the OpenSSL cryptography library, which is a widely used implementation of the Transport Layer Security (TLS) protocol.



 "When it is exploited it leads to the leak of memory contents from the server to the client and from the client to the server."

- Synopsys Inc., 2014.



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- In September 2018, attackers exploited three **Facebook** vulnerabilities and stole access tokens from as many as 50 million users, in order to take over their accounts.





Our main goal is to...

Propose a faster approach to detect bugs and prove correctness of a program

We demonstrate in this paper how to...

Improve the *k*-induction algorithm to work as a meet-in-the-middle bidirectional search by using the information from the counterexample

Background

The k-Induction Algorithm



Bounded Model Checking

 Basic Idea: given a transition system M, check negation of a given property φ up to given depth k:



- Translated into a VC ψ such that: ψ is satisfiable iff φ has counterexample of max. depth k.
- BMC tools are aimed at finding bugs; they cannot prove correctness, unless the bound k safely reaches all program states.

```
1 int main() {
2     uint32_t n;
3     uint64_t sn = 0;
4     for (uint64_t i = 1; i <= n; i++) {
5         sn = sn + 2;
6         assert(sn == i * 2);
7     }
8     assert(sn == n*2 || sn == 0);
9 }</pre>
```



BMC tools such as CBMC, ESBMC or LLBMC typically reproduce the loop k times (lines 4 – 7) and are unable to verify that program unless the loop is fully unrolled, *i.e.*, the unwinding assertion fails if $k < (2^32 - 1)$

The *k*-induction Algorithm

- I. Base case: usual BMC algorithm, tries to find a property violation.
 - Explores all states up to a bound k. Cannot prove correctness.
- II.Forward Condition: checks the completeness threshold (if all loops were unrolled).
 - Cannot find bugs.
- III. Inductive Step: over-approximates loops so all states can be checked without unrolling them completely.
 - Might return spurious counterexamples.

Approach and Uniqueness

Counterexample-Guided k-Induction



Counterexample-Guided k-Induction

- The biggest limitation of k-induction is the fact that it performs three checks for each k (*i.e.*, base case, forward condition and inductive step).
- The inductive step is the most computationally expensive one; it is an over-approximation, forcing the SMT solver to find a set of assignments in a larger state space than the original program.
- Moreover, the computation is *wasted* if a counterexample is found by the inductive step, as it is assumed to be spurious.



Counterexample-Guided k-Induction

- We propose to use the *counterexample* generated by the *inductive step* to *speed up* the bug finding check (*i.e.*, the base case).
- Our extension converts the *k*-induction algorithm into a **bidirectional search** approach by searching simultaneously:

i. both forward (*i.e.*, from the initial state);

- ii. backward (*i.e.*, from the error state ξ detected in the inductive step);
- iii. stop if both searches meet in the middle.



Running Example

Original Program



Running Example

Original Program





Running Example

Original Program



Modified Program





Evaluate our *k*-induction algorithm extension



Experiments

- In order to evaluate our *k*-induction algorithm extension, we selected a number of benchmarks from the International Competition on Software Verification 2018.
- We compare the results from the original k-induction and our extended version.

Experimental setup. All experiments were conducted on a computer with an Intel Core i7-2600 running at 3.40GHz and 24GB of RAM under Fedora 25 64-bit. We used **ESBMC v5.0** and no time or memory limit was set for the verification tasks.

Availability of data & tools. Our experiments are based on a set of publicly available benchmarks. All tools, benchmarks, and the results of our evaluation are available on our web page http://esbmc.org/

• Preliminary evaluation over the SV-COMP 2018 benchmarks.

Benchmark		k-	-induction	1	Extended <i>k</i> -induction		
	LOC	<i>T</i> (s)	M(MB)	k	<i>T</i> (s)	M(MB)	k
sum04.c	19	1	38.7	9	1	38.7	5
sum01.c	18	1	38.9	11	1	38.8	6
sum03.c	25	3	39.1	11	1	38.8	6
diamond1.c	24	13	43.6	51	6	39.1	26
rangesum.c	64	7	66.2	4	1	39.0	2
rangesum05.c	59	11	72.3	6	1	65.4	3
rangesum10.c	59	28	78.2	11	16	47.5	6
Problem01_label15.c	594	7	87.3	5	5	70.3	4
rangesum20.c	59	101	99.9	21	26	78.2	12
rangesum40.c	59	847	269.5	41	90	113.9	22
const.c	20	2606	796.6	1025	890	253.2	513
rangesum60.c	59	80272	1106.9	61	159	134.6	32
Average	88	6991	228.1	104	99	79.8	53
Total	1059	83897	2737.2	1255	1197	957.5	638

verification time is not related to the number of steps or the program size

Preliminary evaluation over the SV-CO

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Preliminary evaluation over

our extension to the *k*-induction algorithm potentially cuts the verification time considerably in cases where the state space explored is large

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for small cases, our extension does not slow things down or use more memory than the original *k*-induction

Preliminary evaluation over

Benchmark		k-	<i>k</i> -induction Extended				
	LOC	$T(\mathbf{s})$	M(MB)	k	<i>T</i> (s)	M(MB)	k
sum04.c	19	1	38.7	9	1	38.7	5
sum01.c	18	1	38.9	11	1	38.8	6
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Preliminary evaluation over

for large cases, the gains are substantial (*e.g.*, the verification time of rangesum60.c is 504x faster)

Benchmark		<i>k</i> -induction			Extended <i>k</i> -induction		
	LOC	$T(\mathbf{s})$	M(MB)	k	$T(\mathbf{s})$	M(MB)	k
sum04.c	19	1	38.7	9	1	38.7	5
sum01.c	18	1	38.9	11	1	38.8	6
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the speed up comes from requiring roughly half the number of steps to find a property violation

Preliminary evaluation over

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Contributions

A novel extension to the *k*-induction algorithm



Contributions

- Our main contribution is a novel extension to the k-induction algorithm, to perform a bidirectional search instead of the conventional iterative deepening search:
 - the preliminary results show that the extension has the potential to substantially improve the verification time for problems with large state space, while maintaining a small verification time for small programs.
- As future work, we plan to expand our evaluation over the SV-COMP benchmarks, where the original k-induction algorithm already proved to be the state-of-art, if compared to other kinduction tools

"The main challenge is scalability: real-world software systems not only include complex control and data structure, but depend on much "context" such as libraries and interfaces to other code, including lower-level systems code. As a result, proving a software system correct requires much more effort, knowledge, training, and ingenuity than writing the software in trial-anderror style."

-E. M. Clarke et al., Handbook of Model Checking, 2018.



