

# A SAT-Based Counterexample Guided Method for Unbounded Synthesis

**Abstract.** Reactive synthesis techniques based on constructing the winning region of the system have been shown to work well in many cases but suffer from state explosion in others. A different approach, proposed recently, applies SAT solvers in a counterexample guided framework to solve the synthesis problem. However, this method is limited to synthesising systems that execute for a bounded number of steps and is incomplete for synthesis with unbounded safety and reachability objectives. We present an extension of this technique to unbounded synthesis. Our method applies Craig interpolation to abstract game trees produced by counterexample-guided search in order to construct a monotonic sequence of may-losing regions. Experimental results based on SYNTCOMP 2015 competition benchmarks show this to be a promising alternative that solves some previously intractable instances.

## 1 Introduction

Reactive systems are ubiquitous in real-world problems such as circuit design, industrial automation, or device drivers. Automatic synthesis can provide a *correct by construction* controller for a reactive system from a specification. Reactive synthesis is formalised as a game between the *controller* and its *environment*. In this work we focus on safety games, in which the controller must prevent the environment from forcing the game into an error state.

The reactive synthesis problem is 2EXPTIME-complete so naive algorithms are infeasible on anything but simple systems. There are several techniques that aim to mitigate this complexity by representing states and transitions of the system symbolically [18, 4, 16]. These techniques incrementally construct a symbolic representation of the set of discovered winning states of the game. The downside of this approach is that keeping track of all discovered winning states can lead to a space explosion even when using efficient symbolic representation such as BDDs or CNFs.

An alternative approach, proposed by Narodytska et al. [17], is to eschew states and focus on *runs* of the game. The method works by exploring a subset of the concrete runs of the game and proving that these runs can be generalised into a winning strategy on behalf of one of the players. In contrast to other existing synthesis methods, it does not store, in either symbolic or explicit form, the set of winning states. Instead, it uses counterexample-guided backtracking search to identify a small subset of runs that are sufficient to solve the game.

This method has been shown to outperform BDDs on certain classes of games; however it suffers from an important limitation: it is only able to solve games

with a bounded number of rounds. In case of safety games, this means proving that the controller can keep the game within the safe region for a bounded number of steps. This is insufficient in most practical situations that require unbounded realizability.

In this paper, we extend the method by Narodytska et al. [17] to unbounded safety games. To this end we enhance the method with computational learning: every time the search algorithm discovers a new counterexample, the learning procedure analyzes the counterexample, extracting a subset of states winning for one of the players from it. The learning procedure ensures that reaching a fixed point in these sets is sufficient to establish unbounded realizability. Our method can be seen as a hybrid between the counterexample-guided algorithm by Narodytska et al. and methods based on losing set computation: we use the former to guide the search, while we rely on the latter to ensure convergence.

We evaluate our method on the benchmarks of the 2015 synthesis competition (SYNTCOMP'15). While our solver solves fewer total instances than competitors, it solves the largest number of unique instances, i.e., instances that could not be solved by any other solver. These results confirm that there exist classes of problems that are hard for traditional synthesis techniques, but can be efficiently solved by our method. While further performance improvements are clearly needed, in its current state the method can be used in a portfolio solver to increase the number of tractable instances.

Section 2 outlines the original bounded synthesis algorithm. In Section 3 we describe and prove the correctness of our extension of the algorithm to unbounded games. In the following sections we evaluate our methodology, and compare our approach to other synthesis techniques.

## 2 Background

A *safety game*,  $G = \langle X, U, C, \delta, I, E \rangle$ , is defined over boolean state variables  $X$ , uncontrollable action variables  $U$ , and controllable action variables  $C$ .  $I$  is the initial state of the game given as a valuation of state variables.  $E(X)$  is the set of error states represented by its characteristic formula. The transition relation  $\delta(X, U, C, X')$  of the game is a boolean formula that relates current state and action to the set of possible next states of the game. We assume deterministic games, where  $\delta(x, u, c, x'_1) \wedge \delta(x, u, c, x'_2) \implies (x'_1 = x'_2)$ .

At every round of the game, the *environment* picks an uncontrollable action, the *controller* responds by choosing a controllable action and the game transitions into a new state according to  $\delta$ . A *run* of a game  $(x_0, u_0, c_0), (x_1, u_1, c_1) \dots (x_n, u_n, c_n)$  is a chain of state and action pairs s.t.  $\delta(x_k, u_k, c_k, x_{k+1})$ . A run is winning for the controller if  $x_0 = I \wedge \forall i \in \{1..n\}(\neg E(x_i))$ . In a *bounded game* with maximum bound  $\kappa$  all runs are restricted to length  $\kappa$ , whereas unbounded games consider runs of infinite length. Since we consider only deterministic games, a run is uniquely described by a list of assignments to  $U$  and  $C$ .

A *controller strategy*  $\pi^c : (X, U) \rightarrow C$  is a mapping of states and uncontrollable inputs to controllable actions. A controller strategy is winning in a bounded game of maximum bound  $\kappa$  if all runs  $(x_0, u_0, \pi^c(x_0, u_0)), (x_1, u_1, \pi^c(x_1, u_1)) \dots (x_n, u_n, \pi^c(x_n, u_n))$  are winning. Bounded *realizability* is the problem of determining the existence of such a strategy for a bounded game.

An *environment strategy*  $\pi^e : X \rightarrow U$  is a mapping of states to uncontrollable actions. A bounded run is winning for the environment if  $x_0 = I \wedge \exists i \in \{1..n\}(E(x_i))$  and an environment strategy is winning for a bounded game if all runs  $(x_0, \pi^e(x_1), c_1), (x_1, \pi^e(x_1), c_1) \dots (x_n, \pi^e(x_n), c_n)$  are winning for the environment. Safety games are zero sum, therefore the existence of a winning controller strategy implies the nonexistence of a winning environment strategy and vice versa.

## 2.1 Counterexample-guided bounded synthesis

We review the bounded synthesis algorithm by Narodytska et al. [17], which is the main building block for our unbounded algorithm.

Realisability for a bounded safety game can be solved by checking a quantified formula consisting of the game's transition relation *unrolled* to the length of the bounded game. The quantifiers represent the two players of the game: universal for the controller and existential for the environment. Just as the players alternate in choosing actions every round of the game, the formula is prefixed by a quantifier alternation over  $U$  and  $C$  for each round.

Instead of solving both quantifiers at once, two competing solvers are used to solve abstractions of the game. Each solver builds a candidate strategy for its corresponding player and uses its opponent's candidate to restrict its own search. The solvers communicate to refine one another's candidate strategies by finding counterexamples. Eventually one solver will be unable to find a counterexample, indicating that its opponent's candidate strategy is a winning strategy for the game.

An abstraction of the game restricts actions available to one of the players. Specifically, we consider abstractions represented as trees of actions, referred to as *abstract game trees*. Figure 1a shows an example abstract game tree for the controller (abstract game trees for the environment are similar). In the abstract game, the controller is required to pick actions from the tree, starting from the root node. After reaching a leaf, it continues playing unrestricted. The tree in Figure 1a restricts the initial controller action to the set  $\{a, d\}$ . After choosing action  $a$ , the controller is required to play action  $b$  in the next round. It then reaches a leaf of the tree and continues playing unrestricted. The root of the tree is annotated by the initial state  $s$  of the abstract game and the bound  $k$  on the number of rounds. We denote  $\text{NODES}(T)$  the set of all nodes of a tree  $T$  and  $\text{LEAVES}(T)$  the subset of leaf nodes.

Given a controller (environment) abstract game tree  $T$  a *partial strategy*  $\text{Strat} : \text{NODES}(T) \rightarrow U$  ( $\text{Strat} : \text{NODES}(T) \rightarrow C$ ) labels each node of the tree with the opponent's action to be played in that node. Figure 1b shows an example partial strategy. The environment starts by choosing action  $\alpha$ . If the

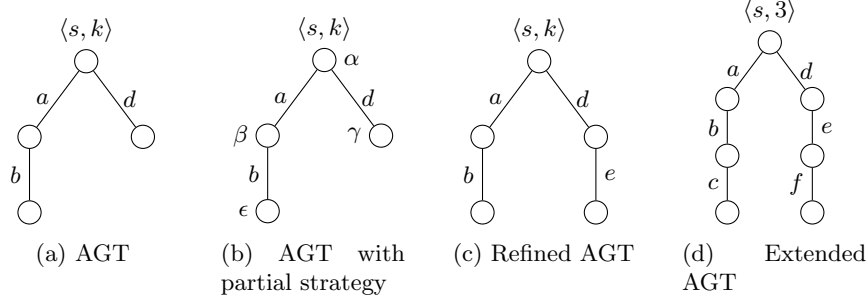


Fig. 1: Abstract game trees

controller plays  $a$ , the environment responds with  $\beta$  in the next round, and so on. Given a partial strategy  $Strat$ , we can map each leaf  $l$  of the abstract game tree to  $\langle s', i' \rangle = \text{OUTCOME}(\langle s, i \rangle, Strat, l)$  obtained by playing all controllable and uncontrollable actions on the path from the root to the leaf.

The bounded synthesis algorithm solves abstract game trees by invoking a SAT solver to search for candidate partial strategies. Candidate strategies are checked and by a call to the opponent solver, which also refines the abstract game tree. The refinements are then solved recursively. The full procedure is illustrated in Algorithm 1.

The algorithm takes a concrete game  $G$  with maximum bound  $\kappa$  as an implicit argument. In addition, it takes a player  $p$  (controller or environment), state  $s$ , bound  $k$  and an abstract game tree  $T$  and returns a winning partial strategy for  $\text{OPPONENT}(p)$ , if one exists. The initial invocation of the algorithm takes the initial state  $I$ , bound  $\kappa$  and an empty abstract game tree  $\emptyset$ . Initially the solver is playing on behalf of the environment since that player takes the first move in every game round. The empty game tree does not constrain opponent moves, hence solving such an abstraction is equivalent to solving the original concrete game.

The algorithm is organised as a counterexample-guided abstraction refinement (CEGAR) loop. The first step of the algorithm uses the `FINDCANDIDATE` function, described below, to come up with a candidate partial strategy for  $T$ . If it fails to find a strategy, this means that no winning partial strategy exists for  $T$ . If, on the other hand, a candidate partial strategy is found, we need to verify if it is indeed winning for  $T$ .

The `VERIFY` procedure searches for a *spoiling* counterexample strategy in each leaf of the candidate partial strategy by calling `SOLVEABSTRACT` for the opponent. The dual solver solves games on behalf of the controller player.

If the dual solver can find no spoiling strategy at any of the leaves, then the candidate partial strategy is a winning one. Otherwise, `VERIFY` returns the move used by the opponent to defeat a leaf of the partial strategy, which is appended to the corresponding node in  $T$  in order to refine it in line (9) as shown in Figure (1c).

**Algorithm 1** Bounded synthesis

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```

1: function SOLVEABSTRACT( $p, s, k, T$ )
2:    $cand \leftarrow \text{FINDCANDIDATE}(p, s, k, T)$  ▷ Look for a candidate
3:   if  $k = 1$  then return  $cand$  ▷ Reached the bound
4:    $T' \leftarrow T$ 
5:   loop
6:     if  $cand = \emptyset$  then return  $\emptyset$  ▷ No candidate: return with no solution
7:      $\langle cex, l, u \rangle \leftarrow \text{VERIFY}(p, s, k, T, cand)$  ▷ Verify candidate
8:     if  $cex = \text{false}$  then return  $cand$  ▷ No counterexample: return candidate
9:      $T' \leftarrow \text{APPEND}(T', l, u)$  ▷ Refine  $T'$  with counterexample
10:     $cand \leftarrow \text{SOLVEABSTRACT}(p, s, k, T')$  ▷ Solve refined game tree
11:  end loop
12: end function
13: function FINDCANDIDATE( $p, s, k, T$ )
14:    $\hat{T} \leftarrow \text{EXTEND}(T)$  ▷ Extend the tree with unfixed actions
15:    $f \leftarrow \text{if } p = \text{cont} \text{ then } \text{TREEFORMULA}(\hat{T}) \text{ else } \overline{\text{TREEFORMULA}(\hat{T})}$ 
16:    $sol \leftarrow \text{SAT}(s(X_{\hat{T}}) \wedge f)$ 
17:   if  $sol = \text{unsat}$  then
18:     if  $\text{unbounded}$  then ▷ Active only in the unbounded solver
19:       if  $p = \text{cont}$  then  $\text{LEARN}(s, \hat{T})$  else  $\overline{\text{LEARN}}(s, \hat{T})$ 
20:     end if
21:     return  $\emptyset$  ▷ No candidate exists
22:   else
23:     return  $\{\langle n, c \rangle \mid n \in \text{NODES}(T), c = \text{SOL}(n)\}$  ▷ Fix candidate moves in  $T$ 
24:   end if
25: end function
26: function VERIFY( $p, s, k, T, cand$ )
27:   for  $l \in \text{leaves}(gt)$  do
28:      $\langle k', s' \rangle \leftarrow \text{OUTCOME}(s, k, cand, l)$  ▷ Get bound and state at leaf
29:      $u \leftarrow \text{SOLVEABSTRACT}(\text{OPPONENT}(p), k', s', \emptyset)$  ▷ Solve for the opponent
30:     if  $u \neq \emptyset$  then return  $\langle \text{false}, l, u \rangle$  ▷ Return counterexample
31:   end for
32:   return  $\langle \text{true}, \emptyset, \emptyset \rangle$ 
33: end function

```

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We solve the refined game by recursively invoking SOLVEABSTRACT on it. If no partial winning strategy is found for the refined game then there is also no partial winning strategy for the original abstract game, and the algorithm returns a failure. Otherwise, the partial strategy for the refined game is *projected* on the original abstract game by removing the leaves introduced by refinements. The resulting partial strategy becomes a candidate strategy to be verified at the next iteration of the loop. In the worst case the loop terminates after all actions in the game are refined into the abstract game.

The CEGAR loop depends on the ability to guess candidate partial strategies in FINDCANDIDATE. For this purpose we use the heuristic that a partial strategy may be winning if each OUTCOME of the strategy can be extended to a run of the game that is winning for the current player. Clearly, if such a partial strategy does

not exist then no winning partial strategy can exist for the abstract game tree. We can formulate this heuristic as a SAT query, which is constructed recursively by `TREEFORMULA` (for the controller) or `TREEFORMULA` (for the environment) in Algorithm 2.

The tree is first extended to the maximum bound with edges that are labeled with arbitrary opponent actions (Algorithm 1, line 14) as shown in Figure 1d. Then copies of state and action variables are introduced for each node in tree and opponent action variables for each edge. Opponent actions are set to  $\text{ACTION}(e)$ , the action that labels the edge of the tree  $e$ . The state and action variables of node  $n$  are connected to successor nodes  $\text{SUCC}(n)$  by an encoding of the transition relation and constrained to the winning condition of the player.

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**Algorithm 2** Tree formulas for Controller and Environment respectively

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1: function TREEFORMULA( $T$ )
2:   if BOUND( $T$ ) = 0 then
3:     return  $\neg E(X_T)$ 
4:   else
5:     return  $\neg E(X_T) \wedge$ 
6:       
$$\bigwedge_{\langle e, n \rangle \in \text{SUCC}(T)} (\delta(X_T, U_e, C_n, X_n) \wedge U_e = \text{ACTION}(e) \wedge \text{TREEFORMULA}(n))$$

7:   end if
8: end function
9: function  $\overline{\text{TREEFORMULA}}(T)$ 
10:  if BOUND( $T$ ) = 0 then
11:    return  $E(X_T)$ 
12:  else
13:    return  $E(X_T) \vee$ 
14:      
$$\bigvee_{\langle e, n \rangle \in \text{SUCC}(T)} (\delta(X_T, U_n, C_e, X_n) \wedge C_e = \text{ACTION}(e) \wedge \overline{\text{TREEFORMULA}}(n))$$

15:  end if
16: end function

```

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### 3 Unbounded Synthesis

Bounded synthesis can be used to prove the existence of a winning strategy for the environment on the unbounded game by providing a witness. For the controller, the strongest claim that can be made is that the strategy is winning as long as the game does not extend beyond the maximum bound.

It is possible to set a maximum bound such that all runs in the unbounded game will be considered. The naïve approach is to use size of the state space as the bound ( $2^{|X|}$ ) so that all states may be explored by the algorithm. A more

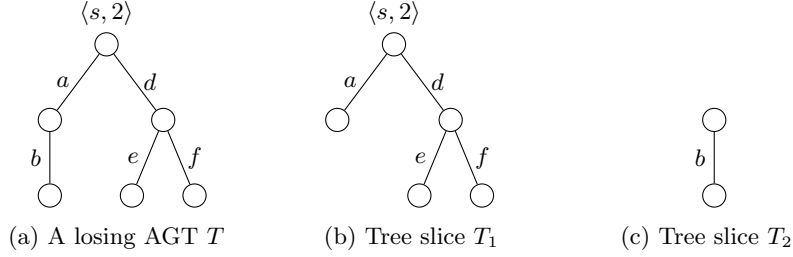


Fig. 2: Splitting of an abstract game tree by the learning procedure.

nuanced approach is to use the diameter of the game [3], which is the smallest number  $d$  such that for any state  $x$  there is a path of length  $\leq d$  to all other reachable states. However, the diameter is difficult to estimate and can still lead to infeasibly long games.

We instead present an approach that iteratively solves games of increasing bound while learning winning states from abstract games using interpolation. We show that reaching a fixed point in learned states is sufficient for completeness.

### 3.1 Learning States with Interpolants

We extend the bounded synthesis algorithm to learn states losing for one of the players from failed attempts to find candidate strategies. The learning procedure kicks in whenever `FINDCANDIDATE` cannot find a candidate strategy for an abstract game tree with initial state  $s$ . At this point we have established that  $s$  is a losing state. We can learn additional losing states from the tree via interpolation. This is achieved in lines 18–20 in Algorithm 1, enabled in the unbounded version of the algorithm, which invoke `LEARN` or `LEARN` to learn controller or environment losing states respectively (Algorithm 3).

Consider the game tree  $T$  in Figure 2a, whose edges are labelled with environment actions. Assume that there does not exist a partial strategy for the controller winning against this tree and that the `FINDCANDIDATE` function could not find a candidate strategy. We choose a non-leaf node  $n$  of  $T$  with maximal depth, i.e., a node whose children are leafs (Algorithm 3, line 3). We then split the tree at  $n$  such that both slices  $T_1$  and  $T_2$  contain a copy of  $n$  (line 4). Figure 2b shows  $T_1$ , which contains all of  $T$  except  $n$ 's children, and  $T_2$  (Figure 2c), which contains only  $n$  and its children. There is no candidate strategy for  $T$  so  $s \wedge \text{TREEFORMULA}(T)$  is unsatisfiable. By construction,  $\text{TREEFORMULA}(T) \equiv \text{TREEFORMULA}(T_1) \wedge \text{TREEFORMULA}(T_2)$  and hence  $s \wedge \text{TREEFORMULA}(T_1) \wedge \text{TREEFORMULA}(T_2)$  is also unsatisfiable. This enables the construction of an *interpolant* that captures losing states at node  $n$ .

Given two formulas  $F_1$  and  $F_2$  such that  $F_1 \wedge F_2$  is unsatisfiable, it is possible to construct a Craig interpolant [8]  $\mathcal{I}$  such that  $F_1 \rightarrow \mathcal{I}$ ,  $F_2 \wedge \mathcal{I}$  is unsatisfiable, and  $\mathcal{I}$  refers only to the intersection of variables in  $F_1$  and  $F_2$ . An interpolant

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**Algorithm 3** Learning algorithms

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**Require:**  $s(X_T) \wedge \text{TREEFORMULA}(T) \equiv \perp$   
**Require:** *Must-invariant* holds  
**Ensure:** *Must-invariant* holds  
**Ensure:**  $s(X_T) \wedge B^M$   
1: **function** LEARN( $s, T$ )  
2:   **if**  $T = \emptyset$  **then return**  
3:    $n \leftarrow$  non-leaf node with min bound  
4:    $\langle T_1, T_2 \rangle \leftarrow \text{GTSPLIT}(T, n)$   
5:    $\mathcal{I} \leftarrow \text{INTERPOLATE}(s(X_T) \wedge \text{TREEFORMULA}(T_1), \text{TREEFORMULA}(T_2))$   
6:    $B^M \leftarrow B^M \vee \mathcal{I}$   
7:   LEARN( $s, T_1$ )  
8: **end function**  
**Require:**  $s(X_T) \wedge \overline{\text{TREEFORMULA}}(T) \equiv \perp$   
**Require:** *May-invariant* holds  
**Ensure:** *May-invariant* holds  
**Ensure:**  $s(X_T) \wedge B^m[\text{BOUND}(T)] \equiv \perp$   
9: **function**  $\overline{\text{LEARN}}$ ( $s, T$ )  
10:   **if**  $T = \emptyset$  **then return**  
11:    $n \leftarrow$  non-leaf node with min bound  
12:    $\langle T_1, T_2 \rangle \leftarrow \text{GTSPLIT}(T, n)$   
13:    $\mathcal{I} \leftarrow \text{INTERPOLATE}(s(X_T) \wedge \overline{\text{TREEFORMULA}}(T_1), \overline{\text{TREEFORMULA}}(T_2))$   
14:   **for**  $i = 1$  to  $\text{BOUND}(n)$  **do**  
15:      $B^m[i] \leftarrow B^m[i] \setminus \mathcal{I}$   
16:   **end for**  
17:    $\overline{\text{LEARN}}(s, T_1)$   
18: **end function**

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can be constructed efficiently from a resolution proof of the unsatisfiability of  $F_1 \wedge F_2$  [19].

We construct an interpolant with  $F_1 = s(X_T) \wedge \text{TREEFORMULA}(T_1)$  and  $F_2 = \text{TREEFORMULA}(T_2)$  (line 5). The only variables shared between  $F_1$  and  $F_2$  are the state variable copies belonging to node  $n$ . By the properties of the interpolant,  $F_2 \wedge \mathcal{I}$  is unsatisfiable, therefore all states in  $\mathcal{I}$  are losing against abstract game tree  $T_2$  in Figure 2c. We also know that  $F_1 \rightarrow \mathcal{I}$ , thus  $\mathcal{I}$  contains all states reachable at  $n$  by following  $T_1$  and avoiding error states.

We have discovered a set  $\mathcal{I}$  of states losing for the controller. We record these newly discovered states in a set  $B^M$  of “bad” states that *must* be losing for the controller (Algorithm 3, line 6). This set is initialised to the error set  $E$  and grows as new losing states are discovered. The  $\text{TREEFORMULA}$  function is modified for the unbounded solver (Algorithm 4) to replace  $E$  with  $B^M$ . This enables further interpolants to be constructed by the learning procedure recursively splitting more nodes from  $T_1$  (Algorithm 3, line 7) since the states that lost to  $T_2$  are now blocked by  $B^M$ .

Learning of states losing for the environment is similar ( $\overline{\text{LEARN}}$  in Algorithm 3). The main difference is that environment-losing states are only losing



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**Algorithm 4** Amended tree formulas for Controller and Environment

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1: function TREEFORMULA( $T$ )
2:   if BOUND( $T$ ) = 0 then
3:     return  $\neg B^M(X_T)$ 
4:   else
5:     return  $\neg B^M(X_T) \wedge$ 
6:       
$$\bigwedge_{\langle e, n \rangle \in \text{succ}(T)} (\delta(X_T, U_e, C_n, X_n) \wedge U_e = \text{ACTION}(e) \wedge \text{TREEFORMULA}(n))$$

7:   end if
8: end function
9: function TREEFORMULA( $T$ )
10:  if BOUND( $T$ ) = 0 then
11:    return  $E(X_T)$ 
12:  else
13:    return  $B^m[\text{BOUND}(T)](X_T) \wedge$ 
14:      
$$E(X_T) \vee \bigvee_{\langle e, n \rangle \in \text{succ}(T)} (\delta(X_T, U_n, C_e, X_n) \wedge C_e = \text{ACTION}(e) \wedge \overline{\text{TREEFORMULA}(n)})$$

15:  end if
16: end function

```

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for a particular bound: given that there does not exist an environment strategy that forces the game into an error state in  $k$  rounds or less; there may still exist a longer environment-winning strategy. We therefore record learned environment-losing states along with associated bounds. To this end, we maintain a conceptually infinite array of sets  $B^m[k]$  that are may-losing for the controller, indexed by bound  $k$ .  $B^m[k]$  are initialized to  $\top$  for all  $k$ . Whenever an environment-losing set  $\mathcal{I}$  is discovered for a node  $n$  with bound  $\text{BOUND}(n)$  in line 13 of Algorithm 3, this set is subtracted from  $B^m[i]$ , for all  $i$  less than or equal to the bound (lines 14–16).

The modified `TREEFORMULA` function (4) constrains the environment to may-losing states, which also allows for recursive learning over the entire tree.

### 3.2 Main synthesis loop

Figure 5 shows the main loop of the unbounded synthesis algorithm. The algorithm invokes the modified bounded synthesis procedure with increasing bound  $k$  until the initial state is in  $B^M$  (environment wins) or  $B^m$  reaches a fixed point (controller wins). We prove correctness in the next section.

### 3.3 Correctness

We define two global invariants of the algorithm. The *may-invariant* states that sets  $B^m[i]$  grows monotonically with  $i$  and that each  $B^m[i+1]$  overapproximates

**Algorithm 5** Unbounded Synthesis

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1: function SOLVEUNBOUNDED( $T$ )
2:    $B^M \leftarrow E$ 
3:    $B^m[0] \leftarrow \top$ 
4:   for  $k = 1 \dots$  do
5:     if  $\text{SAT}(I \wedge B^M)$  then return unrealisable  $\triangleright$  Losing in the initial state
6:     if  $\exists i \ B^m[i] \equiv B^m[i+1]$  then return realisable  $\triangleright$  Reached fixed point
7:      $B^m[k] \leftarrow \top$ 
8:     CHECKBOUND( $k$ )
9:   end for
10: end function
Require: May and must invariants hold
Ensure: May and must invariants hold
Ensure:  $I \notin B^m[k]$  if there exists a winning controller strategy with bound  $k$ 
Ensure:  $I \in B^M$  if there exists a winning environment strategy with bound  $k$ 
11: function CHECKBOUND( $k$ )
12:   return SOLVEABSTRACT( $\text{env}, I, \emptyset$ )
13: end function

```

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the states from which the environment can force the game into  $B^m[i]$ . We call this operation  $Up\text{re}$ , the uncontrollable predecessor. So the *may-invariant* is:

$$\forall i < k. B^m[i] \subseteq B^m[i+1], Up\text{re}(B^m[i]) \subseteq B^m[i+1].$$

The *must-invariant* guarantees that the must-losing set  $B^M$  is an underapproximation of the actual losing set  $B$ :

$$B^M \subseteq B.$$

Both invariants trivially hold after  $B^m$  and  $B^M$  have been initialized in the beginning of the algorithm. The sets  $B^m$  and  $B^M$  are only modified by the functions  $\text{LEARN}$  and  $\overline{\text{LEARN}}$ . Below we prove that  $\overline{\text{LEARN}}$  maintains the invariants. The proof of  $\text{LEARN}$  is similar.

### 3.4 Proof of $\overline{\text{learn}}$

We prove that postconditions of  $\overline{\text{LEARN}}$  are satisfied assuming that its preconditions hold.

Line (11) splits the tree  $T$  into  $T_1$  and  $T_2$ , such that  $T_2$  has depth 1. Consider formulas  $F_1 = s(X_T) \wedge \overline{\text{TREEFORMULA}}(T_1)$  and  $F_2 = \overline{\text{TREEFORMULA}}(T_2)$ . These formulas only share variables  $X_n$ . Their conjunction  $F_1 \wedge F_2$  is unsatisfiable, as by construction any solution of  $F_1 \wedge F_2$  also satisfies  $s(X_T) \wedge \text{TREEFORMULA}(T)$ , which is unsatisfiable (precondition (b)). Hence the interpolation operation is defined for  $F_1$  and  $F_2$ .

Intuitively, the interpolant computed in line (13) overapproximates the set of states reachable from  $s$  by following the tree from the root node to  $n$ , and

underapproximates the set of states from which the environment loses against tree  $T_2$ .

Formally,  $\mathcal{I}$  has the property  $\mathcal{I} \wedge F_2 \equiv \perp$ . Since  $T_2$  is of depth 1, this means that the environment cannot force the game into  $B^m[\text{BOUND}(n)]$  playing against the counterexample moves in  $T_2$ . Hence,  $\mathcal{I} \cap \text{Upred}(B^m[\text{BOUND}(n)]) = \emptyset$ . Furthermore, since the may-invariant holds,  $\mathcal{I} \cap \text{Upred}(i) = \emptyset$ , for all  $i < \text{BOUND}(n)$ . Hence, removing  $\mathcal{I}$  from all  $B^m[i], i \leq \text{BOUND}(n)$  in line (15) preserves the may-invariant, thus satisfying the first post-condition.

Furthermore, the interpolant satisfies  $F_1 \rightarrow \mathcal{I}$ , i.e., any assignment to  $X_n$  that satisfies  $s(X_T) \wedge \overline{\text{TREEFORMULA}(T_1)}$  also satisfies  $\mathcal{I}$ . Hence, removing  $\mathcal{I}$  from  $B^m[\text{BOUND}(n)]$  makes  $s(X_T) \wedge \overline{\text{TREEFORMULA}(T_1)}$  unsatisfiable, and hence all preconditions of the recursive invocation of  $\overline{\text{LEARN}}$  in line (17) are satisfied.

At the second last recursive call to  $\overline{\text{LEARN}}$ , tree  $T_1$  is empty,  $n$  is the root node,  $\overline{\text{TREEFORMULA}(T_1)} \equiv B^m[\text{BOUND}(T)](X^T)$ ; hence  $s(X_T) \wedge \overline{\text{TREEFORMULA}(T_1)} \equiv s(X_T) \wedge B^m[\text{BOUND}(T)](X^T) \equiv \perp$ . Thus the second post-condition of  $\overline{\text{LEARN}}$  holds.

The proof of  $\text{LEARN}$  is similar to the above proof of  $\overline{\text{LEARN}}$ . An interpolant constructed from  $F_1 = s(X_T) \wedge \text{TREEFORMULA}(T_1)$  and  $F_2 = \text{TREEFORMULA}(T_2)$  has the property  $\mathcal{I} \wedge F_2 \equiv \perp$  and the precondition ensures that the controller is unable to force the game into  $B^M$  playing against the counterexample moves in  $T_2$ . Thus adding  $\mathcal{I}$  to  $B^M$  maintains the must-invariant satisfying the first postcondition.

Likewise, in the second last recursive call of  $\text{LEARN}$  with the empty tree  $T_1$  and root node  $n$ :  $\text{TREEFORMULA}(T_1) \equiv \neg B^M(X_T)$ . Hence  $s(X_T) \wedge \text{TREEFORMULA}(T_1) \equiv s(X_T) \wedge \neg B^M(X_T) \equiv \perp$ . Therefore  $s(X_T) \wedge B^M(X_T)$ , the second postcondition, is true.

### 3.5 Proof of Termination

We must prove that  $\text{CHECKBOUND}$  terminates and that upon termination its postcondition holds, i.e., state  $s$  is removed from  $B^m[\kappa]$  if there is a winning controller strategy on the bounded safety game of maximum bound  $\kappa$  or it is added to  $B^M$  otherwise. Termination follows from completeness of counterexample-guided search, which terminates after enumerating all possible opponent moves in the worst case.

Assume that there is a winning strategy for the controller at bound  $\kappa$ . This means that at some point the algorithm discovers a counterexample tree of bound  $\kappa$  for which the environment cannot force into  $E$ . The algorithm then invokes the  $\overline{\text{LEARN}}$  method, which removes  $s$  from  $B^m[\kappa]$ . Alternatively, if there is a winning strategy for the environment at bound  $\kappa$  then a counterexample losing for the controller will be found. Subsequently  $\text{LEARN}$  will be called and  $s$  added to  $B^M$ .

### 3.6 Optimisation: Generalising the initial state

This optimisation allows us to learn may and must losing states faster. Starting with a larger set of initial states we increase the reachable set and hence in-

crease the number of states learned by interpolation. This optimisation requires a modification to SOLVEABSTRACT to handle sets of states, which is not shown.

The optimisation is relatively simple and is inspired by a common greedy heuristic for minimising **unsat** cores. Initial state  $I$  assigns a value to each variable in  $X$ . If the environment loses  $\langle I, k \rangle$  then we attempt to solve for a generalised version of  $I$  by removing one variable assignment at a time. If the environment loses from the larger set of states then we continue generalising. In this way we learn more states by increasing the reachable set. In our benchmarks we have observed that this optimisation is beneficial on the first few iterations of CHECKBOUND.

---

**Algorithm 6** Generalise  $I$  optimisation

---

```

function CHECKBOUND( $k$ )
   $r \leftarrow \text{SOLVEABSTRACT}(\text{env}, I, k, \emptyset)$ 
  if  $r \neq \emptyset$  then return  $r$ 
   $s' \leftarrow I$ 
  for  $x \in X$  do
     $r \leftarrow \text{SOLVEABSTRACT}(\text{env}, s' \setminus \{x\}, k, \emptyset)$ 
    if  $r = \emptyset$  then  $s' \leftarrow s' \setminus \{x\}$   $\triangleright$  Removes the assignment to  $x$  from  $s'$ 
  end for
  return  $\emptyset$ 
end function

```

---

## 4 Evaluation

We evaluate our approach on the benchmarks of the 2015 synthesis competition (SYNTCOMP'15). Each benchmark comprises of controllable and uncontrollable inputs to a circuit that assigns values to latches. One latch is configured as the error bit that determines the winner of the safety game. The benchmark suite is a collection of both real-world and toy specifications including generalised buffers, AMBA bus controllers, device drivers, and converted LTL formulas. Descriptions of many of the benchmark families used can be found in the 2014 competition report [13].

The implementation of our algorithm uses GLUCOSE [2] for SAT solving and PERIPLO [20] for interpolant generation. The benchmarks were run on a cluster of Intel Quad Core Xeon E5405 2GHz CPUs with 16GB of memory. The solver was allowed exclusive access to a node for one hour to solve an instance.

The results of our benchmarking are shown, along with the synthesis competition results [1], in Table 1. The competition was run on Intel Quad Core 3.2Ghz CPUs with 32GB of memory, also on isolated nodes for one hour per instance.

Solver	Solved	Unique
Simple BDD Solver (2)	195	10
AbsSynthe (seq2)	187	2
Simple BDD Solver (1)	185	
AbsSynthe (seq3)	179	
Realizer (sequential)	179	
AbsSynthe (seq1)	173	1
Demiurge (D1real)	139	5
Aisy	98	
Unbounded Synthesis	103	12

Table 1: Synthesis Competition 2015 Results

Our implementation was able to solve 103 out of the 250 specification in the allotted time, including 12 instances that were not solved by any other solver in SYNTCOMP’15. The unique instances we solved are listed in Table 2.

6s216rb0_c0to31	driver_c10n
cnt30y	stay18y
driver_a10n	stay20n
driver_a8n	stay20y
driver_b10y	stay22n
driver_b8y	stay22y

Table 2: Instances uniquely solved by our approach

Five of the instances unique to our solver are device driver instances and another five are from the **stay** family. This supports the hypothesis that different game solving methodologies perform better on certain classes of specifications.

We also present a cactus plot of the number of instances solved over time (Figure 3). For reference we plotted our results along with DEMIURGE [4], the only SAT-based tool in the competition, and the winner of the sequential realisability track SIMPLE BDD SOLVER 2 [21]. We were able to run DEMIURGE on our hardware but show competition results for SIMPLE BDD SOLVER 2.

Whilst our solver is unable to solve as many instances as other tools, it was able to solve more unique instances than any solver in the competition. This confirms that our methodology is able to fill gaps in a state of the art synthesis toolbox by more efficiently solving instances that are hard for other techniques. For this reason our solver would be a worthwhile addition to a portfolio solver. In the parallel track of the competition, DEMIURGE uses a suite of 3 separate but communicating solvers. The solvers relay unsafe states to one another, which is compatible with the set  $B^M$  in our solver. It remains future work to explore the possibility of combining these solvers.

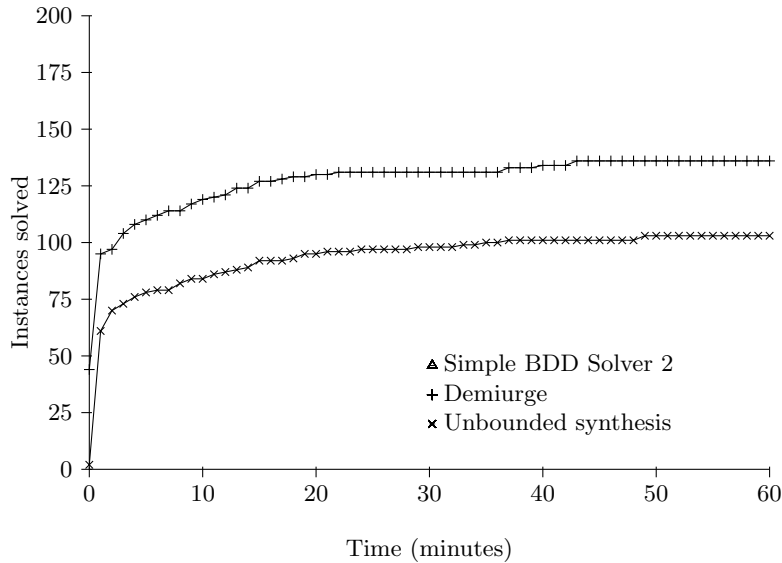


Fig. 3: Number of instances solver over time by the unbounded solver, Demiurge, and Simple BDD Solver.

## 5 Related Work

Synthesis of safety games is a thoroughly explored area of research with most efforts directed toward solving games with BDDs [7] and abstract interpretation [21, 6]. Satisfiability solving has been used previously for synthesis in a suite of methods proposed by Bloem et al [4]. The authors propose a propose employing competing SAT solvers to learn clauses, which is similar to our approach but does not unroll the game. They also suggest QBF solver, template-based, and Effectively Propositional Logic (EPL) approaches.

SAT-based bounded model checking approaches that unroll the transition relation have been extended to unbounded by using conflicts in the solver [14], or by interpolation [15]. However, there are no corresponding adaptations to synthesis. Incremental induction [5] is another technique for unbounded model checking with an equivalent synthesis method [16], which computes the set of safe states incrementally.

There are different approaches to bounded synthesis than the one described here. The authors of [12] suggest a methodology directly inspired by bounded model checking and it has been adapted to symbolic synthesis [10]. Lazy synthesis [11] is a counterexample-guided approach to bounded synthesis that refines an implementation for the game instead of an abstraction of it.

The original bounded synthesis algorithm of Narodytska et al. [17] solves realisability without constructing a strategy. In [9] the realisability algorithm is extended with strategy extraction. The technique relies on interpolation over

abstract game trees to compute the winning strategy. In the present work we use interpolation in a different way in order to learn losing states of the game.

## 6 Conclusion

We presented an extension to an existing bounded synthesis technique that promotes it to unbounded safety games. The approach taken as whole differs from other synthesis techniques by combining counterexample guided game solving with winning set computation. The results show that our approach is able to solve more unique instances than other solvers by performing well on certain classes of games that are hard for other methodologies.

Future work includes incorporating the solver into a parallel suite of communicating solvers [4]. There is evidence that different solvers perform well on different classes of games. Thus we hypothesise that the way forward for synthesis tools is to combine the efforts of many different techniques.

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