

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. However, the reactive synthesis problem is 2EXPTIME-complete so naive algorithms are infeasible on anything but simple systems.

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. In this way the environment is equivalent to an existential search of the game and the controller is universal. Much of the complexity of reactive synthesis stems from managing the interactions of the alternating quantifiers on the state space of the game.

There are several techniques that aim to mitigate this complexity by representing states symbolically. Historically the most successful technique has been to use *Binary Decision Diagrams* (BDDs). BDDs efficiently represent a relation on a set of game variables but in the worst case the representation may be exponential in the number of variables. This means that BDDs are not a one-size-fits-all solution for all reactive synthesis specifications.

Advances in SAT solving technology has prompted research into its applicability to synthesis as an alternative to BDDs. One approach is to find sets of states in CNF [2, 14]. Another approach is to eschew states and focus on *runs* of the game. Previous work has applied this idea to realizability of bounded games [15] by forming abstractions of the game and refining in a counterexample-guided

framework. This has been shown to outperform BDDs on certain classes of game specifications but is only able to find counterexamples of a certain length to the safety property. In this paper, we extend this idea to unbounded games by approximating sets of unsafe states from abstract games. Careful construction ensures that a fixed point in these sets guarantees completeness.

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 discuss optimisations to the algorithm, evaluate our methodology, and compare our approach to other synthesis techniques.

2 Background

A *safety game*, $G = \langle X, L_u, L_c, \delta, I, E \rangle$, is defined over boolean state variables X , uncontrollable label variables L_u , and controllable label variables L_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 $\delta(X, L_u, L_c, X')$ of the game is a boolean formula that relates current state and label 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 label, the *controller* responds by choosing a controllable label and the game transitions into a new state according to δ . 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 label 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* of rank n all runs are restricted to length n , 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 L_c and L_u .

A *controller strategy* $\pi^c : (X, L_u) \rightarrow L_c$ is a mapping of states and uncontrollable inputs to controllable labels. A controller strategy is winning in a bounded game of rank n 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* $\pi^e : X \rightarrow L_u$ is a mapping of states to uncontrollable labels. 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. [15], which is the main building block for our unbounded algorithm.

A set of runs can be represented symbolically by a tree of valuations to controllable and uncontrollable label variables where valuations are allowed to be *unfixed*. An unfixed value symbolically represents all possible valuations. Formally, we define the tree as a set of lists of label valuations and a node in the tree may be identified by the list made by following the path from the root.

The entire set of runs of a bounded game of rank n is symbolically represented by a tree of depth $2n$ (a step is two moves - environment then controller) and width 1 populated by unfixed edges. Fixing some moves and thereby reducing the set of runs forms an *abstract game tree* that symbolically represents a smaller version of the game.

A strategy is equivalent to the set of all runs with the controller's labels obeying the strategy mapping π . Therefore, a strategy can also be represented by a tree. Relaxing the restriction of the strategy mapping allows for a *partial strategy* in which multiple labels are now possible for a single state.

A strategy or partial strategy can also be thought of as an abstract game. A partial strategy for the controller is a restriction only on the controllable labels in the game. So if the environment can not win in the abstract game equivalent to the controller's partial strategy, then all strategies allowable by that partial strategy must be winning.

An abstract game tree can be checked for the existence of a winning run by a SAT solver[15]. The tree must be encoded into CNF by making copies of the transition relation for each game step in tree. The formula must also check whether the error state has been reached in no branch (*respectively*: in all branches) for the controller (environment.) The functions that produce these formulas are shown in Algorithm 1.

Algorithm 1 Tree formulas for Controller and Environment respectively

```

1: function TREEFORMULA(gt)
2:   if RANK(gt) = 0 then
3:     return  $\neg E(x^{gt})$ 
4:   else
5:     return  $\neg E(x^{gt}) \wedge \bigwedge_{n \in \text{succ}(gt)} (\delta(n) \wedge \text{LABEL}(n) \wedge \text{TREEFORMULA}(n))$ 
6:   end if
7: end function
8: function  $\overline{\text{TREEFORMULA}}$ (gt)
9:   if RANK(gt) = 0 then
10:    return  $E(x^{gt})$ 
11:  else
12:    return  $E(x^{gt}) \vee \bigvee_{n \in \text{succ}(gt)} (\delta(n) \wedge \text{LABEL}(n) \wedge \overline{\text{TREEFORMULA}}(n))$ 
13:  end if
14: end function

```

When we produce a formula using TREEFORMULA the SAT solver is playing on behalf on the controller. Any unfixed labels in the tree, controllable or

uncontrollable, will be existentially quantified. This means that if there exists a way for the game to be solved when both players cooperate on unfixed labels the SAT solver will find it. If no winning run exists in an abstract game even when the players are cooperating then there is no winning run when the opponent is playing adversarily.

By checking for the existence of a winning run for the environment in an abstract game tree constructed from a partial controller strategy we are checking if the partial strategy is winning. If no environment-winning run exists within the partial strategy then it is a winning partial strategy, otherwise the spoiling run is a counterexample that proves that the partial strategy is not winning. This forms the basis of a counterexample guided abstraction refinement framework [6] that operates on candidate strategies.

The bounded synthesis algorithm (Algorithm 2) begins with an empty game as seen in Figure 1a. Initially we are playing on behalf of the environment because it chooses the first move in each step. The empty game is passed to the SAT solver, which searches for a candidate environment strategy. If a candidate is found (Figure 1b) then it is checked for a spoiling strategy by solving for the controller. If no spoiling strategy exists, that means our candidate is a winning strategy and the algorithm terminates. Otherwise we find a counterexample (Figure 1c), which is used to refine the empty game tree to include the first move from the controller’s spoiling strategy (Figure 1d). The algorithm continues by finding a new candidate for the environment (Figure 1e), and a new counterexample to refine the game abstraction once again (Figure 1f). The full procedure is listed in Algorithm 2.

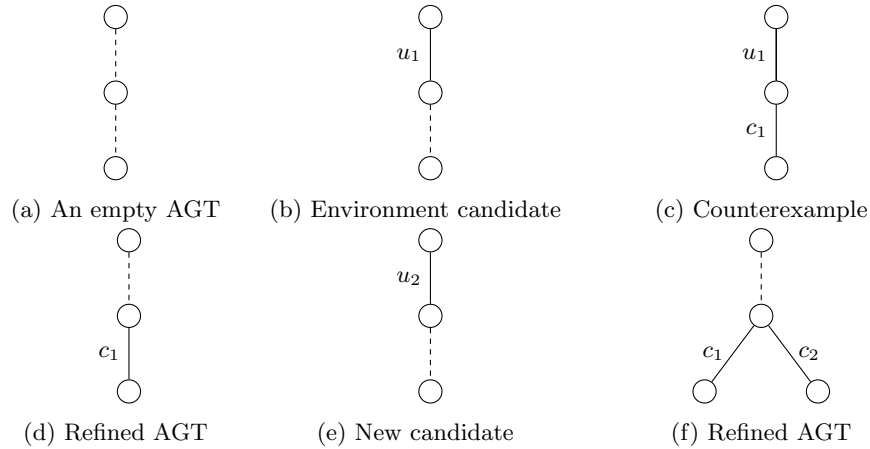


Fig. 1: Abstract game trees

Algorithm 2 Bounded Synthesis

```

1: function SOLVEABSTRACT( $p, \langle s, k \rangle, T$ )
2:    $cand \leftarrow \text{FINDCANDIDATE}(p, \langle s, k \rangle, T)$  ▷ Look for a candidate
3:   if  $k = n - 1$  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:      $\langle cex, l, u \rangle \leftarrow \text{VERIFY}(p, \langle s, k \rangle, T, cand)$  ▷ Verify candidate
8:     if  $cex = \text{false}$  then return  $cand$  ▷ No counterexample: return candidate
9:      $T' \leftarrow \text{GTAPPEND}(T', l, u)$  ▷ Refine AGT with counterexample
10:     $cand \leftarrow \text{SOLVEABSTRACT}(p, \langle s, k \rangle, T')$  ▷ Solve refined AGT
11:  end loop
12: end function

13: function FINDCANDIDATE( $p, \langle s, k \rangle, T$ )
14:    $f \leftarrow \text{if } p = \text{cont} \text{ then } \text{TREEFORMULA}(T) \text{ else } \overline{\text{TREEFORMULA}(T)}$ 
15:    $sol \leftarrow \text{SAT}(s(X_T) \wedge f)$ 
16:   if  $sol = \text{unsat}$  then
17:     if unbounded then ▷ Active only in the unbounded solver
18:        $\sigma \leftarrow \text{GENERALISE}(s)$  ▷ Expand  $s$  to a set of states
19:       if  $p = \text{cont}$  then  $\text{LEARN}(\sigma, T)$  else  $\overline{\text{LEARN}}(\sigma, T)$ 
20:     end if
21:     return  $\emptyset$  ▷ No candidate exists
22:   else
23:     return  $\{\langle n, c \rangle \mid n \in \text{GTNODES}(T), c = \text{SOL}(n)\}$  ▷ Fix candidate moves in  $T$ 
24:   end if
25: end function

26: function VERIFY( $p, \langle s, k \rangle, gt, cand$ )
27:   for  $l \in \text{leaves}(gt)$  do
28:      $\langle k', s' \rangle \leftarrow \text{OUTCOME}(\langle s, k \rangle, gt, l)$  ▷ Get rank and state at leaf
29:      $u \leftarrow \text{SOLVEABSTRACT}(\text{OPPONENT}(p), \langle k', s' \rangle, \emptyset)$  ▷ 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

```

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 bound.

It is possible to set a 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 nuanced approach is to use the diameter of the game [1], 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. This approach is common in bounded model checking but for synthesis it quickly becomes intractable to consider such long runs.

When performing model checking or synthesis with BDDs [5] the set of states that are winning for the environment is iteratively constructed by computing the states from which the environment can force the game into the previous winning set. Eventually this process reaches a fixed point and the total set of environment winning states is known.

A similar concept can be applied to the bounded synthesis algorithm to iteratively increase the bound of the game and terminate when a fixed point is reached. When a strategy is found to be winning on an abstract game tree, we record as winning the states from which the opponent could find no counterexample. To find these states we use interpolation of subformulas of the game tree.

3.1 Extending Bounded Synthesis to Unbounded Games

The unbounded synthesis algorithm (Algorithm 3) effectively consists of two communicating solvers: the counterexample-guided bounded reachability solver and the unbounded solver based on incremental induction. The unbounded solver calls the bounded solver with an increasing bound (line 8) while learning states from abstract game trees that either must or may lose for the controller. When the initial state is contained within the must-losing states the game is known to be unrealisable (line 5).

May-losing states are learned by removing controller-winning states. We maintain a set of states for every rank up the current bound. The states we learn while executing the bounded algorithm can only said to be controller-winning for a particular rank or below. However, we construct each set carefully such that it is monotonically larger than the set of the rank below (see Figure 2) and so that the environment is unable to force play from one set to the next. Due to this careful construction, when two adjacent sets become equivalent we know that the algorithm has reached a fixed point and the controller is winning in the unbounded game (line 6).

When executing the unbounded solver, lines 18 and 19 become active in the bounded solver. These lines call the learning procedures when the solver fails to find a candidate for an abstract game tree. The states symbolically represented

Algorithm 3 Unbounded Synthesis

```

1: function SOLVEUNBOUNDED( $T$ )
2:    $B^M \leftarrow E$ 
3:    $B^m[0] \leftarrow E$ 
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:      $\text{CHECKRANK}(I, k)$ 
9:   end for
10: end function
Require: May and must invariants hold
Ensure: May and must invariants hold
Ensure:  $\neg s \in B^m[k]$  if there is a winning controller strategy of length  $k$  starting at  $s$ 
Ensure:  $s \in B^M$  if there is a winning environment strategy of length  $k$  starting at  $s$ 
11: function CHECKRANK( $s, k$ )
12:   return SOLVEABSTRACT( $\text{env}, \langle s, k \rangle, \emptyset$ )
13: end function

```

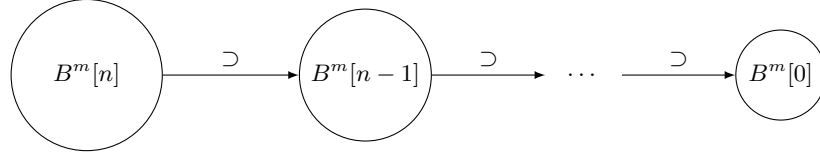


Fig. 2: May-losing states

by nodes in the tree are losing for whichever player could not find a winning candidate and can be extracted from the tree using interpolation.

3.2 Learning States with Interpolants

Given two formulas A and B such that $A \wedge B$ is unsatisfiable, it is possible to construct a Craig interpolant [7] \mathcal{I} such that $A \rightarrow \mathcal{I}$, $B \wedge \mathcal{I}$ is unsatisfiable, and \mathcal{I} refers only to the intersection of variables in A and B . An interpolant can be constructed efficiently from a resolution proof of the unsatisfiability of $A \wedge B$ [16].

Consider the snippet of a game tree in Figure 3. The tree is losing for the controller, the node labelled x_1 is at rank 1, and x_0^0 and x_0^1 are at rank 0. Since the tree is controller-losing we know that at least one run represented by the tree contains the error state. As a result, $\text{TREEFORMULA}(gt)$ is unsatisfiable. If we take the step x_1 to x_0^0 and cut it from the rest of the tree then $\text{TREEFORMULA}(step) \wedge \text{TREEFORMULA}(parent)$ must too be unsatisfiable.

We can construct an interpolant with $A = \text{TREEFORMULA}(parent)$ and $B = \text{TREEFORMULA}(step)$. The only variables shared between A and B are the state variables at x_1 . We know that $B \wedge \mathcal{I}$ is unsatisfiable, therefore all states in \mathcal{I} must

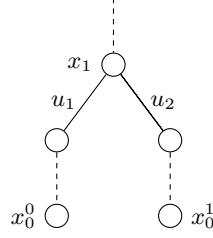


Fig. 3: A controller-losing game tree

lose to the uncontrollable label u_1 . We also know that $A \rightarrow \mathcal{I}$, thus \mathcal{I} contains all states reachable by the parent tree (on runs that avoid the error state.)

Algorithm 4 Amended tree formulas for Controller and Environment respectively

```

1: function TREEFORMULA(gt)
2:   if RANK(gt) = 0 then
3:     return  $\neg B^M(x^{gt})$ 
4:   else
5:     return  $\neg B^M(x^{gt}) \wedge \bigwedge_{n \in \text{succ}(gt)} (\delta(n) \wedge \text{LABEL}(n) \wedge \text{TREEFORMULA}(n))$ 
6:   end if
7: end function
8: function  $\overline{\text{TREEFORMULA}}$ (gt)
9:   if RANK(gt) = 0 then
10:    return  $E(x^{gt})$ 
11:   else
12:    return  $B^m[\text{rank}(gt)](x^{gt}) \wedge$ 
13:     $(E(x^{gt}) \vee \bigvee_{n \in \text{succ}(gt)} (\delta(n) \wedge \text{LABEL}(n) \wedge \overline{\text{treeFormula}}(n)))$ 
14:   end if
15: end function

```

Now we can consider the step x_1 to x_0^1 , and the parent - now without either $x_1 \rightarrow x_0^0$ or $x_1 \rightarrow x_0^1$. The formula $(\text{TREEFORMULA}(\text{parent}) \wedge \mathcal{I}) \wedge \text{TREEFORMULA}(\text{step})$ must be unsatisfiable. \mathcal{I} contains all states that lose to u_1 so any other state reachable at x_1 must lose to u_2 . Therefore we can compute another interpolant that contains states that lose to u_2 .

This is the foundation for a recursive algorithm that consumes an entire tree by removing a single step on each iteration (Algorithm 5). All learned states from which the controller *must* lose are recorded in a set of *bad* states B^M . This algorithm can also be performed on environment-losing trees with the caveat that any state learnt at a node of rank n is only known to lose at ranks less than or equal to n . We negate the interpolants we learn this way and record

them in a mapping of ranks to sets of states B^m which *may* be bad states for the controller.

3.3 Correctness

Algorithm 5 Learning algorithms

Require: $\sigma(X_T) \wedge \text{TREEFORMULA}(T) \equiv \perp$

Require: *Must-invariant* holds

Ensure: *Must-invariant* holds

Ensure: $\sigma(X_T) \wedge B^M$

```

1: function LEARN( $\sigma, T$ )
2:   if  $T = \emptyset$  then return
3:    $n \leftarrow$  non-leaf node with max rank
4:    $\langle T_1, T_2 \rangle \leftarrow \text{GTSPLIT}(T, n)$ 
5:    $\mathcal{I} \leftarrow \text{INTERPOLATE}(\sigma(X_T) \wedge \text{TREEFORMULA}(T_1), \text{TREEFORMULA}(T_2))$ 
6:    $B^M \leftarrow B^M \vee \mathcal{I}$ 
7:   LEARN( $\sigma, T_1$ )
8: end function

Require:  $\sigma(X_T) \wedge \overline{\text{TREEFORMULA}(T)} \equiv \perp$ 
Require: May-invariant holds
Ensure: May-invariant holds
Ensure:  $\sigma(X_T) \wedge B^m[\text{RANK}(T)] \equiv \perp$ 
9: function  $\overline{\text{LEARN}}$ ( $\sigma, T$ )
10:  if  $T = \emptyset$  then return
11:   $n \leftarrow$  non-leaf node with max rank
12:   $\langle T_1, T_2 \rangle \leftarrow \text{GTSPLIT}(T, n)$ 
13:   $\mathcal{I} \leftarrow \text{INTERPOLATE}(\sigma(X_T) \wedge \overline{\text{TREEFORMULA}(T_1)}, \overline{\text{TREEFORMULA}(T_2)})$ 
14:  for  $i = 1$  to  $\text{RANK}(n)$  do
15:     $B^m[i] \leftarrow B^m[i] \wedge \neg \mathcal{I}$ 
16:  end for
17:   $\overline{\text{LEARN}}(\sigma, T_1)$ 
18: end function

```

The correctness of the unbounded synthesis algorithm can be established independently from that of the bounded algorithm. Fortunately, the correctness of the bounded solver has been established in [15].

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 the uncontrollable predecessor of $f^m[i]$:

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

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

$$B^M \subseteq B.$$

The sets B^m and B^M are only modified by the inductive solver, implemented by `LEARN` and `LEARN` functions. Below we prove that these functions indeed maintain the invariants.

3.4 Proof of `learn`

We prove that postconditions of `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 $f_1 = \sigma(X_T) \wedge \overline{\text{TREEFORMULA}}(T_1)$ 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 $\sigma(X_T) \wedge \text{TREEFORMULA}(T)$, 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 σ 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 $B^m[\text{RANK}(n)]$ playing against the counterexample moves in T_2 . Hence, $\mathcal{I} \cap \text{Upred}(B^m[\text{RANK}(n)]) = \emptyset$. Furthermore, since the may-invariant holds, $\mathcal{I} \cap \text{Upred}(i) = \emptyset$, for all $i < \text{RANK}(n)$. Hence, removing \mathcal{I} from all $B^m[i]$, $i \leq \text{RANK}(n)$ 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 $\sigma(X_T) \wedge \overline{\text{TREEFORMULA}}(T_1)$ also satisfies \mathcal{I} . Hence, removing \mathcal{I} from $B^m[\text{RANK}(n)]$ makes $\sigma(X_T) \wedge \overline{\text{TREEFORMULA}}(T_1)$ unsatisfiable, and hence all preconditions of the recursive invocation of `LEARN` in line (17) are satisfied.

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

3.5 Proof of Termination

We must prove that `CHECKRANK` terminates and that upon termination its postcondition holds.

We must prove that `CHECKRANK` terminates and that upon termination its postcondition holds, i.e., state s is removed from $B^m[k]$ if there is a winning controller strategy on the bounded safety game of rank k 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 rank k . This means that at some point the algorithm discovers a counterexample tree of rank k for which the environment cannot force into E . The algorithm then invokes

the $\overline{\text{LEARN}}$ method, adds s to B^M . Alternatively, if there is a winning strategy for the environment at rank k then a counterexample losing for the controller will be found. Subsequently LEARN will be called and s eliminated from $B^m[k]$.

4 Optimisations

4.1 Generalising the initial state

If more states are removed from B^m on each iteration of CHECKRANK the algorithm will converge and terminate sooner. Additionally, any states removed from B^M will reduce the number of states to be considered by the controller in future iterations.

As it is written, the algorithm only considers an overapproximations of states reachable from I for learning. Assuming that the algorithm does not terminate, then the addition of an extra step into the game on each iteration has the potential to greatly increase the reachable states. Considering some of these states earlier than they become reachable may lead to earlier termination.

Algorithm 6 Generalise I optimisation

```

function CHECKRANK( $s, k$ )
   $r \leftarrow \text{SOLVEABSTRACT}(\text{env}, \langle s, k \rangle, \emptyset)$ 
  if  $r \neq \emptyset$  then return  $r$ 
   $s' \leftarrow s$ 
  for  $x \in s$  do
     $r \leftarrow \text{SOLVEABSTRACT}(\text{env}, \langle s' \setminus \{x\}, k \rangle, \emptyset)$ 
    if  $r = \emptyset$  then  $s' \leftarrow s' \setminus \{x\}$ 
  end for
  return  $\emptyset$ 
end function

```

The optimisation that allows this is relatively simple and is inspired by a common greedy heuristic for minimising **unsat** cores. I is a value assignment to each variable in X . If the environment does not win for $\langle I, k \rangle$ then we attempt to solve for a generalised version of I by removing one assignment at a time. If the controller can win from the larger set of states then we continue generalising without it. 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 CHECKRANK .

4.2 Choosing sensible opponent moves

One aspect of the algorithm proposed by Narodytska et al. [15] is that it mimics real-world uses of synthesis by allowing cooperation between system and environment. Unfortunately, allowing the opponents to pick moves for one another

can frequently backfire. It is common when modelling real-world systems to abstract over out of scope failures with transitions that immediately determine the outcome of the game. For example, in a network driver a request to send a packet may fail due to a disconnected wire, which might be modelled as an environment controlled transition to a system-winning state.

This slows down the synthesis process as all erroneous transition are accumulated into the abstract game tree. To mitigate this effect we have a heuristic to guess non-erroneous labels as *default moves* that are used instead of allowing the opponent to choose. This does not effect the correctness of the algorithm. If line (28) previously returned **sat** and is **unsat** with default moves then those moves would eventually have been added to the abstraction in a refinement step. If the formula is **unsat** even with the opponent choosing moves then it must be **unsat** with default moves.

5 Evaluation

We evaluate our approach on the benchmarks of the 2015 synthesis competition (SYNTCOMP'15).

6 Related Work

Synthesis of safety games is a thoroughly explored area of research with most efforts directed toward solving games with BDDs [5] and abstract interpretation [17, 4]. Satisfiability solving has been used previously for synthesis in a suite of methods proposed by Bloem et al [2]. 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 [12], or by interpolation [13]. However, there are no corresponding adaptations to synthesis. Incremental induction [3] is another technique for unbounded model checking with an equivalent synthesis method [14], which computes the set of safe states incrementally.

There are different approaches to bounded synthesis than the one described here. The authors of [11] suggest a methodology directly inspired by bounded model checking and it has been adapted to symbolic synthesis [9]. Lazy synthesis [10] is a counterexample-guided approach to bounded synthesis that refines an implementation for the game instead of an abstraction of it.

The algorithm presented in this paper solves realisability for safety games. There is a method for extracting strategies from abstract game trees that is compatible with our method [8]. It involves a similar interpolation approach for discovering states in game tree nodes.

7 Conclusion

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