# SMT Solver raSAT for Polynomial Constraints

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**Abstract.** This paper presents an SMT solver **raSAT** for polynomial constraints, which aims to handle them over both reals and integers with unified methodologies, (1) **raSAT** loop for inequations, which extends the interval constraint propagation with testing to accelerate SAT detection, and (2) the Intermediate Value Theorem for equations over reals.

### 1 Introduction

Polynomial constraint solving is to find an instance that satisfies given polynomial inequations/equations. Various techniques are implemented in SMT solvers. For solving over reals ( $QF\_NRA$ ), techniques vary **QE-CAD** (RAHD [15], Z3 from 4.3 [10]), **Virtual substitution** (SMT-RAT [5], Z3 from 3.1), **Interval constraint propagation** (**ICP**) [1] (iSAT3 [6], dReal [8], RSolver [16]), and **Linearization** (CORD [7]). For that over integers ( $QF\_NIA$ ), we have **Bitblasting** (UCLID [3], MiniSmt [17]) and **Linearization** (Barcelogic [2]).

This paper presents an SMT solver **raSAT** (refinement of approximations for SAT) for polynomial constraints over both reals and integers. For inequations, it applies a simple iterative approximation refinement, **raSAT** *loop*, which extends ICP with testing to accelerate SAT detection. For equations, a non-constructive reasoning based on the Intermediate Value Theorem is employed (Section 4).

In a floating point arithmetic, round-off errors may violate the soundness. To get rid of such traps, we apply the outward rounding [9] in an interval arithmetic. We also integrate **iRRAM**<sup>3</sup>, which guarantees the round-off error bounds, to confirm that a detected SAT instance is really SAT.

Currently, **raSAT** applies an incremental search, *incremental widening* and *deepening*, and an SAT-directed strategy based on measures, *SAT likelihood* and *sensitivity* (Section 3), but does not have UNSAT-directed strategies, e.g., UNSAT core. Note that the sensitivity works only with Affine intervals [14].

At the SMT Competition 2015, **raSAT** participated two categories of main tracks,  $QF\_NRA$  and  $QF\_NIA$ . **raSAT** is originally developed for  $QF\_NRA$ , however  $QF\_NIA$  is fairly easy to adapt, i.e., stop interval decompositions when the width becomes smaller than 1, and generate integer-valued test instances.

<sup>3</sup> http://irram.uni-trier.de

As the overall rating (Main Track),  $\mathbf{raSAT}$  is  $8^{th}$  among 19 SMT solvers<sup>4</sup>. The results are summarized as

- $-3^{rd}$  in  $QF_NRA$ , **raSAT** solved 7952 over 10184 (where Z3 4.4 solves 10000).
- $-2^{nd}$  in QF\_NIA, raSAT solved 7917 over 8475 (where Z3 4.4 solves 8459; CVC4 (exp) solves 8277, but with one wrong detection).

# ICP Overview and raSAT Loop

Our target problem is solving nonlinear constraints. First, we discuss on solving polynomial inequations, and that for equations are shown later in Section 4. Let  $\mathbb{R}$  be the set of real numbers and  $\mathbb{R}^{\infty} = \mathbb{R} \cup \{-\infty, \infty\}$ . The normal arithmetic on  $\mathbb{R}$  is extended to those on  $\mathbb{R}^{\infty}$  as in [13]. The set of all intervals is defined as  $\mathbb{I} = \{[l,h] \mid l \leq h \in \mathbb{R}^{\infty}\}$ . A box for a sequence of variables  $x_1, \dots, x_n$  is of the form  $B = I_1 \times \dots \times I_n$  where  $I_1, \dots, I_n \in \mathbb{I}$ .

**Definition 1.** A polynomial inequality constraint is 
$$\psi(x_1,\cdots,x_n) = \bigwedge_{j=1}^m p_j(x_1,...,x_n) > 0$$

where  $p_j(x_1, \dots, x_n) > 0$  is an atomic polynomial inequation (API). When  $x_1, \dots, x_n$  are clear from the context, we denote  $\psi$  for  $\psi(x_1, \dots, x_n)$ ,  $p_i$  for  $p_i(x_1, \dots, x_n)$ , and  $var(p_i)$  for the set of variables appearing in  $p_i$ .

As an SMT problem,  $\psi$  is satisfiable (SAT) if there exists an assignment on variables that makes it true. Otherwise,  $\psi$  is said to be unsatisfiable (UNSAT). Let  $\mathbb{S}(\psi) = \{(r_1, \dots, r_n) \in \mathbb{R}^n \mid \psi(r_1, \dots, r_n) = true\}.$ 

**Algorithm 1** ICP starting from the initial box  $B_0 = I_1 \times \cdots \times I_n$ 

```
2: while S \neq \emptyset do
        B \leftarrow S.choose()
3:
                                                                        ▷ Get one box from the set
        B' \leftarrow prune(B, \psi)
4:
        if B' = \emptyset then
5:
                                                      ▶ The box does not satisfy the constraint
6:
            S \leftarrow S \setminus \{B\}
7:
            continue
8:
        else if B' satisfies \psi by using IA then
9:
            return SAT
```

1:  $S \leftarrow \{B_0\}$ 

<sup>10:</sup>  $\triangleright$  IA cannot conclude the constraint  $\implies$  Refinement Step  $\{B_1, B_2\} \leftarrow split(B')$  $\triangleright$  split B' into two smaller boxes  $B_1$  and  $B_2$ 11:  $S \leftarrow (S \setminus \{B\}) \cup \{B_1, B_2\}$ 12:

end if 13: 14: end while

<sup>15:</sup> return UNSAT

<sup>4</sup> http://smtcomp.sourceforge.net/2015/results-competition-main.shtml

#### 2.1 ICP Overview

Starting with a box B, ICP [1] tries to prove UNSAT/SAT of  $\psi$  inside B by an interval arithmetic (IA). If it fails, it iteratively decomposes boxes. Algorithm 1 describes the basic ICP for solving polynomial inequations where two functions  $prune(B,\psi)$  and split(B) satisfy the following properties.

- If  $B' = prune(B, \psi)$ , then  $B' \subseteq B$  and  $B' \cap \mathbb{S}(\psi) = B \cap \mathbb{S}(\psi)$ . - If  $\{B_1, B_2\} = split(B)$ , then  $B = B_1 \cup B_2$  and  $B_1 \cap B_2 = \emptyset$ .
- ICP concludes SAT (line 8) only when it finds a box in which the constraint becomes valid by an IA. Although the number of boxes increases exponentially, ICP always detects SAT of the inequations  $\psi$  if  $I_1, \dots, I_n$  are bounded (Fig. 1a). However, ICP may miss to detect UNSAT in cases of *kissing* and *convergence* (Fig. 1c,d).

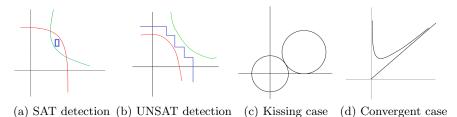


Fig. 1: Scenarios of solving polynomial inequations with ICP

# 2.2 raSAT Loop

ICP is extended to **raSAT** loop [11], which is displayed in Algorithm 2.

Its implementation **raSAT** adapts various IAs including Affine Intervals (AI) [4, 14, 11] and Classical Interval (CI) [13]. An AI introduces noise symbols  $\epsilon$ 's, which are interpreted to values in [-1,1]. AIs vary depending on the treatments of the multiplication among noise symbols. For the multiplication of the same noise symbols,  $AF_2$  [12] describes by  $\epsilon_+$  (or  $\epsilon_-$ ), which is interpreted in [0,1] (or [-1,0]), and CAI [11] describes  $\epsilon \epsilon = |\epsilon| + [-\frac{1}{4},0]$ . Mostly, the product of different noise symbols are simply regarded as any value in [-1,1] (e.g.,  $\epsilon_+$ ).

Although precision is incomparable, an AI partially preserves the dependency among values, which is lost in CI. For instance, consider  $x \in [2, 4] = 3 + \epsilon$ . Then, x - x is evaluated to [-2, 2] by CI, where 0 by an AI.

Example 1. Let  $g = x^3 - 2xy$ ,  $x = [0, 2] = 1 + \epsilon_1$ , and  $y = [1, 3] = 2 + \epsilon_2$ . CI estimates the range of g as [-12, 8],  $AF_2$  does  $-3 - \epsilon_1 - 2\epsilon_2 + 3\epsilon_+ + 3\epsilon_\pm$  (= [-9, 6]), and CAI does  $[-4, -\frac{11}{4}] + [-\frac{1}{4}, 0]\epsilon_1 - 2\epsilon_2 + 3|\epsilon_1| + [-2, 2]\epsilon_\pm$  (= [-8, 4.5]).

# 3 SAT directed Strategies of raSAT

Performance of ICP is affected by the number of variables because the initial box  $I_1 \times \cdots \times I_n$  will be decomposed into exponentially many boxes.

**Algorithm 2 raSAT** loop starting from the initial box  $\Pi = \bigwedge_{i=1}^{n} x_i \in I_i^0$ 

```
1: while \Pi is satisfiable do
                                                                                                                    \triangleright Some more boxes exist
             \pi = \{x_i \in I_{ik} \mid i \in \{1, \cdots, n\}, k \in \{1, \cdots, i_k\}\} \leftarrow \text{a solution of } \Pi
            B \leftarrow \text{the box represented by } \bigwedge_{i=1}^{n} \bigwedge_{k=1}^{i_k} x_i \in I_{ik}
if B does not satisfy \psi by using IA then
II \leftarrow II \land \neg (\bigwedge_{i=1}^{n} \bigwedge_{k=1}^{i_k} x_i \in I_{ik})
else if B satisfies \psi by using IA then
II \leftarrow II \land \neg (\bigwedge_{i=1}^{n} \bigwedge_{k=1}^{i_k} x_i \in I_{ik})
 3:
 4:
 5:
 6:
                   return SAT
 7:
 8:
             else if B satisfies \psi by using testing then
                                                                                                                           \triangleright Different from ICP
 9:
                   return SAT
10:
              else \triangleright Neither IA nor testing conclude the constraint \implies Refinement Step
11:
                    choose (x_i \in I_{ik}) \in \pi such that \forall k_1 \in \{1, \dots, i_k\} I_{ik} \subseteq I_{ik_1}
                                                               \triangleright split I_{ik} into two smaller intervals I_1 and I_2
12:
                    \{I_1, I_2\} \leftarrow split(I_{ik})
                    \Pi \leftarrow \Pi \land (x_i \in I_{ik} \leftrightarrow (x_i \in I_1 \lor x_i \in I_2)) \land \neg (x_i \in I_1 \land x_i \in I_2)
13:
14:
             end if
15: end while
16: return UNSAT
```

#### 3.1 Incremental Search

Two incremental search strategies are prepared in raSAT.

Incremental Widening. Given  $0 < \delta_0 < \delta_1 < \cdots < \delta_k = \infty$ , incremental widening starts with  $B_0 = [-\delta_0, \delta_0] \times \cdots \times [-\delta_0, \delta_0]$ , and if  $\psi$  remains UNSAT, then enlarge the box to  $B_1 = [-\delta_1, \delta_1] \times \cdots \times [-\delta_1, \delta_1]$ . This continues until either timeout or the result obtained. In **raSAT**,  $AF_2$  is used for  $B_i$  if  $i \neq k$ , and CI is used for  $\delta_k = \infty$ .

Incremental Deepening. To combine depth-first-search and breadth-first search among decomposed boxes,  $\mathbf{raSAT}$  applied incremental deepening. Let  $\gamma_0 > \gamma_1 > \cdots > 0$ . It applies a threshold  $\gamma$ , such that no more decomposition occurs when an interval becomes smaller than  $\gamma$ .  $\gamma$  is initially  $\gamma_0$ . If neither SAT nor UNSAT is detected,  $\mathbf{raSAT}$  restarts with the threshold  $\gamma_1$  (Fig. 2 (b)). This continues until either timeout or the result obtained.

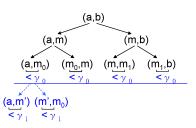


Fig. 2: Incremental Deepening

### 3.2 SAT Directed Heuristics Measure

To reduce an explosion of the number of decomposed boxes, **raSAT** prepares a strategy to select a variable at a box decomposition. (1) First, select a least likely satisfiable *API* with respect to *SAT*-

likelihood. (2) Then, choose a most likely influential variable in such API with respect to *sensitivity*. We assume an Affine interval (AI) for an interval arithmetic (IA).

In line 3 of Algorithm 2, let an AI estimate the range  $range(g_j, B)$  of each polynomial  $g_j$  in a box B as  $[c_1, d_1]\epsilon_1 + \cdots + [c_n, d_n]\epsilon_n$ . Then,  $range(g_j, B)$  is obtained by instantiating [-1, 1] to  $\epsilon_i$ . We define

- The SAT-likelihood of an API  $g_j > 0$  is  $|I \cap (0, \infty)|/|I|$  for  $I = range(g_j, B)$ .
- The sensitivity of a variable  $x_i$  in an API  $g_j > 0$  is  $max(|c_i|, |d_i|)$ .

Example 2. In Example 1, SAT-likelihood of g is  $0.4 = \frac{6}{9-(-6)}$  by  $AF_2$  and  $0.36 = \frac{4.5}{4.5-(-8)}$  by CAI. The sensitivity of x is 1 by  $AF_2$  and  $3\frac{1}{4}$  by CAI, and that of y is 2 by both.

Our strategy consists of three steps:

- 1. Choice of an API with the least SAT likelyhood.
- 2. Choice of a variable with the largest *sensitivity* in the API.
- 3. Choice of a box with the largest SAT likelyhood, where the SAT-likelihood of a box B is the least SAT-likelihood among APIs on B.

The first two steps selects a variable to apply the interval decomposition and the testdata generation. After a box decomposition is applied, the last step compares SAT-likelihood of all boxes (including newly decomposed boxes) to select one to explore next. At the testdata generation,  $\mathbf{raSAT}$  observes the sign of the coefficient of the noise symbol with the largest sensitivity. If positive, first take the upper bound; otherwise, the lower bound. The rest is generated randomly.

The strategy is evaluated on Zankl and Meti-Tarski families of  $QF\_NRA$ . As a comparison with other ICP-based solvers, we compare  $\mathbf{raSAT}$  with a random choice (Random),  $\mathbf{raSAT}$  with the strategy above  $(\mathbf{raSAT})$ ,  $\mathbf{iSAT3}$ , and  $\mathbf{dReal}$ .

Note that (1) **iSAT3** solves over [-1000, 1000] due to the system restriction, while all others solve over  $[-\infty, \infty]$ , and (2) SAT of **dReal** is  $\delta$ -SAT (SAT under tolerance of the width  $\delta$ ); thus **dReal** sometimes answers SAT even for UNSAT problems. The experiments are performed with Intel Xeon E5-2680v2 2.80GHz and 4GB of RAM. The timeout is set to 500 seconds, and the time shows the total of successful cases (either SAT or UNSAT).

Benchmark	Random		ra	SAT	iS.	AT3	dReal		
Matrix-1 (SAT )	19	230.39(s)	25	414.99	11	4.68	46*	3573.43	
Matrix-1 (UNSAT)	2	0.01(s)	2	0.01	3	0.00	_ ~	0.00	
Matrix-2,3,4,5 (SAT)	1	13.43(s)	11	1264.77	3	196.40	19*	2708.89	
Matrix-2,3,4,5 (UNSAT)		0.0.(5)		0.00		0.00	_ ~	0.00	
Meti-Tarski (SAT)	3451	895.14(s)	3473	419.25	2916	811.53	3523*	441.35	
Meti-Tarski (UNSAT)	1060	233.46(s)	1052	821.85	1225	73.83	1197	55.39	

(\* means  $\delta$ -SAT)

We observe that the strategy is effective for SAT-detection in large problems, like Matrix-2,3,4,5 (in Zankl benchmarks), which often have more than 50 variables (Meta-Tarski has mostly less than 10 variables, and Matrix-1 has mostly less than 30 variables). Comparing with the state-of-the-art tool **Z3 4.4** on Matrix-2,3,4,5, the differences appear that **Z3 4.4** solely solves Matrix-3-7/4-12/5-6 (which have 75, 200, and 258 variables), and raSAT solely solves Matrix-2-3/2-8/3-5/4-3/4-9 (which have 57, 17, 81, 139, and 193 variables).

# Extension for Equations Handling

**Single Equation.** A single equation (g=0) can be solved by finding 2 test cases with g > 0 and g < 0. Then, g = 0 holds somewhere in between by the Intermediate Value Theorem.

**Lemma 1.** For  $\psi = \bigwedge_{j=1}^m g_j > 0 \land g = 0$ . Suppose a box B and let  $[l_g, h_g] = range(g, B),$ 

- (i) If either  $l_g > 0$  or  $h_g < 0$ , then g = 0 (thus  $\psi$ ) is UNSAT in B. (ii) If  $\bigwedge_{j=1}^m g_j > 0$  is IA-valid in B and there are  $\mathbf{t}, \mathbf{t}' \in B$  with  $g(\mathbf{t}) > 0$  and  $g(\mathbf{t'}) < 0$ , then  $\psi$  is SAT.

If neither (i) nor (ii) holds, raSAT continues the decomposition.

Example 3. Let  $\varphi = f(x,y) > 0 \land g(x,y) = 0$ . Suppose we find a box  $B = [a, b] \times [c, d]$  such that f(x, y) > 0 is IA-VALID in B. (Fig. 3a). In addition, if we find two points  $(u_1, v_1)$  and  $(u_2, v_2)$  in B such that  $g(u_1, v_1) > 0$ and  $g(u_2, v_2) < 0$ , then the constraint is satisfiable by Lemma 1.

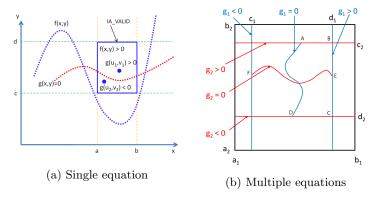


Fig. 3: Example on solving equations using the Intermediate Value Theorem

**Multiple Equations.** Multiple equations are solved by repeated applications of the Intermediate Value Theorem. Let  $\bigwedge_{j=1}^m g_j = 0$  and  $B = [l_1, h_1] \times \cdots [l_n, h_n]$  with  $m \leq n$ . Let  $V = \{x_1, \cdots, x_n\}$  be the set of variables. For  $V' = \{x_{i_1}, \cdots x_{i_k}\} \subseteq V$ , we denote  $B \downarrow_{V'}$  and  $B \uparrow_{V'}$  for  $\{(r_1, \cdots, r_n) \in B \mid r_i = l_i \text{ for } i = i_1, ..., i_k\}$  and  $\{(r_1, \cdots, r_n) \in B \mid r_i = h_i \text{ for } i = i_1, ..., i_k\}$ , respectively.

**Definition 2.** A sequence  $(V_1, \dots, V_m)$  of subsets of V is a check basis of  $(g_1, \dots, g_m)$  in a box B, if, for each j, j' with  $1 \le j, j' \le m$ ,

- 1.  $V_j(\neq \emptyset) \subseteq var(g_j)$ ,
- 2.  $V_j \cap V_{j'} = \emptyset$  if  $j \neq j'$ , and
- 3. either  $g_j > 0$  on  $B \uparrow_{V_j}$  and  $g_j < 0$  on  $B \downarrow_{V_j}$ , or  $g_j < 0$  on  $B \uparrow_{V_j}$  and  $g_j > 0$  on  $B \downarrow_{V_j}$ .

Lemma 2. For a polynomial constraint containing multiple equations

$$\psi = \bigwedge_{j=1}^{m} g_j > 0 \land \bigwedge_{j=m+1}^{m'} g_j = 0$$

and  $B = [l_1, h_1] \times \cdots [l_n, h_n]$ , assume that

- 1.  $\bigwedge_{j=1}^{m} g_j > 0$  is IA-valid in B, and
- 2. there is a check basis  $(V_{m+1}, \dots, V_{m'})$  of  $(g_{m+1}, \dots, g_{m'})$  in B.

Then,  $\psi$  has a SAT instance in B.

The idea is, from the Intermediate Value Theorem, each  $j \in \{m+1, \cdots, m'\}$ ,  $g_j$  has a  $n-|V_j|$  dimensional surface of null points of  $g_j$  between  $B \uparrow_{V_j}$  and  $B \downarrow_{V_j}$ . Since  $V_j$ 's are mutually disjoint (and  $g_j$ ' are continuous), we have the intersection of all such surfaces of null points with the dimension  $n-\sum_{j=m+1}^{m'} |V_j|$ . Thus, this method has a limitation that the number of variables must be greater than or equal to the number of equations.

Example 4. Fig. 3b illustrate Lemma 2 for m=0 and m'=n=2. The blue and red lines represent the null points of  $g_1(x,y)$  and  $g_2(x,y)$  in  $[c_1,d_1]\times[c_2,d_2]$ , respectively.

Benchmark	raSAT			Z3 4.3					iSAT3				
		SAT	UNSAT		SAT		UNSAT			SAT		UNSAT	
Zankl (15)	11	0.07 (s)	4	0.17 (s)	11	0.17 (s)	4	0.02	(s)	0	0.00 (s)	4	0.05 (s)
Meti-Tarski (3528/1573)	875	174.90 (s)	781	401.15 (s)									
Keymaera (612)	0	0.00 (s)	312	66.63 (s)	0	0.00 (s)	610	2.92	(s)	0	0.00 (s)	226	1.63 (s)

Table 1: Comparison among SMT solvers with equations

### 5 Conclusion

This paper presented an SMT solver **raSAT** for polynomial constraints. There are lots of future works, including

- Support mixed integers (QF\_NIRA).
- Implement UNSAT-directed strategies, e.g. UNSAT core.
- Set search bounds based on QE-CAD.
- Apply Groebner basis to overcome current limitation that the number of variables must be greater than or equal to the number of equations.

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