

SMT-based Robot Transition Repair

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Abstract

State machines are a common model for robot behaviors that combine a number of individual controllers with a transition function that switches between them. Transition functions often rely on parameterized conditions to model preconditions for the controllers, where the correct values of the parameters depend on factors relating to the environment or the specific robot. In the absence of specific calibration procedures a roboticist must painstakingly adjust the parameters through a series of trial and error experiments. In this process, identifying when the robot has taken an incorrect action, and what should be done instead is straightforward, but finding the right parameter values can be difficult. Inspired by this idea we present an alternative approach that we call, *interactive SMT-based Robot Transition Repair* (SRTR). During execution we record an *execution trace* of the transition function, and we ask the roboticist to identify a few instances where the robot has transitioned incorrectly, and what the correct transition should have been. A user supplies these *corrections* based on the type of error to repair. Either by directly identifying them in the trace when a transition should occur, or by generating corrections via forward simulation when a transition should not occur. Using these corrections, an automated analysis of the traces *partially evaluates* the transition function for each correction. Simplifying the transition function to a system of constraints that describe the correct behavior in terms of the repairable parameters. This system of constraints is then formulated as a MaxSMT problem, where the solution is a minimal adjustment to the parameters that satisfies the maximum number of constraints. In order to identify a repair that accurately captures user intentions and generalizes to novel scenarios, solutions are explored by iteratively adding constraints to the MaxSMT problem to yield sets of alternative repairs. We test with state machines from multiple domains including robot soccer and autonomous driving, and we evaluate solver based repair with respect to solver choice and optimization hyperparameters. Our results demonstrate that SRTR can repair a variety of states machines and error types 1) quickly, 2) with small numbers of corrections, while 3) not overcorrecting state machines and harming generalized performance. Finally, we show that a state machine corrected with SRTR can outperform an expert-tuned state machine deployed in a real-world scenario.

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1. Introduction

In robotics complex behaviors often use state machines to combine feedback controllers as *states* by using a transition function to select the correct actions. Even when the individual controllers performs as intended, the transitions between states are often dependent on a set of parameters that require tuning to maximize performance. It is often the case that a single set of parameters will be optimal on one robot, or in one environment, but fail when transferred to another. Figure 1 shows an example failure using two trajectories of a robotic soccer player as it tries to kick a moving ball. A very small change to its parameter values is the difference between success and failure.

No single good solution to this problem exists. For special cases, calibration procedures can be used to adjust parameters automatically (e.g., [1]), but these are application specific. More general optimization techniques are subject to local minimal because robot performance is often non-convex with respect to parameter values, and exhaustive-search, while applicable, is impractical even for relatively simple robots. Therefore, manually adjusting parameters to iteratively improve performance is the primary approach used by roboticists.

In manually tuning these values the first step a roboticist takes is to identify what has gone wrong, and what the robot should have done instead. In comparison to the tedious task of identifying the correct parameter values, this is a simple task. When debugging a state machine for robot control this requires a roboticist to identify when the robot is in an incorrect state, and what the correct state should be. This results in a *partial specification* of the intended behavior: it specifies only a subset of the correct behavior without any information about how to realize that behavior. These partial specifications are the first step in the standard iterative adjustment procedure for robot behaviors, but actually realizing the desired behavior through iterative adjustment is much more difficult.

In this article, we present *Interactive SMT-based Robot Transition Repair* (SRTR) a technique for treating these partial specifications as user *corrections*, and we show that these corrections alone are adequate inputs for an automatic parameter repair procedure that automatically realizes the desired behavior without additional user effort. This repair procedure leverages Satisfiable Modulo Theories (SMT) in order to model transition functions and corrections in first-order logic. SMT is an expressive model of computation that is commonly used in applications such as program verification, synthesis, and a model checking. With the addition of optimizing SMT solvers [2] SMT can be used to complete models of computation while also optimizing objective functions. While least squares optimization or mixed integer linear programming are more popular optimization techniques in robotics, they cannot model problems that contain conditionals that SMT can. SMT based optimization uses techniques similar to MILP solvers for optimization, but combines arithmetic optimization and SMT solving to model a wider variety of problems, including those with conditionals. In some cases these problems may reduce to MILP problems, but SMT solvers can find solutions even in these edge cases.

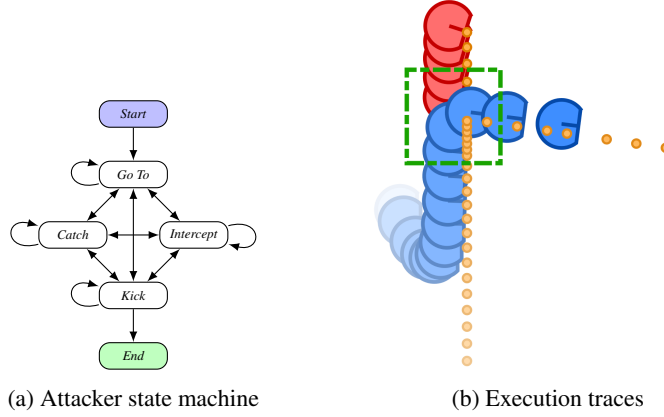


Figure 1: A robot soccer attacker a) state machine, with b) successful (blue) and unsuccessful (red) traces to *Intercept* a ball (orange) and *Kick* at the goal. The green box isolates the error: the successful trace transitions to *Kick*, the unsuccessful trace remains in *Intercept*.

In order to construct and solve the first-order logic problem SRTR first logs an execution trace of the transition function that captures program structure, program state, and information about the world relevant to the transition function. After execution, the roboticist examines the trace and provides one or more corrections. Based on the type of error a user can provide either *immediate corrections* that identify exact desired behavior in the execution trace, or utilize *continue corrections* to fork the world state and generate a sequence of corrections that delay a desired transition (Section 4.2). SRTR then utilizes information from the execution trace, analysis of the transitions function, and the set of user corrections to construct a formula in first-order logic suitable for a solver (Section 4.4). When a user supplies more than one correction they may not all be satisfiable, and so there may be several possible models that partially satisfy user intent. In order to explore these solutions SRTR iteratively updates and solves a MaxSMT problem that seeks to maximize the number of satisfied corrections while minimizing the magnitude of the repairs to the parameters (Section 4.5). At each iteration the MaxSMT problem is updated with additional constraints that guide the solver to novel solutions such that a set of potential solutions is presented to the user.

To evaluate SRTR we use it as a repair procedure for state machines in a number of domains, and we evaluate properties of the MaxSMT formulation and solvers used, as well as the overall performance of SRTR both with respect to success rate and solution time. We demonstrate experimentally that SRTR: 1) is more computationally tractable than exhaustive parameter search; 2) is scalable and can generate meaningful repairs with different backend solvers; 3) can be applied to various state machines in different domains; 4) generalizes to unseen situations; 5) can provide robust repairs even in special cases where the trace and corrections do not provide a single ideal repair; and 6) when applied to simple robot soccer attacker, can outperform a more complicated, expert-tuned attacker that won the lower bracket finals at *RoboCup 2017*.

2. Related Work

Configuration parameters are common in many software systems, and represent a large source of error across disciplines [3, 4, 5]. In robotics, behaviors often rely on environment-dependent parameters for robust and accurate execution. Using models of the desired structure and properties of behaviors, robot software can be designed at a higher level of abstraction that allows for automatic parameter adaptation to hardware, software, and architectural changes to achieve system objectives [6]. If a precise model of the dependency between parameters and behaviors is available, it may be possible to design a *calibration procedure* that executes a specific sequence of actions and to recover correct parameter values (*e.g.*, [1]). If a calibration procedure cannot be designed, but the effect of parameters is well-understood, it may be possible to optimize for the parameters using a functional model [5]. Model-based diagnosis can diagnose faulty parameters [7] if the behavior of the robot in its environment can be formally defined. Properties such as liveness, timeliness, etc can be modeled for monitoring correctness as in RoboChart [8], which uses finite state machines to verify behaviors. Similar to our approach is [9], which uses human input to identify error types in robot behavior and attempts to identify predicates in the code that are relevant to the failure in order to localize the faults.

In systems, approaches to handling system configuration error fall into two major categories designing systems to negate or minimize the impact of configuration errors, or supplying user end tools to automatically identify and troubleshoot configuration errors that may occur [3]. One such tool, [10] measures system resilience to configuration errors by injecting automatically generated configuration errors into the system and profiling performance. A test suite can be used to model correct behavior, as in DirectFix [11], which formulates program repair as a MaxSMT problem and deems a program fixed when all tests. In domains that are not amenable to unit-testing user input can be used as a specification for correction behavior. For example, Tortoise [12] propagates complete system configuration fixes from a user shell to a system configuration specification.

SRTR uses the existing code structure of FSMs to model behaviors without special procedures for individual behaviors, and thus can repair parameters without a descriptive model of the robot’s behavior. Deterministic test cases cannot be run on physical robots, so SRTR leverages user-provided corrections as a partial specification of how a behavior is incorrect and the desired change. Since these corrections can be contradictory MaxSMT is used to minimize changes and maximize the number of satisfied corrections, such that resulting repairs automatically yield the desired behavior while generalizing to other scenarios.

2.1. Behavior Synthesis

In many cases the problem of configuration repair in robotics can be seen as improving behavior, as is the focus of SRTR. Improving behaviors is a widely studied problem in robotics, and many modern approaches focus on behavior synthesis, either by learning complete behaviors, or by synthesizing partial control structure. Reinforcement learning approaches are a popular method for learning policies using Markov decision processes. Examples of reinforcement learning include learning the RoboCup

keep-away task with episodic SMDP Sarsa learning [13], and Q-value reuse leveraged for transfer learning of a simpler behavior to a more complex one using a Nao humanoid robot [14]. More recently [15] uses a two-tiered approach which combines policy search and Q-learning to learn an action-selection policy with parameterized actions. Hierarchical state machines can be used for reinforcement learning, as in [16] which uses hierarchies of abstract machines to short-circuit and speed up Q-learning by identifying internal transitions.

Deep learning techniques have become an extremely popular and promising approaches for behavior synthesis in recent years [17]. These approaches have been successful in simulated continuous domains using techniques such as proximal policy optimization [18], or on real robots for grasping as in [19] which combines CNNs for success prediction with a continuous servoing mechanism. Alternatively, learning action sequences and parameters has been applied in humanoid robot soccer to teach a full goal scoring policy using parameterized action spaces [20]. Similar to learning a transition function between tasks [21] formulates task switching as a Markov decision process and uses a Dueling Deep Q-Network to find the optimally policy. This method speeds up execution of a policy by identifying specific *stimuli* which are significant sensory inputs in the switch decision.

Human input can help overcome the limitations of autonomous algorithms [22, 23]. Learning from demonstration (LfD) [24] and inverse reinforcement learning (IRL) [25] allow robots to learn new behaviors from human demonstrations. LfD can also overcome model errors by correcting portions of the state space [26]. These approaches require demonstrations in the full high-dimensional state space of the robot, which can be tedious for users to provide. When human demonstrations do not specify *why* an action was applied to a state, it can be hard to generalize to a new situation. [27] attempts to address this by using statistical reasoning and control theory to convert continuous demonstrations to more generalized discrete representations and modeling multi-step tasks with finite-state representations. [28] uses LfD to approach the problem of goal and action learning for new environments using a task specific model for shelf-arrangements, along with learning strategies that allow varying amounts of human specification for the task parameters.

Robot behavior can also be repaired by dynamic synthesis of new control structures and through program synthesis [29], such as automatic synthesis of new FSMs [30], synthesis of code from a context-free motion grammar with parameters derived from human-inspired control [31]. *Programming by example* synthesizes programs from a small number of examples [32] and can also support noisy data [33]. When automated synthesis is intractable, a user-generated specification in a domain-specific language can be used to synthesize a plan [34], or to specify high-level behavior using abstractions such as Instruction Graphs [35].

SRTR is not intended to synthesize new program structure, but to repair structurally sound behaviors when their parameters do not reflect the hardware or environment. The assumption is made that the FSM does not need new structure, but that failures are due to *incorrect triggering* of the transition function arising from incorrect environment-dependent parameter values. The correct values for these parameters are determined by using corrections as a partial specification of the behavior in a new environment. SRTR works by leveraging the existing structure of the behavior alongside a small

number of samples to provide the minimal parameter adjustments which satisfy user expectations. This minimal adjustment uses inferred dependencies from the code to generalize.

3. Background

We use a real-world example to motivate SRTR: a robot soccer attacker that 1) goes to the ball if the ball is stopped, 2) intercepts the ball if it is moving away from the attacker, 3) catches the ball if it is moving toward the attacker, and 4) kicks the ball at the goal once the attacker has control of the ball. Each of these sub-behaviors is a distinct, self-contained feedback controller (*e.g.*, ball interception [36], two-stage optimal control [37], or omnidirectional time optimal control [38]). At each time-step, the attacker 1) switches to a new controller if necessary and 2) invokes the current controller to produce new outputs. We represent the attacker as a *robot state machine* (RSM), where each state represents a controller (Figure 1a).

In this paper, we assume that the output of each controller is nominally correct: there may be minor *performance* degradation when environmental factors change, but we assume that they are *convergent*, and will eventually produce the correct result. Each controller has preconditions that describe properties of the robot and world state that should be true when they operate. A nominally correct controller will eventually produce the desired result if executed when its preconditions are met. These preconditions are not trivial to define, and it is the goal of the transition function to approximate them with parameters in order to transfer operation between controllers. However, environmental factors also affect the transition function. For example, the friction coefficient between the ball and the carpet affects when the attacker transitions from *Intercept* to *Kick*; and the mass of the ball affects when the attacker transitions from *Kick* to *Done*. These factors vary from one environment to another. Since transition functions do not have any self-correcting mechanisms, robots are prone to behaving incorrectly when their parameters are incorrect for the given environment.

3.1. Robot State Machines

A robot state machine (RSM) is a discrete-time Mealy machine that is extended with continuous inputs, outputs, and program variables. Formally, an RSM is a 9-tuple $\langle S, S_0, S_F, V, V_0, Y, U, T, G \rangle$, where S is the finite set of states, $S_0 \in S$ is the start state, $S_F \in S$ is the end state, $V \in \mathbb{R}^m$ is the set of program variable values, $V_0 \in \mathbb{R}^m$ are the initial values of the program variables, $Y \in \mathbb{R}^n$ are the continuous inputs, $U \in \mathbb{R}^l$ are the continuous actuation outputs, $T : S \times Y \times V \rightarrow S$ is the transition function, and $G : S \times Y \times V \rightarrow U \times V$ is the emission function. At each time step t , the RSM first uses the transition function to select a state and then the emission function to run the controller associated with that state. The transition function can only update the current state, whereas the emission function can update program variables and produce outputs.

3.2. Transition Errors

In general, transition errors occurs when the values of the parameter in the transition function do not reflect the environment or properties of the hardware. A transition error occurs when at a timestep t the output of the transition function is either: a state representing a controller whose preconditions are not met and so the controller fails, or a state other than some behavior critical state with preconditions that are met. Automatically identifying when either type of error has occurred is a non-trivial problem which does not generalize between RSMs, and so SRTR uses human input to identify incorrect triggering of the transition function.

Figure 1b shows two traces of the attacker described above. In the blue trace, the attacker correctly intercepts the moving ball and kicks it at the goal. But, in the red trace, the attacker fails to kick: it remains stuck in the *Intercept* state and never transitions to *Kick*. Over the course of several trials (e.g., a robot soccer game), we may find that the attacker only occasionally fails to kick. When this occurs, it is usually the case that the high-level structure of the transition function is correct, but that the values of the parameters need to be adjusted. Unfortunately, since there are 11 real-valued parameters in the full attacker RSM, the search space is large.

To efficiently search for new parameter values, we need to reason about the structure of the transition function. To do so, the next section describes how we systematically convert it to a formula in propositional logic, extended with arithmetic operators. This formula encodes the structure of the transition function along with constraints from the user corrections, and allows an SMT solver to efficiently find new parameters to correct the errant transition(s).

4. Interactive Robot Transition Repair

The SRTR algorithm has four inputs: 1) the transition function, 2) a map from parameters to their values, 3) an execution trace, and 4) a set of user-provided corrections. The result of SRTR is a set of corrected parameter maps that each attempt maximize the number of corrections satisfied and minimizes the changes to the input parameter map. (The trade-off between these objective is a hyperparameter.)

SRTR has three major steps. 1) A user observes transition errors, identifies their locations in the execution trace recorded during operation, and makes a correction that specifies the desired alternate transition(s) throughout the trace (Section 4.2). 2) For each user-provided correction, SRTR *partially evaluates* the transition function for the inputs and variable values at the time of correction, yielding *residual transition functions* (Section 4.3). 3) Finally, it uses the residual transition functions to formulate an optimization problem for an off-the-shelf solver that can support first order logic, for the majority of this evaluation we use z3, an optimizing MaxSMT, but we also evaluate the performance of dReal, an automated reasoning tool for solving first-order logic problems that specializes in nonlinear real functions in Section 4.6. The solution to this problem is a set of possible adjustments to the parameter values (Section 4.4).

To illustrate the SRTR algorithm, we present as a running example a simplified attacker RSM that is only capable of handling a stationary ball on the field (Figure 3). Therefore, the RSM has four states (Start, GoTo, Kick, and End) and its transition function (Figure 5a) has four parameters (aimMargin_p , maxDist_p , viewAng_p , and

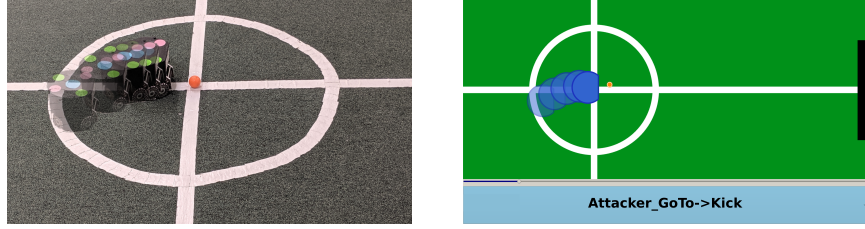


Figure 2: Example playback of attacker trace where the robot moves into a kicking position and fails to transition from GoTo to Kick. The dropdown menu shows the user supplied correction. The black bar represents the goal.

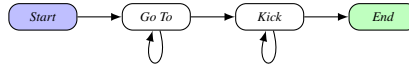


Figure 3: Simplified attacker RSM.

kickTimeout_p). We run the RSM with initial parameter values and observe the behavior shown in Figure 2 which shows an example execution and playback trace where the attacker fails to transition. In the execution trace from the RSM (Figure 5b) a user identifies that at time-step $t = 5$ the transition function produces an incorrect result (GoTo), and provides the desired output (Kick) as a correction in Figure 2.

The goal of SRTR is to find an adjustment to the parameters such that the transition function produces the corrected next state instead of the recorded state at time $t + 1$. With this example in mind, we present how SRTR uses the transition function code, an execution trace, and a correction to identify that an adjustment to just one of the parameters, maxDist_p, is sufficient to satisfy this correction (Figure 5c).

4.1. Transition Functions and SRTR Inputs

To abstract away language-specific details of our repair procedure, we present SRTR for an idealized imperative language that only has features essential for writing transition functions. Figure 6 lists the syntax for a transition function written in SRTR-repairable form using a notation that is close to standard BNF. In general, the transition function consists of sequences of statements comprised of expressions over 1) the current state s , 2) program inputs x_y , 3) parameters x_p , and 4) program variables x_v . Based on computations over these identifiers, the transition function returns the next state. Figure 6 has a list of operators that often appear in transition functions, such as arithmetic and trigonometric functions, but the list is *not* exhaustive. As a concrete example of a transition function written in repairable form, Figure 5a shows the transition function for the running example: it branches on the current state (s) and returns the next state. The crux of the transition function are the conditions that determine when the transition from GoTo to Kick occur.

A parameter map (P) specifies the parameters of a transition function. Figure 5b shows the parameter map of our example before running SRTR. The output of SRTR will be a set of adjustments to this parameter map.

An execution trace is a sequence of *trace elements* τ_t . A trace element records the values of sensor inputs, program variables, and the state at the start of time-step t .

Finally, a user-provided *correction* (c_t) specifies the expected state at the end of time-step t , and optionally a set of parameters U to consider for repair, if no U is provided, all parameters will be considered for repair. In our example, the attacker should have transitioned to the Kick state at $t = 5$. Figure 5b shows the trace element and a user correction for the running example: since the correction c_5 refers only to the time-step $t = 5$, only the relevant trace element τ_5 is shown.

4.2. Providing Corrections

Repairs with SRTR require human input for identifying what went wrong during RSM execution. In order to facilitate the best repairs, SRTR supports two interaction models for identifying corrections. Each correction technique is useful for identifying corrections with respect to different error types. We call these correction techniques *immediate corrections* and *continue corrections*.

Immediate corrections are made using the exact states in the execution trace, the user identifies a timestep t in the trace when an error occurred, the desired output state s_d , and optionally a set of parameters to repair U . These corrections allow the user to consider all of the world states that are explored in an execution trace, and to specify behavior modification based on exact world and program states that resulted in errors. Allowing the user to specify U gives some flexibility to the specificity of a repair. When specific parameters are known to be wrong identifying them apriori can simplify the repair process and yield more controlled results, when the incorrect parameters are unknown SRTR will identify the appropriate parameters to repair based on the desired transitions. Immediate corrections are effective in general when the user can isolate states where a desired transition *should* occur, and many immediate corrections can be combined for more complex repairs.

However, it is sometimes the case that a user identifies a state with a premature transition into a state s_e , and the desired behavior is to remain in the prior state s_p . In many such cases a *should* transition correction with respect to state s^p is equivalent to a *should not* transition correction with respect to s^e . A single correction of this form results in repairs that either do not fully specify the transition function output, or that yield minimal changes. Since individual controllers converge on a desired world state, the most common result of using immediate corrections in these scenarios is to modify the behavior for a single timestep before allowing the undesirable transition again. This repair output is desirable if the erroneous transition was only a single timestep early, but in many cases the desired behavior is actually for the RSM to *continue* without transitioning to s^e for a number of timesteps.

To illustrate this, consider a case of the attacker transitioning to kick prematurely as in Figure 4a. In this example the attacker transitions well before the desired preconditions for kick are met, there is no point in the trace where the correct world state for the transition is observed. However, giving a correction of the form *do not transition to kick* at the timestep where this transition occurs will yield the behavior shown in Figure 4b. The difference in the two world states can be hard to see, because the end result is that the attacker *continues* the GoTo state for one timestep longer than it did prior to the repair. Using immediate corrections we would need to repair and test continuously in order to reach the desired preconditions for kick.

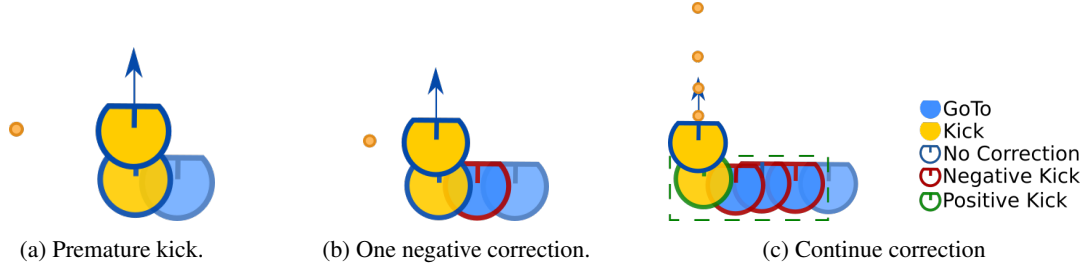


Figure 4: Example traces of attacker execution illustrating continue corrections. Ball is in orange, robot states are represented by the fill, and the outline labels when a correction was applied. The green box shows the set of corrections that result from a continue correction.

A user signals a continue correction by identifying a trace element τ_t , the state s^c that was incorrectly output at τ_t , and optionally a set of parameters to repair U . This signals the user's desire to continue execution from the state described in τ_t while *not* transitioning to s^c . However, the trace will not contain future timesteps where the observed transition did not occur, and so new trace elements need to be generated. To do this SRTR forks the world state by using τ_t to calculate an initial world state and RSM configuration for forward simulation. The RSM configuration prevents the transition function from transitioning to s^c and during simulation a negative correction is generated for each timestep until the user identifies a timestep n where the behavior should transition to s^c . The end result is a set of negative constraints $D = \{c_t, \dots, c_{t+n}\}$, a single positive constraint $c_{t+n} ::= s_{t+n+1}^c$, and corresponding U for all constraints. Specifying U can be particularly useful for continue corrections because the negative constraints only need to invalidate one subclause of a transition clause to prevent a transition, as opposed to positive constraints that must satisfy the entire clause. In this case the specification of U can guide the solver towards specific subclauses, which may improve generalization in some cases.

Figure 4c visualizes an example execution trace after forking the world state in a continue correction for the attacker RSM. Robot outlines in red represent locations where a negative constraint was created, while the green outline shows the single positive kick constraint. The green box shows all of the corrections generated in the forked world state of the continue correction. In this example four corrections were generated with a continue correction that otherwise would have required iterative repair after each correction to yield the same result with immediate corrections.

Using immediate and continue corrections together allows a user to specify immediate transition points present in an execution trace, as well as to create corrections that delay premature transitions until a desired state is reached. A user may supply corrections using either or both techniques, and then repair with SRTR. Additionally, if the behavior is functioning correctly in some scenarios and not in others, then the user can use execution traces of desirable behavior to provide a set of n corrections $N = \{c_i, \dots, c_n\}$ that are representative of nominal transition behavior. In this case the supplied c_i do not specify alternative transitions, but instead reinforce existing transition behavior. Providing N alongside a number of corrections to erroneous transitions adds constraints that directs the solver to find repairs that fix the error cases if possible, but that equally attempts to maintain the nominal transitions behavior described by N .

Transition function (T)

```

1  if (s == "START") {
2    return "GOTO";
3  } else if (s == "GOTO") {
4    relLoc := ballLocy - robotLocy;
5    aimErr := AngleMod(targetAngy - robotAngy);
6    robotYAxis := (sin(robotAngy), -cos(robotAngy));
7    relLocY := robotYAxis · relLoc;
8    maxYLoc := maxDistp · sin(viewAngp);
9    if (aimErr < aimMargin ∧ ||relLoc|| < maxDistp ∧
10       ||relLocY|| < maxYLoc ∧
11       timey > lastKickv + kickTimeoutp) {
12       return "KICK";
13     } else return "GOTO";
14   } else if (s == "KICK" ∧
15             timeInKickv > kickTimeoutp) {
16     return "END";
17   } else return "KICK";

```

(a) A simple RSM and its transition function.

Parameter map (P)

$P = \langle \text{aimMargin}_p \mapsto \pi/50, \text{maxDist}_p \mapsto 80, \text{viewAng}_p \mapsto \pi/6, \text{kickTimeout}_p \mapsto 2 \rangle$

Trace element (τ_5)

$\tau_5.\text{in} = \langle \text{ballLoc}_y \mapsto \langle 30, 40 \rangle, \text{robotLoc}_y \mapsto \langle 0, 0 \rangle, \text{robotAng}_y \mapsto 0, \text{targetAng}_y \mapsto \pi/60, \text{time}_y \mapsto 5 \rangle$
 $\tau_5.\text{vars} = \langle \text{lastKick}_v \mapsto 2, \text{timeInKick}_v \mapsto 0 \rangle$

Trace (\mathcal{R})

$\mathcal{R} = \langle \dots \tau_5 \dots \rangle$

Correction (c_5)

$c_5 ::= s_6 \mapsto \text{"KICK"}$

(b) Inputs to SRTR.

Repairable and unrepairable parameters

$\text{Rep}(T) = \{\text{aimMargin}_p, \text{maxDist}_p, \text{kickTimeout}_p\}$
 $\text{Unrep}(T) = \{\text{viewAng}_p\}$

Result of $\text{MakeResidual}(T, \tau_5, P)$

```

1  if ( $\pi/60 < \text{aimMargin}_p \wedge 50 < \text{maxDist}_p \wedge$ 
2      $40 < \text{maxDist}_p \cdot 0.5 \wedge 5 > 2 + \text{kickTimeout}_p$ ) {
3    return "KICK";
4  } else return "GOTO";

```

Result of $\text{CorrectOne}(T, \tau_5, P, c_5)$:

$\phi = \exists \delta^1, \delta^2, \delta^3 : \pi/60 < \pi/50 + \delta^1 \wedge 50 < 80 + \delta^2 \wedge$
 $40 < (80 + \delta^2) \cdot 0.5 \wedge 5 > 2 + (2 + \delta^3)$

Result of $\text{CorrectAll}(T, P, \mathcal{R}, \{c_5\})$:

$\Phi = \exists \delta^1, \delta^2, \delta^3, w^1 : w^1 = H \vee (w^1 = 0 \wedge \phi)$

Result of $\text{SRTR}(T, P, 1, \mathcal{R}, \{c_5\})$ for $H = 1$:

$\arg \min_{w^1, \delta^1 \dots \delta^3} w^1 + \|\delta^1\| + \|\delta^2\| + \|\delta^3\|$ constrained by Φ
 $= \langle w^1 = 0, \delta^1 \mapsto 0, \delta^2 \mapsto 0.5, \delta^3 \mapsto 0 \rangle$

(c) Each step of the SRTR algorithm.

Figure 5: SRTR applied to a simplified robot soccer attacker with a single correction.

The end result of either correction technique is a set of corrections $C = \{c_t, \dots, c_{t+n}\}$ that specifies the desired alternative behavior that should result from the final SRTR repair. In the case of our simple running example we have a single immediate correction c_5 , as shown in Figure 5b.

4.3. Residual Transition Functions

For each correction (c_t) SRTR needs to translate the transition function and c_t into a formula for an SMT solver. To do this SRTR first simplifies the problem by specializing the transition function using the state, variables, and inputs recorded at time t . We call this simplified transition function the *residual transition function*. A residual transition function consists only of real numbers and expressions containing parameters, or only those containing the parameters in U if one U is specified, and considers only the branch of the transition function corresponding to c_t . This is achieved by substituting the input and variable identifiers with concrete values from the trace element and simplifying expressions as much as possible using an approach known as *partial evaluation* [39]. Figure 5c shows the output of MakeResidual for our example correction at $t = 5$. Since the state at this time-step ($\tau_5.\text{state}$) is GoTo, the residual transition function only has the code from the branch that handles this case (*i.e.*, the code from lines 3–13) and contains only the information SRTR will need to translate the residual transition function into a formula for an SMT solver.

A potential problem with this approach is that many solvers do not have decision procedures that support nonlinear arithmetic such as trigonometric functions, which occur frequently in RSMs. Our example also uses trigonometric functions in several expressions. Fortunately, most of these trigonometric functions are applied to inputs and variables, thus they are substituted with concrete values in the residual. For example, line 6 calculates $\sin(\text{robotAng}_y)$ and $\cos(\text{robotAng}_y)$, but robotAng_y is an input. Thus, the residual substitutes the identifier with its value from the trace element ($\tau_5.\text{robotAng}_y = 0$) and simplifies the trigonometric expressions. In contrast, line 8

Unary Operators	Binary Operators
$op_1 ::= - \mid \sin \mid \cos \mid \dots$	$op_2 ::= + \mid - \mid * \mid > \mid \dots$
Expressions	Statements
$e ::= k$ Constants $\mid s$ State $\mid x_v$ Variables $\mid x_y$ Inputs $\mid x_p$ Parameters $\mid op_1(e)$ $\mid e_1 \ op_2 \ e_2$	$m ::= \text{return } s;$ Return the next state s $\mid x_v := e;$ Update x_v to e $\mid \text{if } (e) \ m_1 \ \text{else } m_2$ Conditional $\mid \{ m_1 \dots m_n \}$ Statement block
Transition Functions	Parameter Maps
$T ::= \{ m_1; \dots; m_n \}$	$P ::= \langle x_p^1 \mapsto k^1 \dots x_p^n \mapsto k^n \rangle$
	Designated Parameters
	$U ::= \{ x_p^i \in P \}$ Subset of P to repair.
	Traces
	$\mathcal{R} ::= [\tau_1 \dots \tau_n]$
	Corrections
	$c_t ::= s \in S, U ::= \{ x_p^1 \dots x_p^k \}$
Trace Elements	
$\tau_t ::= \{ \text{in} = \langle \bigvee_{i=1}^m x_y^i \mapsto k^i \rangle, \text{vars} = \langle \bigvee_{j=1}^n x_v^j \mapsto k'^j \rangle, \text{state} = s_t \mapsto k'' \}$	

Figure 6: Syntax of transition functions, traces, and corrections.

applies a trigonometric function to a parameter ($\sin(\text{viewAng}_p)$). This makes viewAng_p an *unrepairable parameter* for many solvers that cannot appear in the residual transition function. SRTR substitutes unrepairable parameters with their concrete values from the parameter map when the backend solver does not support them.

In general, the `MakeResidual` function of SRTR (lines 11–15 in Figure 7) takes a transition function (T), a trace element (τ_t), a parameter map (P), and a set of possible parameters to repair (U) and produces a residual transition function by partially evaluating the transition function with respect to the trace element and the unrepairable parameters. We use a simple dataflow analysis to calculate the unrepairable parameters ($\text{Unrep}(T)$) and a canonical partial evaluator (`Peval`) [39].

4.4. Transition Repair as a MaxSMT Problem

Given the procedure for calculating residual transition functions, SRTR proceeds in three steps. 1) It translates each correction c_i into an independent formula ϕ_i . A solution to ϕ_i corresponds to parameter adjustments that satisfy the correction c_i . Note however that no solution exists if c_i cannot be satisfied. 2) It combines the formulas $\phi_{1\dots n}$ for all corrections $c_{1\dots n}$ from the previous step into a single formula Φ with independent penalties w^i for each sub-formula ϕ_i . A solution to Φ corresponds to parameter adjustments that satisfy a subset of the corrections. Any unsatisfiable corrections incur a penalty. 3) Finally, it formulates a MaxSMT problem that minimizes the magnitude of adjustments ($\|\delta^j\|$) to the parameters, and the penalty (w^i) of violated sub-formulas.

The `CorrectOne` function transforms a single correction into a formula. This function 1) calculates the residual transition function (Figure 7, line 18), 2) gets the repairable parameters (line 19) and, and 3) produces a formula (line 20) with a variable for each repairable parameter in U for the current correction. In our running example, the transition function has four parameters and no U is specified, but, as explained in the previous section, the residual has only three parameters since viewAng_p is unrepairable. Therefore, the formula that corresponds to this residual (Figure 5c) has three variables

```

1 // Takes a transition function  $T$ , and returns a partially evaluated residual transition
2 // function  $T'$  by eliminating identifiers  $x^i$  using their values  $k^i$ .
3 def Peval( $T, x^1 \mapsto k^1 \dots x^n \mapsto k^n$ );
4
5 // Returns the list of repairable parameters of the transition function  $T$ 
6 def Rep( $T$ );
7
8 // Returns the list of unrepairable parameters of the transition function  $T$ 
9 def Unrep( $T$ );
10
11 def Residual( $T, \tau_t, P, U$ ):
12   {in =  $\langle \bigvee_{i=1}^l x_y^i \mapsto k^i \rangle$ , vars =  $\langle \bigvee_{j=1}^m x_v^j \mapsto k'^j \rangle$ , state =  $s_t \mapsto k''_s$ } :=  $\tau_t$ 
13   { $x_p^1, \dots, x_p^n$ } = Unrep( $T, U$ )
14    $T' := \text{Peval}(T, \bigvee_{i=1}^l x_y^i \mapsto k^i, \bigvee_{j=1}^m x_v^j \mapsto k'^j, \bigvee_{k=1}^n x_p^k \mapsto P(x_p^k), s_t \mapsto k''_s)$ 
15   return  $T'$ 
16
17 def CorrectOne( $T, \tau_t, P, U, c_t$ ):
18    $T' := \text{Residual}(T, \tau_t, P, U)$ 
19   { $x_p^1, \dots, x_p^m$ } := Rep( $T$ )
20   return  $\exists \delta^1, \dots, \delta^m : c_t = T'(s_1, x_p^1 + \delta^1, \dots, x_p^m + \delta^m)$ 
21
22 def CorrectAll( $T, P, U, \mathcal{R}, \{c_t^1, \dots, c_t^n\}$ ):
23   { $x_p^1, \dots, x_p^m$ } = Rep( $T$ )
24    $\Phi = \text{true}$ 
25   for  $i \in [1 \dots n]$ :
26      $\exists \delta^1, \dots, \delta^m : \phi_i = \text{CorrectOne}(T, \mathcal{R}[t], P, U, c_t^i)$ 
27      $\Phi = \Phi \wedge (w^i = H \vee (w^i = 0 \wedge \phi_i))$ 
28   return  $\exists \delta^1, \dots, \delta^m, w^1, \dots, w^n : \Phi$ 
29
30 def SRTR( $T, P, U, k, \mathcal{R}, \{c_t^1, \dots, c_t^n\}$ ):
31    $\Phi = \text{CorrectAll}(T, P, U, \mathcal{R}, \{c_t^1, \dots, c_t^n\})$ 
32    $S = \{\}$ 
33   for  $i \in [1 \dots k]$ :
34     assert( $\Phi$ )
35     minimize( $\sum_{i=1}^l w^i + \sum_{j=1}^m \|\delta^j\| : \Phi$ )
36      $r = \langle w_i \in \{0, H\}, \delta^j \mapsto a^j \rangle$ 
37      $S = S \cup r$ 
38      $\Phi = \Phi \wedge (\exists w^i : w^i = 0 \wedge w^i \in r \neq 0)$ 
39      $\Phi = \Phi \wedge (\exists w^i : w^i = H \wedge w^i \in r \neq H)$ 
40   return  $S$ 

```

Figure 7: The core SRTR algorithm.

(δ^1 , δ^2 , and δ^3). Moreover, since the correction (c_5) requires the next-state to be Kick, which only occurs when the residual takes the true-branch (line 3 of the residual), the body of the formula is equivalent to the conditional expression (lines 1–2), but with each parameter replaced by the sum of its concrete value (from P) and its adjustment (a δ). For example, the formula replaces aimMargin_p by $\pi/50 + \delta^1$. Therefore, when $\delta^1 = 0$, the parameter is unchanged.

The CorrectAll function supports multiple corrections and uses CorrectOne as a sub-routine. The function iteratively builds a conjunctive formula Φ , where each clause has a distinct penalty w^i and two mutually exclusive cases: either $w^i = 0$ thus the clause has no penalty and the adjustments to the parameters satisfy the i th correction (line 27); or a penalty is incurred ($w^i = H$) and the i th correction is violated. Thus $H \in \mathbb{R}^+$ is a hyperparameter that induces a trade-off between satisfying more corrections vs. minimizing the magnitude of the adjustments: large values of H satisfy more corrections with larger adjustments, whereas small values of H satisfy fewer corrections with smaller adjustments. The final formula has m real-valued variables δ^i for adjustments to the corresponding m repairable parameters x_p^i , and n discrete variables w^j that represent the penalty of violating formula ϕ_j corresponding to correction c_t^j .

Our example (Figure 5c) has one correction and three repairable parameters. Therefore, CorrectAll produces a formula with four variables: a single penalty (w^1) and the three adjustments discussed above (δ^1 , δ^2 , and δ^3). The formula is a single exclusive-or: either the penalty is zero and formula is equivalent to the result of CorrectOne or the penalty is one and the result of CorrectOne is ignored.

4.5. MaxSMT Solutions

In order to solve for adjustments to parameters the function SRTR uses CorrectAll as a subroutine and invokes the MaxSMT solver. This function 1) stores the formula returned by CorrectAll as Φ , 2) initializes an empty solution set S , 3) and iteratively solves and updates a version of the MaxSMT problem k times as specified by the user. To solve the MaxSMT problem at each iteration the current problem Φ is asserted, and then SRTR directs the solver to minimize the sum of the penalties and the sum of the magnitude of parameter changes (line 35 in Figure 7). The resulting weights w^i and real-valued adjustments a^j to the δ^j are stored as r , and added to the solution set S .

At this point in SRTR we have a single solution $r \in S$ that represents a possible adjustment to the parameters that satisfies some subset of the user corrections. Applying this to our running example we can see that the minimum-cost solution in the first iteration has $\delta^2 = 0.5$ with other variables set to zero. *i.e.*, we can satisfy the correction by adjusting maxDist_p from 80 to 80.5. In many cases this initial solution will be the best solution to the problem, and in cases such as our example, the only solution.

However, when there are multiple corrections and it is not possible or desirable to satisfy all user corrections there may be many partially satisfying solutions. The goal of SRTR is to capture user intent accurately by identifying the best repair out of the possible solutions, and this is done in part by iteratively solving updated version of the MaxSMT problem in SRTR. The single iteration MaxSMT approach, also the first solution in S , assumes that the best solution is the one which satisfies the largest number of corrections while minimizing the parameter adjustments. Adjusting the value of the hyperparameter H adjusts the weighting between minimizing adjustments and maximizing satisfied corrections, and uses the same weight for all corrections. This method is sensible when there is not a priority ranking between corrections, or when all corrections aim to achieve similar repairs to the behavior.

Alternatively, in the case where there is clear user preference between supplied corrections, a separate weighting system can be used that gives corrections individual weights according to their priority, such that more important corrections are more likely to be satisfied. However, it is infrequently known apriori what the relative weights between all constraints should be, and so it is difficult for a user to accurately weight corrections as they are made.

An alternative to these apriori weights is to instead utilize the solver to explore other possible models iteratively, through a process called *model enumeration*. Model enumeration for SMT works by adding a constraint to the problem after each iteration of solutions that excludes the previous model from the possible valid solutions. For our problem we consider a constraint system with n corrections as discussed in Section 4.4:

$$\Phi = \exists\{\delta^1 \dots \delta^m\}, \{w^1 \dots w^n\} : w^i = H \vee (w^i = 0 \wedge \phi^i), \min \sum_{i=0}^n w^i + \sum_{j=0}^m \|\delta^j\| \quad (1)$$

After one iteration the solver returns a solution of the form:

$$r = \langle w^i = 0 \vee H, \delta^j \mapsto a^j \rangle \quad (2)$$

for some real number adjustments to parameters a^j . In order to enumerate a new model constraint we would search for a new solution r' under the new constraint $r' \neq r$. This type of model enumeration works well for SAT problems, and SMT problems that are not optimizing an objective function. However, for our formulation this type of model enumeration is not sufficient to generate meaningfully different models. The fact that our objective functions seeks to minimize the real valued δ^i 's gives the solver room to make minimal real valued changes that do not yield meaningfully different final models.

To force the system to find novel solutions with conflicting parameter sets SRTR implements a type of solution exploration in lines 36 – 39 in Figure 7. At each iteration a new solution r is calculated by the solver and Φ is updated with a two-part constraint that prohibits the previous solution and forces solutions with novel changes at the correction level. Given Φ and r the first constraint requires that some correction that was previously satisfied should not be satisfied in the new solution, (line 38 in Figure 7). This alone can allow an optimization that only satisfies fewer constraints, so we also add a constraint that requires some previously unsatisfied correction to be satisfied, (line 39 in Figure 7). Using these additional constraints we can search for new models iteratively by adding further restrictions after each new solution, up to some iteration limit, or until all possible models have been explored. The end result is a set of solutions S and the satisfied corrections for each repair which can be evaluated as needed by the user.

In summary, SRTR adjusts parameters to satisfy user provided corrections. It is not always possible to find an adjustment that satisfies all corrections. Moreover, there is a tradeoff between making larger adjustments and satisfying more corrections. Therefore SRTR uses a MaxSMT model to formulate parameter adjustment. This model captures the tradeoffs between satisfying correction and minimizing adjustments, and allows for the exploration of different solutions when not all corrections are satisfiable.

4.6. Alternate Solvers

We formulate the optimization problem used by SRTR as a MaxSMT problem that attempts to minimize the adjustments to parameters while maximizing the number of corrections satisfied. This formulation can then be fed to an off-the-shelf solver, and different solvers offer different potential advantages. In this article we evaluate the performance of two solvers with SRTR by comparing Z3 [40], an SMT theorem prover, and dReal [41] an automated reasoning tool for solving problems encoded as first-order logic formulas over the real numbers. We have chosen these two solvers because Z3 is a popular SMT solver, and because dReal has potential advantages for our applications in robotics.

In particular, dReal specializes in handling problems that involve nonlinear real functions, such as trigonometric functions, which could reduce the amount of partial evaluation needed, and allow SRTR to repair parameters even when they are used in nonlinear functions. To evaluate dReal with nonlinear functions we considered the single SRTR correction shown here:

$$\phi = \exists \delta^1 : 10.0 < 20 * \sin(\pi + \delta^1)$$

In this simple example we have a case of a tuneable parameters (δ^1) inside a trigonometric function, where a solution is simple, adjust δ^1 by roughly -0.5 . A MaxSMT solver such as Z3 cannot find a solution to this problem, but dReal quickly finds a minimal change of $\delta^1 = -0.524$. However, since dReal is not an SMT solver, it is not designed for MaxSMT, and so does not support soft-constraints. The MaxSMT formulation is a major component of SRTR as it enables continue corrections, solution exploration, and conflicting correction sets in a straightforward manner. In order to test dReals capability to handle these properties we modeled the MaxSMT optimization problem described in Section 4.4 using first-order logic and the single correction ϕ to generate the following problem:

$$\Phi = \exists \delta^1, w^1 : w^1 = H \vee (w^1 = 0 \wedge \phi)$$

Given this new formulation the solver now has the option to optimize between satisfying the correction, and minimizing the cost. For the same ϕ we would expect the correction to only be unsatisfied if the value of H is greater than the magnitude of the adjustment needed to repair. Since here we repair with a $H > 1.0$ the expected outcome is the same as before. Despite this, the result from dReal is neither optimal, nor satisfies the constraint, as it suggests a repair of $\delta^1 = 2886.58$.

This result suggests that even formulated in first order logic, the full MaxSMT formulation of SRTR cannot be used with dReal. However, the core of SRTR can be modeled in dReal, and so dReal is an alternative solution when nonlinear arithmetic is more prevalent than the need for solution exploration and MaxSMT. We further evaluate the performance of dReal, alongside z3 in Section 5.2.

5. Evaluation

In this section we evaluate SRTR using four RSMs and their respective success rates as follows. The *attacker* (Figure 1a) fills the main offensive role in robot soccer. Its success rate is the fraction of the test scenarios where it successfully kicks the ball into the goal. The *deflector* (Figure 8a) plays a supporting role in robot soccer, performing one-touch passing [42]. Its success rate is the fraction of the test scenarios where it successfully deflects the ball. The *docker* (Figure 8b) is a non-soccer behavior which drives a differential drive robot to line up and dock with a charging station. Its success rate is the fraction of the test scenarios where it successfully docks with the charging station. Finally, the *passing* behavior (Figure 8c) is a simple autonomous car behavior which attempts to move through slower traffic in a safe manner. The success rate for passing is the fraction of the test scenarios where it successfully passes all slower cars without coming too close to any other vehicle in the process. We use these RSMs in a number of experiments to evaluate:

1. How SRTR compares to exhaustive search;
2. The solution time and success rate of repairs with two different solver as the number of correction used varies;
3. The affect of immediate corrections on RSM success rate as compared to the effects of expert tuning;

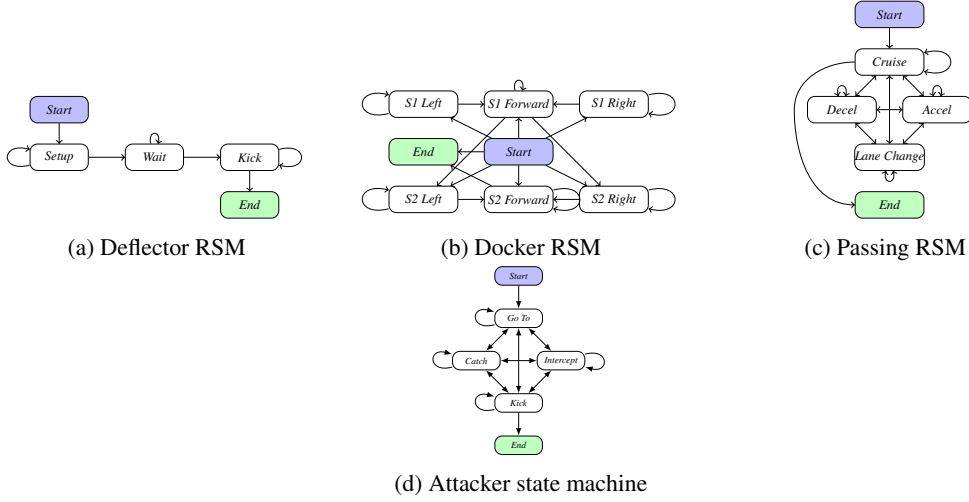


Figure 8: RSMs used for experiments.

4. Continue corrections, techniques for improving generalization, and their performance with respect to premature immediate corrections;
5. How solution exploration quantitatively and qualitatively affects the performance of the attacker RSM; and finally
6. If SRTR can be used to improve the performance of a real-world competitive soccer robot.

5.1. Comparison To Exhaustive Search

Using the attacker, we compare SRTR to an exhaustive search to show that 1) SRTR is dramatically faster and 2) the adjustments found by SRTR are as good as those found by exhaustive search. To limit the cost of exhaustive search, the experiment only repairs the six parameters that affect transitions into the Kick state; we bound the search space by the physical limits of the parameters; and we discretize the resulting hypercube in parameter space. We evaluate each parameter set using 13 simulated positions and manually specify if the position should transition to the Kick state.

We evaluate the initial parameter values, the SRTR-adjusted parameters, and the parameters found by exhaustive search on 20,000 randomly generated scenarios. Table 1 reports the success rate and running time of each approach. SRTR and exhaustive search achieve a comparable success rate. However, SRTR completes in 10 ms whereas exhaustive search takes 1,300 CPU hours (using 100 cores).

5.2. Performance

Using the attacker, we evaluate how the number of corrections affects SRTR performance in terms of time to solution and success rate while comparing two different

Method	Success Rate (%)	CPU Time
Initial Parameters	44	—
Exhaustive Search	89	1,300 hr
SRTR	89	10 ms

Table 1: Success rate and CPU time compared to exhaustive search.

backend solvers, dReal, and Z3. We evaluate the performance of the attacker in simulation by discretizing a simulated soccer field into discrete x,y positions, and starting the attacker at the center of the field. For each x,y position we set the initial velocity of the ball to a fixed speed, and vary the angle between 10 uniformly distributed angles. For evaluating performance we start with an initial parameter configuration that yields a $\sim 30\%$ success rate on these trials, and generate a set of 150 correction using failures taken randomly from this dataset. To generate these corrections we employ a nominal parameter configuration that is successful on a large set of test cases. For each test case we generate an execution trace using both the nominal parameters, and a failing parameter set. We identify a correction at the first point where the two traces diverge, such that the corrected state is the state in the nominal trace element. This trace element represents the first case where the poorly performing transition function output a different state than the nominal configuration. Since Z3 cannot repair parameters used within nonlinear functions, and dReal does not support the MaxSMT formulation used for handling conflicting corrections, only corrections with no conflict and no unsatisfiable parameters are used, such that all combinations are solvable with either solver.

We then sample a test dataset of 1000 trials from 100 positions across the field not used for corrections. Each trial applies SRTR to a subset of the corrections, solves the resulting formulation with both Z3 and dReal, and evaluates the performance on the test dataset. We repeat this procedure 30 times for each number of corrections $N \in [1, 30]$, selecting N random corrections at each iteration, for a total of 900,000 total trials.

We show the success rate for each solver in Figure 9. It is possible for a single informative correction to dramatically increase the success rate, or for a particularly under-informative correction to have little effect. Therefore we also report the mean success rate and show the 99% confidence interval in gray. Both graphs show that even a small number of corrections can be sufficient for repair, but they also show a general trend of performance improvement as more corrections are used up to ~ 25 corrections. Up to this point both solvers yield comparable final repair performance, with a peak success rate of 87%, a substantial improvement over the initial 30%, however with > 20 corrections dReal repair success rate starts to degrade slightly, to 84% at the lowest. In terms of success rate both solvers yield significant performance improvement when applicable, but when large numbers of corrections are used, Z3 is preferable.

For evaluating solver time we use the same correction and test datasets as for success rate, and evaluate using values of $N \in [1, 40]$. The solution times for each solver are show in Figure 10. Using Z3 solution time increases linearly with the number of corrections, and the variance in the time taken is relatively small as the corrections used vary, with $N = 40$ z3 solution time is less than .03 seconds. In contrast, dReal solution time is highly dependent on the correction set used, and for $N = 40$ varies between .03 seconds and > 750 seconds, with an average performance around 250 seconds. In

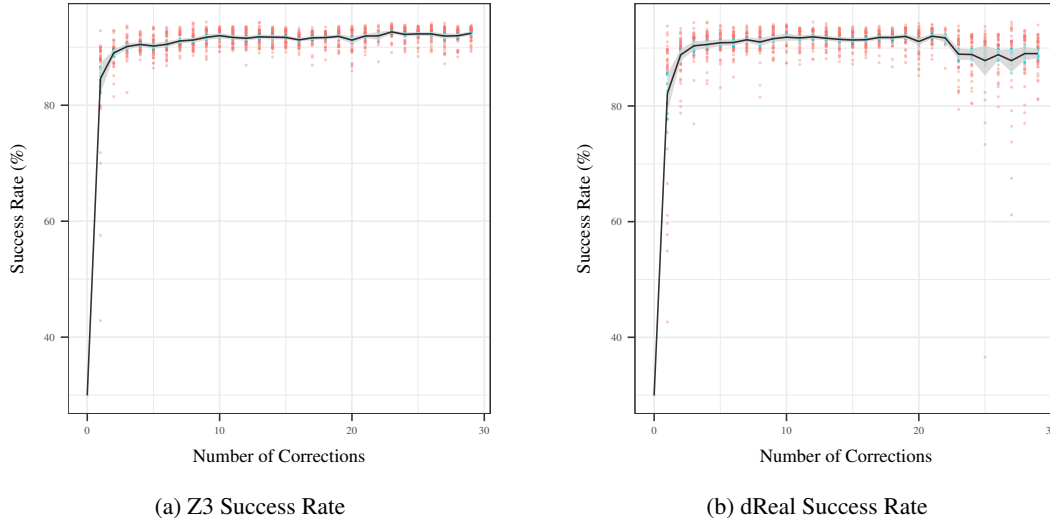


Figure 9: Success rate with different solvers and numbers of corrections. We report the mean as a line, the 99% confidence interval in grey, inliers in blue, and outliers in red. Darker points represent more occurrences.

terms of time to solution Z3 is preferable to dReal for our use case on average, with less execution time variance.

In general this experiment shows that the core of SRTR can be used with different backend solvers, each with different advantages. For the majority of this paper we evaluate with Z3 because it supports the MaxSMT formulation that SRTR makes use of, but SRTR can be translated to other solvers. As such, in the future SRTR can expect to leverage emerging technologies and advances in first-order logic solvers.

5.3. Objective Tradeoff

We evaluate the effect of the objective tradeoff parameter H using Z3. The value of this parameter determines the weight given to satisfying user corrections with respect to the magnitude of the adjustment that must be made to satisfy them. The higher the value of H the greater an adjustment to parameters can be and still be acceptable for satisfying a correction. Lower values will favor smaller adjustments to the parameter over satisfying the corrections.

In testing this tradeoff we also test two optimization models, pareto and lexicographic optimization. Pareto optimization seeks to optimize all of the objectives simultaneously, while lexicographic optimizes each objective in sequence, treating the earlier objectives as constraints on the later ones. We use pareto optimization for all cases where we desire a weighting between the two parameters, and lexicographic optimization for when we want to satisfy as many corrections as possible regardless of parameter adjustments. We do not test the case where we minimize adjustments lexicographically above maximizing corrections, as this would always result in no repair regardless of corrections used.

For this test we vary the weighting between lexicographically optimizing in favor of satisfied corrections, and pareto optimization with a value range for H of 0.1 – 10.0

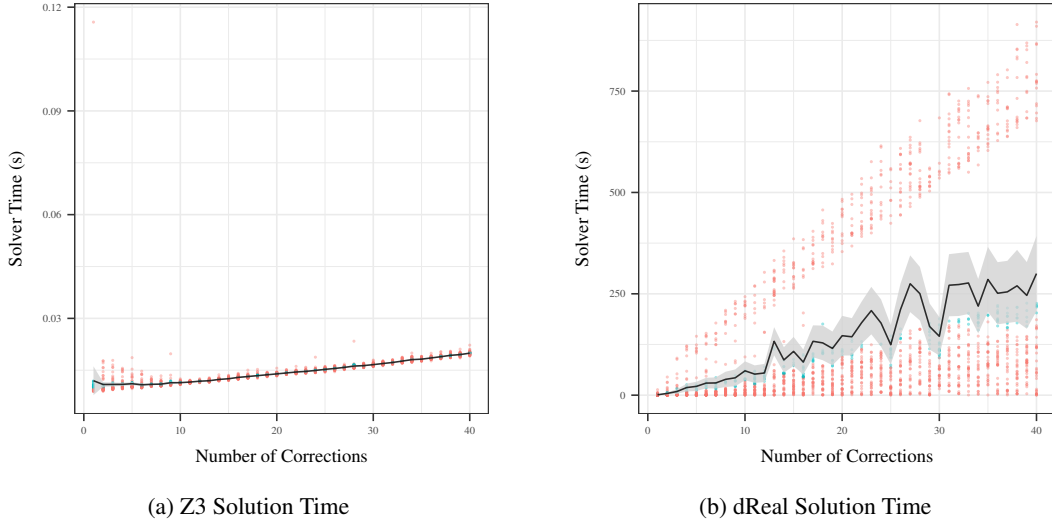


Figure 10: Solver time with different solvers and numbers of corrections. We report the mean as a line, the 99% confidence interval in grey, inliers in blue, and outliers in red. Darker points represent more occurrences.

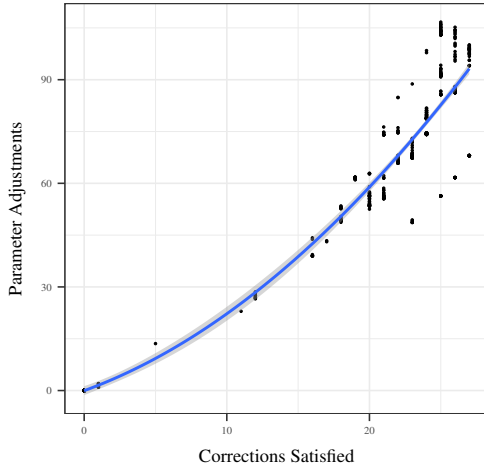
increasing by 0.1. We test by using 10 sets of 30 corrections for the attacker RSM, and we show the number of satisfied corrections and sum of the parameter percent changes in Figure 11a. This graph demonstrates that the parameter adjustment magnitudes, and the number of satisfied correction both increase as H increases.

We show in Figure 9 that success rate generally increases as the number of user corrections increases. This is by design, as in SRTR the user acts as an oracle describing the proper behavior for the RSM. In that case lexicographic optimization, or values of H favoring satisfying corrections are generally preferable for success rate. In terms of performance we graph solver time against the number of corrections using pareto optimization in Figure 11b, which show that in general lexicographic optimization is preferable to pareto optimization in terms of solution speed.

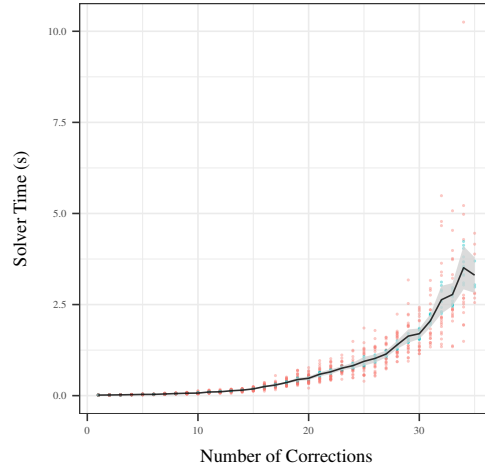
5.4. Immediate Corrections

Immediate corrections are one of two correction methods used by SRTR. These corrections are used when the desired transition preconditions are recorded in an execution trace such that an exact world state for a correction can be identified. We use four RSMs to show that when immediate corrections are used 1) SRTR-adjusted parameters generalize to new scenarios and that 2) SRTR outperforms a domain-expert who has 30 minutes to manually adjust parameters.

Table 2 summarizes the results of this experiment. We evaluate the success rate of the Attacker, Deflector, Docker, and Passing RSMs on test datasets with several thousand test scenarios each. The baseline parameters that we use for these RSMs have a low success rate. We give a domain expert complete access to the RSM code (*i.e.*, the transition and emission functions), and subsequently our simulator for 30 mins. In that time, the expert is able to dramatically increase the success rate of the Deflector, moderately increase the passing performance, but has minimal impact on the



(a) Correlation between parameter percent change, and corrections satisfied.



(b) Solver time with pareto optimization and varying numbers of corrections.

Figure 11: SRTR performance with pareto optimization and varying values of H .

RSM	Params	SRTR Corrections	Tests	Success Rates (%)		
				Baseline	Expert	SRTR
Attacker	12	2	57,600	42	44	89
Deflector	5	3	16,776	1	65	80
Docker	9	3	5,000	0	0	100
Passing	5	2	17296	50.4	71.4	86.1

Table 2: Success rates for baseline, expert, and SRTR parameters.

success rate of the Attacker and the Docker. Finally, we apply SRTR using a handful of corrections and the baseline parameters. The SRTR-adjusted parameters perform significantly better than the baseline and domain-expert parameters.

The heat maps in Figure 12 illustrates how parameters found by the domain-expert, and by SRTR generalize to novel scenarios with the Attacker. In both heat maps, the goal is the green bar and the initial position of the Attacker is at the origin. Each coordinate corresponds to an initial position of the ball and for each position we set the ball's initial velocity to 12 uniformly distributed angles. With the expert-adjusted parameters, the Attacker performs well when the ball starts in its immediate vicinity, but performs poorly otherwise. However, with SRTR-adjusted parameters, the Attacker is able to catch or intercept the ball from most positions on the field. For this result, we required only two corrections and the cross-marks in the figure show the initial position of the ball for both corrections. Therefore, although SRTR only adjusted parameters to account for these two corrections, the result generalized to many other positions on the field.

The second major correction method used by SRTR is continue corrections. To evaluate continue corrections we first demonstrate the failings of premature immediate corrections, evaluate the performance change of continue corrections alone, and finally

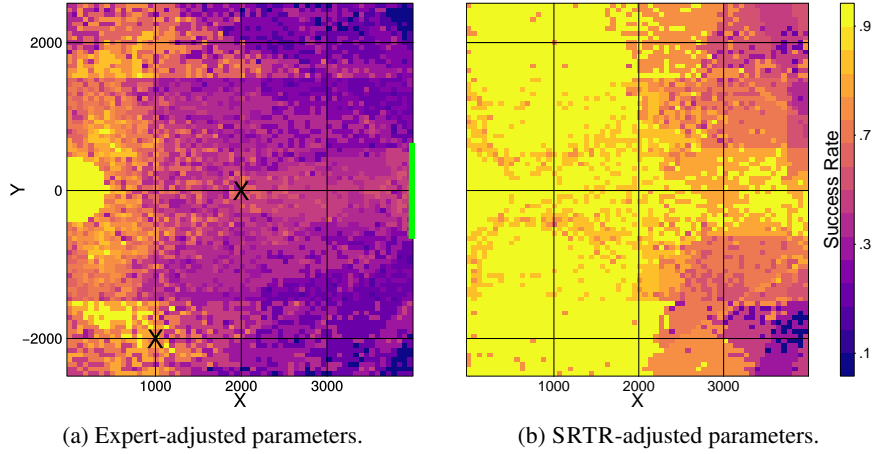


Figure 12: Attacker success rate with respect to different initial ball positions. The corrections are marked with a cross.

show that continue correction performance coupled with generalization performance yields substantially improved success rates over premature immediate corrections.

We evaluate the need for continue corrections and their performance using the attacker, the experimental procedure described in Section 5.4, an initial parameter configuration which results in premature transitions, and four sets of corrections: 1) A single negative constraint which negates the transition into kick, 2) 26 negative constraints and 1 positive constraint generated using a continue correction, 3) the continue correction constraints +20 positive constraints representing pre-repair behavior that we want to maintain, and 4) the continue correction constraints, restricted to modifying a subclause of the kick transition by user specification.

The initial parameter set yields the heatmap shown in Figure 13a, which has degraded performance from nominal in several regions of the field yielding a success rate of 78.5%. To illustrate the need for continue corrections we show the change in success rate after a single negative correction in Figure 13b. The change in success rate is minimal, comparable to the magnitude of the noise in the system, yielding a success rate of 78.6% over all trials, and further repair would require manual iteration. In comparison, Figure 14a shows the results of the single continue correction, which shows a more substantial change in performance overall, but some performance degradation resulting from poor generalization, with a final success rate of 78.3%.

5.5. Continue Corrections

We evaluated two methods for improving generalizability, user specification of clauses to adjust, and additional kick constraints. To test user specification we took the continue correction from Figure 13b and restricted the clause adjusted to line 7 of Figure 5a, which contains one of the two parameters adjusted to yield these failures. For additional kick constraints we sampled 20 successful kick transitions at random from the premature kicking scenario and used them alongside our continue correction for repairs. We show the results for constrained clause adjustment and additional kick

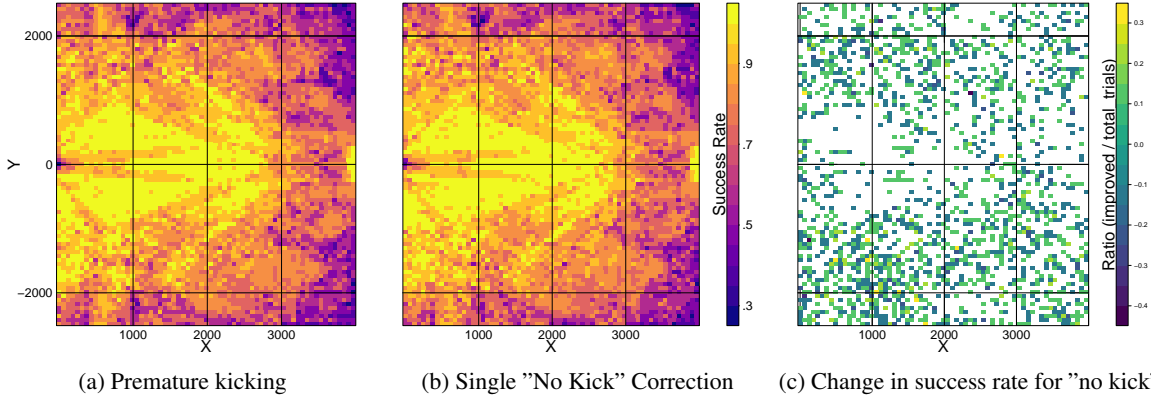


Figure 13: Success rate for the attacker with an imperfect configuration and after one negative correction, as well as change in success rate between the two. White space represents locations with no change in success rate.

constraints in Figure 14b and Figure 14c respectively. Both show much improved generalization over a single continue correction, and improved success rate overall with a success rate of 82.4% for user guided clause adjustment, and 82.6% with additional kick constraints.

The results of this evaluation show the failings of immediate corrections when desired transition states cannot be found in a trace, and the ability of continue corrections to remedy this issue. While continue corrections alone are overly restrictive of the transitions being corrected, when coupled with techniques that improve generalization continue corrections yield improved parameter performance while removing the need for arduous repeated experimentation.

5.6. Solution Exploration

SRTR utilizes a variant on model enumeration in order to present various possible solutions to a user. In order to evaluate the significance of enumerated models versus the first MaxSMT solution we use the attacker RSM and evaluate performance using varying ball positions as described in Section 5.4. We start with a parameter set that yields a roughly 30% success rate, and a set of ten corrections with several conflicts.

We show the success rate for the initial configuration in Figure 15a, and the success rate for three different enumerated models in Figure 15. The initial configuration performs very poorly in most cases, and all three enumerated models represent a significant improvement over the baseline. Figure 15b and Figure 15d lead to very similar performance, as the final solutions are not substantially different, both yielding a success rate of roughly 85%. However, the Figure 15c has different performance characteristics in different regions of the field, particularly near the sides of the goal, but a lower success rate overall of 80%. While the solution found in this third iteration is not the optimal solution in terms of cost or success rate, it represents a reasonable alternative solution when user has supplied conflicting corrections without comparative weights, which favors success near the goal over other locations.

The four heatmaps in Figure 15, and their corresponding models shown in Table 3, demonstrate the ability of SRTR to present qualitatively and quantitatively different

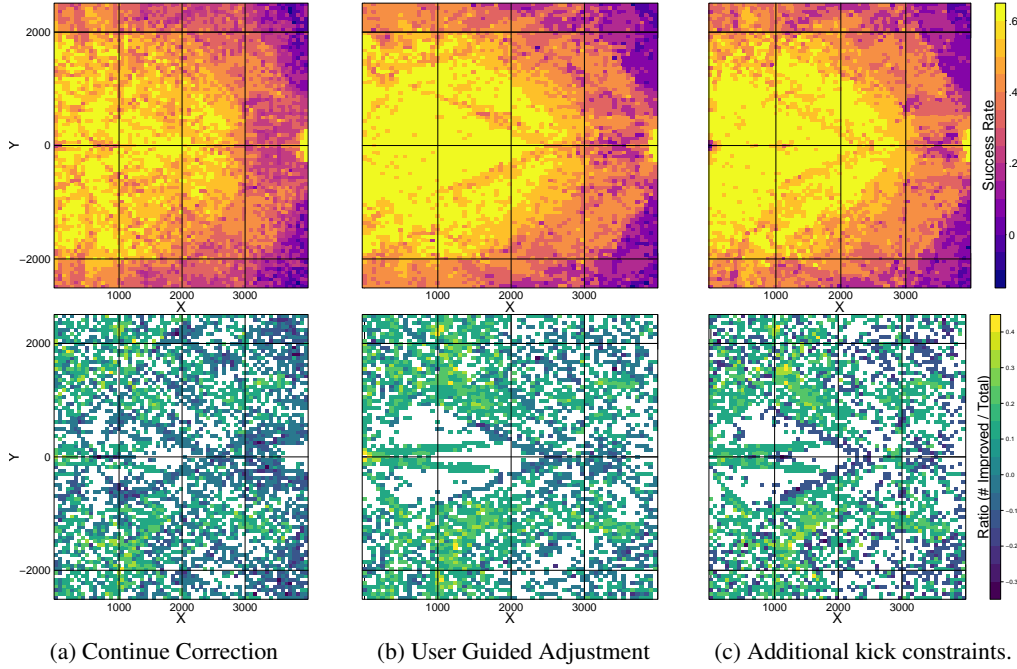


Figure 14: Success rate for the attacker after repairs. The top row shows the full success rate heatmaps, and the bottom row visualizes the change in success rate compared to the premature kick scenario.

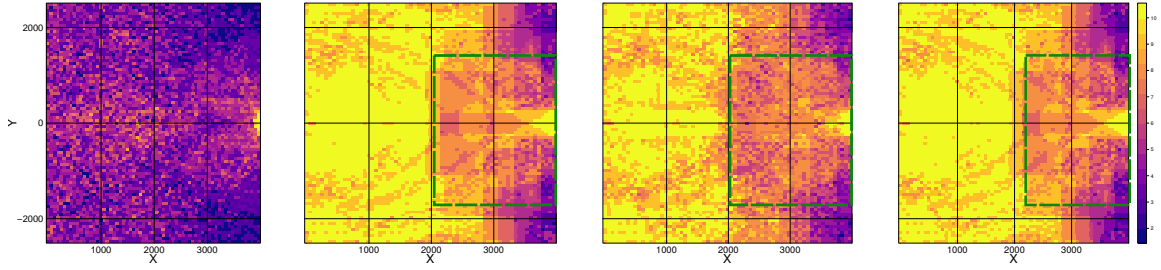
Iteration	δ^0	δ^1	δ^2	δ^3	δ^4	δ^5	δ^6	δ^7
Degraded	0	0	0	0	0	0	0	0
1	12.861	4.445	13.891	464.106	0	-500.05	40.38	0
2	5.189	-0.027	12.41	463.63	0	0	39.84	0
3	12.444	3.029	12.476	463.689	0	-500.05	39.0007	0

Table 3: δ^i values for enumerated models results shown in Figure 15.

models given a set of conflicting corrections without specific user input on the relative importance of the corrections. All of the models produced by SRTR represent a significant performance increase over the degraded parameter configuration, and the variation between them represent different interpretations of the correction intent.

5.7. Case Study: SRTR In The Real World

To evaluate SRTR in the real world, we follow the same procedure that experts use (summarized in Table 4): we develop the Attacker in a simulator, we adjust parameters until it performs well in simulation, and then we find that it performs poorly in the real world. To evaluate the success rate of the attacker in the real world, we start the ball from 18 positions on the field and repeat each position five times with the same velocity (*i.e.*, 90 trials). The parameters from simulation have a 25% success rate. Using the execution logs of this experiment, we apply SRTR with three corrections. The adjusted parameters increase the success rate to 73%. In practice, an expert would iteratively adjust parameters, so we apply SRTR again with 2 more corrections, which



(a) Degraded performance. (b) First enumerated model. (c) Second enumerated model. (d) Third enumerated model.

Figure 15: Success rate heatmaps for degraded performance and three different solutions found via solution exploration. The green box highlights the region where performance changes between solutions.

Trial	Success Rate (%)
Competition Attacker	75
Parameters from Simulation	24
Real World SRTR Tuning 1	73
Real World SRTR Tuning 2	85

Table 4: Attacker success rates on a real robot.

increases the success rate to 86%. Finally, our group has an attacker that we tested and optimized extensively for RoboCup 2017, where it was part of a team that won the lower bracket. This *Competition Attacker* has additional states to handle special cases that do not occur in our tests. On our tests, the *Competition Attacker*’s success rate is 76%. Therefore, with two iterations of SRTR, the simpler Attacker actually outperforms the *Competition Attacker* in typical, real-world scenarios.

6. Conclusion

In this article we presented a solver based repair technique for Robot State Machines. Our method, SMT-based Robot Transition Repair (SRTR) is a semi-automatic white-box approach for adjusting the transition parameters in RSMs. SRTR leverages different types interaction methods for user provided corrections to handle different failure modes, and uses solution exploration to generate repairs that best model the user intent. We demonstrate that SRTR: 1) increases success rate for multiple behaviors; 2) finds new parameters quickly using a small number of annotations; 3) produces solutions which generalize well to novel situations; and 4) improves performance in a real world robot soccer application. These results show the effectiveness logical solver based techniques are applicable to real world problems in robotics. Using transition function repair we showed that these techniques are a viable approach for applications that are both conditional dependent and require real-valued arithmetic optimization. Future work will seek to leverage solver based repair and human in the loop techniques for broader problems in robotics.=

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References

- [1] J. Holtz, J. Biswas, Automatic Extrinsic Calibration of Depth Sensors with Ambiguous Environments and Restricted Motion, in: IROS, 2017, pp. 2235–2240.
URL https://www.joydeepb.com/Publications/delta_calibration.pdf
- [2] N. Bjørner, A.-D. Phan, L. Fleckenstein, ν Z-an optimizing SMT solver, in: International Conference on Tools and Algorithms for the Construction and Analysis of Systems, 2015, pp. 194–199.
- [3] T. Xu, Y. Zhou, Systems Approaches to Tackling Configuration Errors: A Survey, ACM Comput. Surv. (2015) 70:1–70:41 doi:10.1145/2791577.
URL <http://doi.acm.org/10.1145/2791577>
- [4] A. Weiss, A. Guha, Y. Brun, Tortoise: Interactive System Configuration Repair, in: Automated Software Engineering, ASE 2017, 2017, pp. 625–636.
URL <http://dl.acm.org/citation.cfm?id=3155562.3155641>
- [5] J. Cano, A. Bordallo, V. Nagarajan, S. Ramamoorthy, S. Vijayakumar, Automatic Configuration of ROS Applications for Near-Optimal Performance, in: IROS, 2016, pp. 2217–2223.
- [6] J. Aldrich, D. Garlan, C. Kaestner, C. Le Goues, A. Mohseni-Kabir, I. Ruchkin, S. Samuel, B. Schmerl, C. S. Timperley, M. Veloso, I. Voysey, J. Biswas, A. Guha, J. Holtz, J. Camara, P. Jamshidi, Model-based adaptation for robotics software, IEEE Software 36 (2) (2019) 83–90. doi:10.1109/MS.2018.2885058.
- [7] R. Reiter, A Theory of Diagnosis from First Principles, Artificial Intelligence (1987) 57–95.
- [8] A. Miyazawa, P. Ribeiro, W. Li, A. Cavalcanti, J. Timmis, Automatic property checking of robotic applications, in: IROS, 2017, pp. 3869–3876. doi:10.1109/IROS.2017.8206238.
- [9] A. Taylor, S. Elbaum, C. Detweiler, Co-diagnosing Configuration Failures in Co-Robotic Systems, in: IROS, 2016, pp. 2934–2939. doi:10.1109/IROS.2016.7759454.
- [10] L. Keller, P. Upadhyaya, G. Candea, ConfErr: A tool for assessing resilience to human configuration errors, in: Dependable Systems and Networks With FTCS and DCC (DSN), 2008, pp. 157–166. doi:10.1109/DSN.2008.4630084.
- [11] S. Mehtaev, J. Yi, A. Roychoudhury, DirectFix: Looking for Simple Program Repairs, in: ICSE, 2015, pp. 448–458.

- [12] A. Weiss, A. Guha, Y. Brun, Tortoise: Interactive System Configuration Repair, in: ASE, 2017, pp. 625–636.
- [13] P. Stone, R. S. Sutton, G. Kuhlmann, Reinforcement learning for robocup soccer keepaway, *Adaptive Behavior* 13 (3) (2005) 165–188. *arXiv*:<https://doi.org/10.1177/105971230501300301>, doi:10.1177/105971230501300301. URL <https://doi.org/10.1177/105971230501300301>
- [14] S. Barrett, M. E. Taylor, P. Stone, Transfer learning for reinforcement learning on a physical robot, in: Ninth International Conference on Autonomous Agents and Multiagent Systems - Adaptive Learning Agents Workshop (AAMAS - ALA), 2010. URL <http://www.cs.utexas.edu/users/ai-lab/?AAMASWS10-barrett>
- [15] W. Masson, P. Ranchod, G. Konidaris, Reinforcement learning with parameterized actions, in: Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, AAAI’16, AAAI Press, 2016, pp. 1934–1940. URL <http://dl.acm.org/citation.cfm?id=3016100.3016169>
- [16] A. Bai, S. Russell, Efficient Reinforcement Learning with Hierarchies of Machines by Leveraging Internal Transitions, in: ICRA, 2017.
- [17] N. Sünderhauf, O. Brock, W. J. Scheirer, R. Hadsell, D. Fox, J. Leitner, B. Uppcroft, P. Abbeel, W. Burgard, M. Milford, P. I. Corke, The limits and potentials of deep learning for robotics, *I. J. Robotics Res.* 37 (2018) 405–420.
- [18] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, O. Klimov, Proximal policy optimization algorithms, *CoRR* abs/1707.06347. *arXiv*:1707.06347. URL <http://arxiv.org/abs/1707.06347>
- [19] S. Levine, P. Pastor, A. Krizhevsky, J. Ibarz, D. Quillen, Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection, *The International Journal of Robotics Research* 37 (4-5) (2018) 421–436. *arXiv*:<https://doi.org/10.1177/0278364917710318>, doi:10.1177/0278364917710318. URL <https://doi.org/10.1177/0278364917710318>
- [20] M. Hausknecht, P. Stone, Deep reinforcement learning in parameterized action space, in: Proceedings of the International Conference on Learning Representations (ICLR), 2016.
- [21] A. Mohseni-Kabir, M. Veloso, Robot task interruption by learning to switch among multiple models, in: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18, International Joint Conferences on Artificial Intelligence Organization, 2018, pp. 4943–4949. doi:10.24963/ijcai.2018/686. URL <https://doi.org/10.24963/ijcai.2018/686>
- [22] E. Kamar, Directions in Hybrid Intelligence: Complementing AI Systems with Human Intelligence, in: ICRA, 2016.

- [23] S. Nashed, J. Biswas, Human-in-the-Loop SLAM, in: AAAI, 2018.
- [24] B. D. Argall, S. Chernova, M. Veloso, B. Browning, A Survey of Robot Learning From Demonstration, *Robotics and Autonomous Systems* (2009) 469 – 483 doi:<https://doi.org/10.1016/j.robot.2008.10.024>.
URL <http://www.sciencedirect.com/science/article/pii/S0921889008001772>
- [25] P. Abbeel, A. Y. Ng, Inverse reinforcement learning, in: *Encyclopedia of machine learning*, Springer, 2011, pp. 554–558.
- [26] Ç. Meriçli, M. Veloso, H. L. Akın, Multi-resolution corrective demonstration for efficient task execution and refinement, *International Journal of Social Robotics* (2012) 423–435.
- [27] S. Niekum, S. Osentoski, G. Konidaris, S. Chitta, B. Marthi, A. G. Barto, Learning grounded finite-state representations from unstructured demonstrations, *The International Journal of Robotics Research* 34 (2) (2015) 131–157. arXiv:<https://doi.org/10.1177/0278364914554471>, doi:10.1177/0278364914554471.
URL <https://doi.org/10.1177/0278364914554471>
- [28] Y. S. Liang, D. Pellier, H. Fiorino, S. Pesty, M. Cakmak, Simultaneous end-user programming of goals and actions for robotic shelf organization, in: *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2018, pp. 6566–6573. doi:10.1109/IROS.2018.8593518.
- [29] S. Gulwani, A. Polozov, R. Singh, *Program Synthesis*, Vol. 4, NOW, 2017.
URL <https://www.microsoft.com/en-us/research/publication/program-synthesis/>
- [30] K. W. Wong, R. Ehlers, H. Kress-Gazit, Correct High-level Robot Behavior in Environments with Unexpected Events, in: *RSS*, 2014. doi:10.15607/RSS.2014.X.012.
- [31] N. Dantam, A. Hereid, A. Ames, M. Stilman, Correct Software Synthesis for Stable Speed-Controlled Robotic Walking, in: *RSS*, 2013. doi:10.15607/RSS.2013.IX.040.
- [32] S. Gulwani, Automating string processing in spreadsheets using input-output examples, in: *ACM SIGPLAN Notices*, ACM, 2011, pp. 317–330.
- [33] J. Devlin, J. Uesato, S. Bhupatiraju, R. Singh, A. Mohammad, P. Kohli, Robust-Fill: Neural program learning under noisy I/O, in: *ICML*, 2017.
- [34] S. Nedunuri, S. Prabhu, M. Moll, S. Chaudhuri, L. E. Kavraki, SMT-based synthesis of integrated task and motion plans from plan outlines, in: *ICRA*, 2014, pp. 655–662.

- [35] C. Mericli, S. D. Klee, J. Paparian, M. Veloso, An Interactive Approach for Situated Task Specification Through Verbal Instructions, in: AAMAS, 2014, pp. 1069–1076.
URL <http://dl.acm.org/citation.cfm?id=2617388.2617416>
- [36] Biswas, Mendoza, Zhu, Choi, Klee, Veloso, Opponent-driven planning and execution for pass, attack, and defense in a multi-robot soccer team, in: AAMAS, 2014, pp. 493–500.
- [37] D. Balaban, A. Fischer, J. Biswas, A real-time solver for time-optimal control of omnidirectional robots with bounded acceleration, 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (2018) 8027–8032.
- [38] T. Kalmár-Nagy, R. D’Andrea, P. Ganguly, Near-Optimal Dynamic Trajectory Generation and Control of an Omnidirectional Vehicle, Robotics and Autonomous Systems (2004) 47–64.
- [39] N. D. Jones, C. K. Gomad, P. Sestoft, Partial Evaluation and Automatic Program Generation, Prentice-Hall, Inc., 1993.
- [40] L. De Moura, N. Bjørner, Z3: An Efficient SMT Solver, Tools and Algorithms for the Construction and Analysis of Systems (2008) 337–340.
- [41] S. Gao, S. Kong, E. M. Clarke, dreal: An smt solver for nonlinear theories over the reals, in: Proceedings of the 24th International Conference on Automated Deduction, CADE’13, Springer-Verlag, Berlin, Heidelberg, 2013, pp. 208–214.
doi : 10.1007/978-3-642-38574-2_14.
URL http://dx.doi.org/10.1007/978-3-642-38574-2_14
- [42] J. Bruce, S. Zickler, M. Licitra, M. Veloso, CMDragons: Dynamic Passing and Strategy on a Champion Robot Soccer Team, in: ICRA, 2008, pp. 4074–4079.