Behavior Composition in the Presence of Failure

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Abstract

In this paper we articulate theoretical bases for *robust* behavior composition of multiple modules (e.g. agents, devices, etc.) by relying on the formal notion of *simulation*. Specifically, we consider the problem of synthesizing a fully controllable target behavior from a library of available partially controllable behaviors that are to execute within a shared, fully observable, but partially predictable environment. Both behaviors and environment are represented as finite state transition systems. While previous solutions to this problem assumed full reliability, here we consider *unforeseen potential failures*, such as a module, or the environment, unexpectedly changing it state, or a module becoming temporarily unavailable or dropping out permanently. Based on the notion of *simulation*, we propose an alternative synthesis approach and show how to *refine* the solution at hand, either *on-the-fly* or *parsimoniously*, so as to cope with failures. Interestingly, it turns out that the proposed simulation-based technique is computationally an improvement over previously known methods that assumed full-reliability.

Introduction

In this paper we articulate theoretical bases for robust behavior composition of multiple modules (e.g. agents, devices, etc.). Specifically, we consider the problem of synthesizing a *fully controllable* target behavior from a library of available *partially controllable* behaviors that are to execute within a shared, fully observable, but *partially predictable* environment (De Giacomo & Sardina 2007; Sardina, Patrizi, & De Giacomo 2007). A behavior stands for the logic of any artifact that is able to operate in the environment. For example, consider a painting blocks-world scenario in which blocks are painted and processed by different robotic arms; different behaviors stand for different type of arms, all acting in the same environment. The aim is to realize a desired (intelligent) virtual painting system by suitably "combining" the available arms.

Technically, we abstract the actual behaviors and environment as finite state *transition systems*. More precisely, each available module is represented as a nondeterministic (to model partial controllability) transition system; the target behavior is represented as a deterministic (to model full controllability) transition system; and the environment is represented as a finite nondeterministic (to model partial predictability) transition system, whose states are fully accessible by the other transition systems. Working with finite state transition systems allows us to leverage on research in the area of Verification (Piterman, Pnueli, & Sa'ar 2006; Tan & Cleaveland 2001; Kupferman & Vardi 1996; Alura, Henzinger, & Kupferman 2002; Clarke, Grumberg, & Peled 1999).

Solving the composition problem consists in automatically synthesizing —(Pnueli & Rosner 1989)— a *controller* that coordinates the (partially controllable) available behaviors to obtain the target behavior (De Giacomo & Sardina 2007). This synthesis problem can be recast in a variety of forms within several sub-areas of AI, including web-service composition (McIlraith & Son 2002; Berardi *et al.* 2005; Muscholl & Walukiewicz 2007), agent-oriented programming (Georgeff & Lansky 1987), robotics (Pettersson 2005), planning (Ghallab, Nau, & Traverso 2004), and plan coordination and monitoring (Katz & Rosenschein 1993; Grosz & Kraus 1996; Tripathi & Miller 2001).

In the literature, the above behavior composition setting has so far always been studied under the *full reliability* assumption for all available modules and, as a result, the (default) approach for dealing with behavior failures is to "replan" for a new solution, if any, from scratch. It is obvious that full reliability is an unrealistic assumption in many dynamic settings, where modules may become unexpectedly unavailable for various reasons. For instance, an agent (e.g., a RoboCup robot player) may, at some point, break down or opt not to participate in the composition anymore, possibly because it has agreed to join another behavior composition. It could also be the case that, while still cooperating, the agents may move too far apart losing the communication. The unavailability of a behavior may be temporary, i.e., the behavior will eventually resume operation, or permanent, i.e., the behavior will not participate any more in the overall system.

In this paper, we propose a solution for the composition problem that is able to cope with unexpected behavior failures in an incremental, and often fully reactive, way. Specifically, we propose a novel technique to synthesize the controller that is based on the formal notion of *simulation* (Milner 1971; Henzinger, Henzinger, & Kopke 1995). We argue that, when it comes to behavior failures, the composition solution obtained is *robust* in two ways. First, it can handle temporary behavior unavailability as well as unexpected behavior/environment evolution in a totally *reactive* and *on-the-fly* manner, that is, without any extra effort or "replanning" required to continue the realization of the target behavior, if at all possible. Second, the composition solution can be *parsimoniously refined* when a module becomes permanently unavailable, or unexpectedly resumes operation.

Interestingly, the results here show that the computational complexity of synthesizing such robust solutions remains the same as in the case of full-reliability. In fact, the technique we propose improves the known results by better characterizing the sources of complexity (cf. Theorem 2).

We remark that it is not the objective of this work to guarantee up-front to stand (any) potential failures. That could possibly be achieved by extending each behavior with a distinguished "failure" state and adding corresponding transitions from where failure may occur. Instead, if we think of each available module's transition system as a "contract," what we want is to address *unforeseen* breaches of such contract. The failures we investigate here can therefore be seen as the "core" ways of breaking the contract represented by the transition systems.

CHECK! The rest of the paper is organized as follows. We first describe the general setting and problem we are concerned on. After that, we explain the role of potential failures within such framework. Then, we propose a new approach to the problem at hand by appealing to the notion of simulation. In the next two sections, we show how the new approach can be used to cope with the discussed failures. We end the paper by drawing some conclusions.

The Framework

The setting we are concerned with is that in (De Giacomo & Sardina 2007), summarized below. For the sake of brevity we make some minor and non-substantial simplifications with respect to the original one. In particular, we drop "final states" in transition systems—every state may be considered "final."

Environment and behaviors We assume to have a shared fully observable environment, which provides an abstract account of actions' preconditions and effects, and a mean of communication among modules. In doing so, we take into consideration that, in general, we have *incomplete information* about the actual preconditions and effects of actions (akin to an action theory). Therefore, we allow the environment to be *nondeterministic* in general. In other words, the incomplete information on the actual world, and hence its partial predictability, shows up as nondeterminism in our setting. Formally, an *environment* is a tuple $\mathcal{E} = \langle \mathcal{A}, E, e_0, \rho \rangle$ where:

- $\mathcal{A}$ is a finite set of shared actions;
- *(ii)* E is a finite set of possible environment states;
- $e_0 \in E$ is the initial state of $\mathcal{E}$; and
- $\rho \subseteq E \times \mathcal{A} \times E$ is the transition relation among states: $\langle e, a, e' \rangle \in \rho$, or $e \xrightarrow{a} e'$ in $\mathcal{E}$, denotes that action a performed in state e may lead the environment to a successor state e'.

A behavior is essentially a program for an agent –or the logic of some available device– which provides, step by step, the agent with a set of actions that can be performed. Precisely, at each step, the agent selects one action among those provided and executes it. Then, a new set of actions is provided, the agent selects one, executes it, and so on. Obviously, behaviors are not intended to be executed on their own but, rather, to interact with the environment (cf. above). Hence, they are equipped with the ability to test conditions (i.e., guards) on the environment, when needed. Formally, a *behavior* over an environment $\mathcal{E} = \langle \mathcal{A}, E, e_0, \rho \rangle$ is a tuple $\mathcal{B} = \langle B, b_0, G, \varrho \rangle$, where:

- B is the finite set of behavior's states;
- $b_0 \in B$ is the single initial state of $\mathcal{B}$;
- G is a set of *guards*, i.e., boolean functions $g : E \rightarrow \{\texttt{true}, \texttt{false}\}$; and
- $\delta \subseteq B \times G \times \mathcal{A} \times B$ is the behavior's transition relation, where $\langle b, g, a, b' \rangle \in \varrho$, or $b \xrightarrow{g,a} b'$ in $\mathcal{B}$, denotes that action a executed in behavior state b, when the environment is in a state e such that $g(e) = \texttt{true}$, may lead the behavior to a successor state b'.

Observe that behaviors are, in general, *nondeterministic*, that is, given a state and an action, there may be several transitions whose guards evaluate to true. Consequently, when choosing the action to execute next, one cannot be certain of the resulting state, and hence of which actions will be available later on, since this depends on what particular transition happens to take place. In other words, nondeterministic behaviors are only *partially controllable*.

We say that a behavior $\mathcal{B} = \langle B, b_0, G, \varrho \rangle$ over an environment $\mathcal{E} = \langle \mathcal{A}, E, e_0, \rho \rangle$ is *deterministic* if there are no behavior state $b \in B$ and no environment state $e \in E$ for which there exist two (distinct) $b \xrightarrow{g_1,a} b'$ and $b \xrightarrow{g_2,a} b''$ in $\mathcal{B}$ such that $b' \neq b''$ and $g_1(e) = g_2(e) = \texttt{true}$. Notice that, given a state in a deterministic behavior and a legal action in that state, we always know exactly *the* next behavior's state. In other words, deterministic behaviors are indeed *fully controllable* through the selection of the next action to perform.

A *system* $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E} \rangle$ is built from an environment $\mathcal{E}$ and n predefined, possibly nondeterministic, *available behaviors* $\mathcal{B}_i$ over $\mathcal{E}$. A *target behavior* is a *deterministic* behavior over $\mathcal{E}$ that represents the fully controllable desired behavior to be obtained through the available behaviors.

Example 1. Figure 1 depicts an *extended* version of the painting arms scenario described in (De Giacomo & Sardina 2007). The overall aim of the system is to process existing blocks, which can be cleaned and painted. Before processing, a block needs to be prepared; only one block at a time can be processed. Finally, cleaning and painting require resources, namely, water and paint, respectively: we assume there are two tanks, for water and paint, and that both are recharged simultaneously by pressing a recharging button.

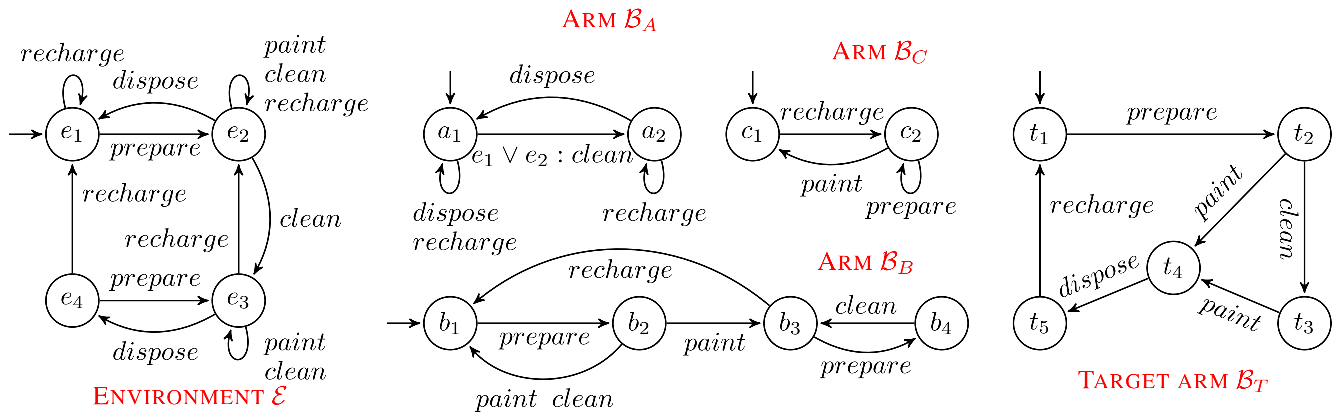


Figure 1: The painting arms system $\mathcal{S} = \langle \mathcal{B}_A, \mathcal{B}_B, \mathcal{B}_C, \mathcal{E} \rangle$ and the target arm $\mathcal{B}_T$.

The (nondeterministic) environment $\mathcal{E}$ provides the general rules of the domain. For instance, blocks can be painted or cleaned *only* after they have been prepared. It also includes some information about a water tank used to clean blocks: in states e_1 and e_2, the water tank is not empty; whereas in states e_3 and e_4, it is.

The desired behavior of an arm-agent module that one would like to have is given by the (deterministic) target behavior $\mathcal{B}_T$. Notice that it is optional to clean blocks when using $\mathcal{B}_T$—only some dirty blocks may need to be washed before being painted. Observe also that $\mathcal{B}_T$ is "conservative," in that it always recharges the tanks after processing a block.

The desires arm $\mathcal{B}_T$ *does not* exist in reality. Nonetheless, there are three different arms available. The first arm $\mathcal{B}_A$, a cleaning-disposing arm, is able to clean and dispose blocks. The second arm $\mathcal{B}_B$ is capable of preparing, cleaning, and painting blocks. Finally, the third arm $\mathcal{B}_C$ is a paint arm, which can also prepare blocks for processing. All three arms are able to press the recharge button to refill tanks. Notice that arm $\mathcal{B}_B$ behaves nondeterministically when it comes to painting a block. This nondeterminism shows the incomplete information we have of $\mathcal{B}_B$'s internal logic. Observe also the requirement of arm $\mathcal{B}_A$ to be in an (environment) state (e_1 or e_2) where water is available to perform a clean action. It is still physically conceivable, though, to clean a block in environment state e_3, by some method that does not rely on water (cf. $\mathcal{E}$). ■

System and target enacted behaviors Given a behavior $\mathcal{B} = \langle B, b_0, G, \varrho \rangle$ over an environment $\mathcal{E} = \langle \mathcal{A}, E, e_0, \rho \rangle$, we define the *enacted behavior* of $\mathcal{B}$ over $\mathcal{E}$ as a tuple $\mathcal{T}_\mathcal{B} = \langle S, \mathcal{A}, s_0, \delta \rangle$, where:

- $S = B \times E$ is the (finite) set of $\mathcal{T}_\mathcal{B}$'s states –given a state $s = \langle b, e \rangle$, we denote b by $beh(s)$ and e by $env(s)$;
- $\mathcal{A}$ is the (finite) set of shared actions, those in $\mathcal{E}$;
- $s_0 \in S$, with $beh(s_0) = b_0$ and $env(s_0) = e_0$, is the initial state of $\mathcal{T}_\mathcal{B}$;
- $\delta \subseteq S \times \mathcal{A} \times S$ is the enacted transition relation, where $\langle s, a, s' \rangle \in \delta$, or $s \xrightarrow{a} s'$ in $\mathcal{T}_\mathcal{B}$, iff: *(i)* $env(s) \xrightarrow{a} env(s')$ in $\mathcal{E}$; and *(ii)* $beh(s) \xrightarrow{g,a} beh(s')$ in $\mathcal{B}$, with $g(env(s)) = \texttt{true}$ for some $g \in G$.

Enacted behavior $\mathcal{T}_\mathcal{B}$ is technically the synchronous product of the behavior and the environment, and represents all possible executions obtained from those of behavior $\mathcal{B}$ once guards are evaluated and actions are performed in the environment $\mathcal{E}$. In general, the sources of nondeterminism in enacted behaviors are twofold: the environment (effects of actions on the environment are nondeterministic); and the behavior itself (which may be nondeterministic).

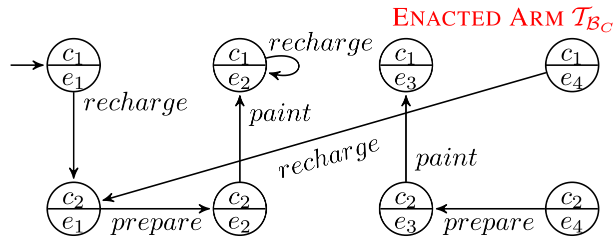
All available behaviors in a system are to act concurrently, in an interleaved fashion, in the same environment. **better**
To refer to the behavior that emerges from their joint execution, we define the notion of enacted system behavior. **cut?**

Let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E} \rangle$ be a system, where $\mathcal{E} = \langle \mathcal{A}, E, e_0, \rho \rangle$ and $\mathcal{B}_i = \langle B_i, b_{i0}, G_i, \varrho_i \rangle$, for $i \in \{1, \ldots, n\}$. The *enacted system behavior* of $\mathcal{S}$ is the tuple $\mathcal{T}_\mathcal{S} = \langle S_\mathcal{S}, \mathcal{A}, \{1, \ldots, n\}, s_{\mathcal{S}0}, \delta_\mathcal{S} \rangle$, where:

- $S_\mathcal{S} = B_1 \times \cdots \times B_n \times E$ is the finite set of $\mathcal{T}_\mathcal{S}$'s states; when $s_\mathcal{S} = \langle b_1, \ldots, b_n, e \rangle$, we denote b_i by $beh_i(s_\mathcal{S})$, for $i \in \{1, \ldots, n\}$, and e by $env(s_\mathcal{S})$;
- $s_{\mathcal{S}0} \in S_\mathcal{S}$ with $beh_i(s_{\mathcal{S}0}) = b_{i0}$, for $i \in \{1, \ldots, n\}$, and $env(s_{\mathcal{S}0}) = e_0$, is $\mathcal{T}_\mathcal{S}$'s initial state;
- $\delta_\mathcal{S} \subseteq S_\mathcal{S} \times \mathcal{A} \times \{1, \ldots, n\} \times S_\mathcal{S}$ is $\mathcal{T}_\mathcal{S}$'s transition relation, where $\langle s_\mathcal{S}, a, k, s'_\mathcal{S} \rangle \in \delta_\mathcal{S}$, or $s_\mathcal{S} \xrightarrow{a,k} s'_\mathcal{S}$ in $\mathcal{T}_\mathcal{S}$, iff:
  - $env(s_\mathcal{S}) \xrightarrow{a} env(s'_\mathcal{S})$ in $\mathcal{E}$;
  - $beh_k(s_\mathcal{S}) \xrightarrow{g,a} beh_k(s'_\mathcal{S})$ in $\mathcal{B}_k$, with $g(env(s_\mathcal{S})) = \texttt{true}$, for some $g \in G_k$; and
  - $beh_i(s_\mathcal{S}) = beh_i(s'_\mathcal{S})$, for $i \in \{1, \ldots, n\} \setminus \{k\}$.

Note that the enacted system behavior $\mathcal{T}_\mathcal{S}$ is technically the asynchronous product of the available behaviors plus the synchronous product with the environment. It is analogous to an enacted behavior except for the presence of index k in transitions. The presence of such index makes explicit which behavior in the system is the one performing the action in the corresponding transition—all other behaviors remain still.

Example 2. The enacted behavior $\mathcal{T}_{\mathcal{B}_C}$ describes the evolution of arm $\mathcal{B}_C$ if it were to act alone in the environment.



Observe that some joint states may in fact be reached (only) when other behaviors are also acting: state $\langle c_1, e_4\rangle$ would be reached after actions $prepare$, $clean$, and $dispose$ are executed. ■

Controller and composition The *controller* is a system component able to activate, stop, and resume any of the available behaviors, by instructing them to execute an action among those allowed in their current state (of course, taking also the environment into account). The controller has *full observability* on the available behaviors, that is, it can keep track (at runtime) of the current state each available behavior is in. Although other choices are possible, full observability is the natural one in this context, since available behaviors are already suitable abstractions for *actual* modules: if details have to be hidden, this can be done directly within the abstract behavior exposed, by means of nondeterminism.

do we need the 2 notions?

To formally define controllers, we first need the following technical notions. A <u>*trace*</u> for a given enacted behavior $\mathcal{T}_{\mathcal{B}} = \langle S, \mathcal{A}, s_0, \delta\rangle$ is a, possibly infinite, sequence of the form $s^0 \xrightarrow{a^1} s^1 \xrightarrow{a^2} \cdots$, such that *(i)* $s^0 = s_0$; and *(ii)* $s^j \xrightarrow{a^{j+1}} s^{j+1}$ in $\mathcal{T}_{\mathcal{B}}$, for all $j > 0$. A <u>*history*</u> is just a finite prefix $h = s^0 \xrightarrow{a^1} \cdots \xrightarrow{a^\ell} s^\ell$ of a trace. We denote s^ℓ by $last(h)$, and ℓ by $length(h)$. The notions of trace and history extend immediately to enacted system behaviors: system traces have the form $s^0 \xrightarrow{a^1,k^1} s^1 \xrightarrow{a^2,k^2} \cdots$, and system histories have the form $s^0 \xrightarrow{a^1,k^1} \cdots \xrightarrow{a^\ell,k^\ell} s^\ell$.

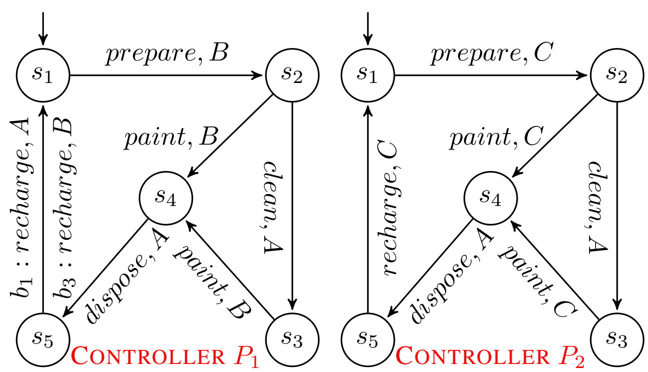
Let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E}\rangle$ be a system and $\mathcal{H}$ be the set of its system histories (i.e., histories of $\mathcal{T}_{\mathcal{S}}$). A <u>*controller*</u> for system $\mathcal{S}$ is a function $P : \mathcal{H} \times \mathcal{A} \to \{1, \ldots, n, u\}$ which, given a system history $h \in \mathcal{H}$ and an action $a \in \mathcal{A}$ to perform, selects a behavior –actually, returns its index– to delegate a to for execution. For technical convenience, a special value u ("undefined") may be returned, thus making P a total function which returns a value even for irrelevant histories or actions that no behavior can perform after a given history.

The problem we are interested in is the following: given a system $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E}\rangle$ and a deterministic *target* behavior $\mathcal{B}_t$ over $\mathcal{E}$, *synthesize a controller P which realizes the target behavior $\mathcal{B}_t$ by suitably delegating each action requested by $\mathcal{B}_t$ to one of the available behaviors $\mathcal{B}_i$ in $\mathcal{S}$.* A solution to such problem is called a <u>*composition*</u>.

Intuitively, the controller realizes a target if for every trace of the enacted target, at every step, it returns the index of an available behavior that can perform the requested action. Note that these controllers are somewhat akin to an advanced form of conditional plans and, in fact, the problem itself is related to planning (Ghallab, Nau, & Traverso 2004), being both synthesis tasks. Here, though, we are not planning for choosing the next action, but for *who shall execute the next action*, whatever such action happens to be at runtime.

One can formally define when a controller realizes the target behavior —a solution to the problem— as done in (De Giacomo & Sardina 2007). In particular, one first defines when a controller P <u>*realizes a trace*</u> of the target $\mathcal{B}_t$. Then, since the target behavior is a deterministic transition system, and thus its behavior is completely characterized by its set of traces, one defines that a *controller P* <u>*realizes the target behavior*</u> $\mathcal{B}_t$ iff it realizes all its traces.

Example 3. Let P_1 and P_2 be the two finite controllers depicted below. Their main difference has to do with the arm used to paint blocks: while P_1 uses arm $\mathcal{B}_B$, the latter uses arm $\mathcal{B}_C$. Also, P_1 recharges the tanks with either $\mathcal{B}_A$ or $\mathcal{B}_B$, depending on $\mathcal{B}_B$'s state: if arm $\mathcal{B}_B$ is in state b_1, then arm $\mathcal{B}_A$ is used to recharge; and if arm $\mathcal{B}_B$ is in state b_3, then arm $\mathcal{B}_B$ is used instead. On the other hand, controller P_2 always uses arm $\mathcal{B}_C$ to recharge the tanks.



The controller P_1 is indeed a composition of $\mathcal{B}_T$ on $\mathcal{E}$, that is, P_1 realizes all the traces of $\mathcal{T}_{\mathcal{B}_T}$. This is not the case for controller P_2, which does not even realize the simple one-action trace $\langle t_1, e_1\rangle \xrightarrow{prepare} \langle t_2, e_2\rangle$ of $\mathcal{T}_{\mathcal{B}_T}$. **CHECK! true?**

Finally, take P_1' to be like P_1 but with the link from s_5 to s_1 re-labeled "$recharge, A$" (i.e., action $recharge$ is to be *always* delegated to arm $\mathcal{B}_A$). Then, P_1' would only realize those traces where behavior $\mathcal{B}_B$ always happens to evolve to state b_1 after doing a $paint$ action. Because of that, P_1' would not count as a solution either. ■

We close this section by pointing out that techniques for checking the existence of (and indeed synthesizing) a controller are known (De Giacomo & Sardina 2007; Sardina, Patrizi, & De Giacomo 2007). Such techniques are based on a reduction to PDL satisfiability (Harel, Kozen, & Tiuryn 2000), and provide an EXPTIME upper-bound to the computational complexity, being at most exponential in the number of states of the available behaviors, of the environment, and of the target behavior. Note that this bound is actually tight since EXPTIME-hardness was shown in (Muscholl & Walukiewicz 2007).

On Behavior Failures

In discussing the above behavior composition problem, we have *implicitly* assumed that the available component modules are fully reliable—they are always available and behave "correctly" relative to the behavior/environment specification provided to the system.

Nonetheless, there are many situations and domains in which assuming full-reliability of components is not adequate. For example, in multi-agent complex and highly dynamic domains, one cannot rely on the total availability nor on the reliability of all the existing modules. There are a variety of reasons why modules may stop being available at some point or another. Devices may break down, agents may decide to stop cooperating, communication with agents may drop, exogenous events may change the state of the environment, and so on. Similarly, behaviors may possibly re-appear into the system at a later stage, thus creating new "opportunities" for the overall system.

As mentioned before, behaviors' and environment's specifications can be seen as contracts, and failures as the ones above, as breaches of such contracts. We identify five core ways of breaking contracts, namely:[1]

(a) A behavior *temporarily freezes*, that is, it stops responding and remains still, then eventually resumes in the same state it was in. As a result, while frozen, the controller cannot delegate actions to it.

(b) A behavior unexpectedly and arbitrarily (i.e., without respecting its transition relation) *changes its current state*. The controller can in principle keep delegating actions to it, but it ought to take into account the behavior's new state.

(c) The *environment* unexpectedly and arbitrarily changes its current state. The controller has to take into account that this affects both the target and the available behaviors.

(d) A behavior *dies*, that is, it becomes permanently unavailable. The controller has to completely stop delegating actions to it.

(e) A behavior that was assumed dead unexpectedly *comes alive* again in a certain state. The controller can exploit such an opportunity and start delegating actions to it again.

The composition techniques in (De Giacomo & Sardina 2007; Sardina, Patrizi, & De Giacomo 2007) do not address the above cases, since they assume that controllers always deal with fully reliable modules. As a consequence, upon any of the above failures, we are left only with the option of "re-planning" from scratch for a whole new controller.

What we shall propose in the remainder of this paper, is an alternative way of solving the composition problem (i.e., synthesizing controllers) that is *intrinsically more robust*. Roughly speaking, this alternative approach deals with unexpected failures by suitably *refining* the solution at hand, either *on-the-fly* (for cases (a), (b), and (c)), or *parsimoniously* (for cases (d) and (e)), thus avoiding full re-planning.

[1] Obviously, we assume an infrastructure that is able to distinguish between these failures.

Composition via Simulation

Let us next present our approach for synthesizing composition solutions that are suitable for dealing with faults. Such an approach is inspired by that presented in (Berardi *et al.* 2008), developed in the context of service composition and based on the standard notion of *simulation* (Milner 1971; Henzinger, Henzinger, & Kopke 1995). Intuitively, a (transition) system S_1 "simulates" another system S_2 if it (i.e., S_1) is able to *match* all of S_2's moves. Due to (devilish) nondeterminism of the environment and available behaviors, we cannot use the off-the-shelf notion of simulation, but a variant which we call ND-simulation.

Let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E} \rangle$ be a system, $\mathcal{B}_t$ be the target behavior over $\mathcal{E}$, and let $\mathcal{T}_\mathcal{S} = \langle S_\mathcal{S}, \mathcal{A}, \{1, \ldots, n\}, s_{\mathcal{S}0}, \delta_\mathcal{S} \rangle$ and $\mathcal{T}_t = \langle S_t, \mathcal{A}, s_{t0}, \delta_t \rangle$ be the enacted system and enacted target behaviors corresponding to $\mathcal{S}$ and $\mathcal{B}_t$, respectively.

An <u>*ND-simulation relation*</u> of $\mathcal{T}_t$ by $\mathcal{T}_\mathcal{S}$ is a relation $R \subseteq S_t \times S_\mathcal{S}$, such that $\langle s_t, s_\mathcal{S} \rangle \in R$ implies:

1. $env(s_t) = env(s_\mathcal{S})$;
2. for all $a \in \mathcal{A}$, there exists a $k \in \{1, \ldots, n\}$ such that for all transitions $s_t \xrightarrow{a} s'_t$ in $\mathcal{T}_t$:
   - there exists a transition $s_\mathcal{S} \xrightarrow{a,k} s'_\mathcal{S}$ in $\mathcal{T}_\mathcal{S}$ with $env(s'_\mathcal{S}) = env(s'_t)$; and
   - for all transitions $s_\mathcal{S} \xrightarrow{a,k} s'_\mathcal{S}$ in $\mathcal{T}_\mathcal{S}$ with $env(s'_\mathcal{S}) = env(s'_t)$, we have $\langle s'_t, s'_\mathcal{S} \rangle \in R$.

In words, if a pair is in the ND-simulation, then *(i)* they share the same environment; and *(ii)* for all moves of the target (with respect to the environment), there exists an available behavior k, which regardless of its nondeterminism, always evolves to a *successor state* which is still in the ND-simulation relation with the target.

We say that a state $s_t \in S_t$ *is ND-simulated by* a state $s_\mathcal{S} \in S_\mathcal{S}$ (or $s_\mathcal{S}$ *ND-simulates* s_t), denoted $s_t \preceq s_\mathcal{S}$, iff there exists an ND-simulation R of $\mathcal{T}_t$ by $\mathcal{T}_\mathcal{S}$ such that $\langle s_t, s_\mathcal{S} \rangle \in R$. Observe that this is a coinductive definition. As a result, the relation $\preceq$ is itself an ND-simulation, and it is in fact the *largest ND-simulation relation*, i.e., all ND-simulation relations are contained in $\preceq$. The largest ND-simulation can be computed by the following *NDS* algorithm.

Roughly speaking, the algorithm works by iteratively removing those tuples for which the conditions of the ND-simulation definition do not apply.

Example 4. Figure 2 shows a fragment of the largest ND-simulation relation for our painting blocks-world example. For instance, state $\langle\langle a_1, b_3, c_2 \rangle, e_2 \rangle$ in $\mathcal{T}_\mathcal{S}$ *ND-simulates* state $\langle t_2, e_2 \rangle$ in $\mathcal{T}_{\mathcal{B}_T}$, shown in the picture by the same fillling pattern. Every conceivable action taken in $\langle t_2, e_2 \rangle$ can be replicated in $\langle\langle a_1, b_3, c_2 \rangle, e_2 \rangle$, and moreover, this property propagates to the new resulting states. Observe that state $\langle\langle a_1, b_1, c_1 \rangle, e_1 \rangle$ in $\mathcal{T}_\mathcal{S}$ *ND-simulates* two states in $\mathcal{T}_{\mathcal{B}_T}$: $\langle t_1, e_1 \rangle$ and $\langle t_5, e_1 \rangle$.

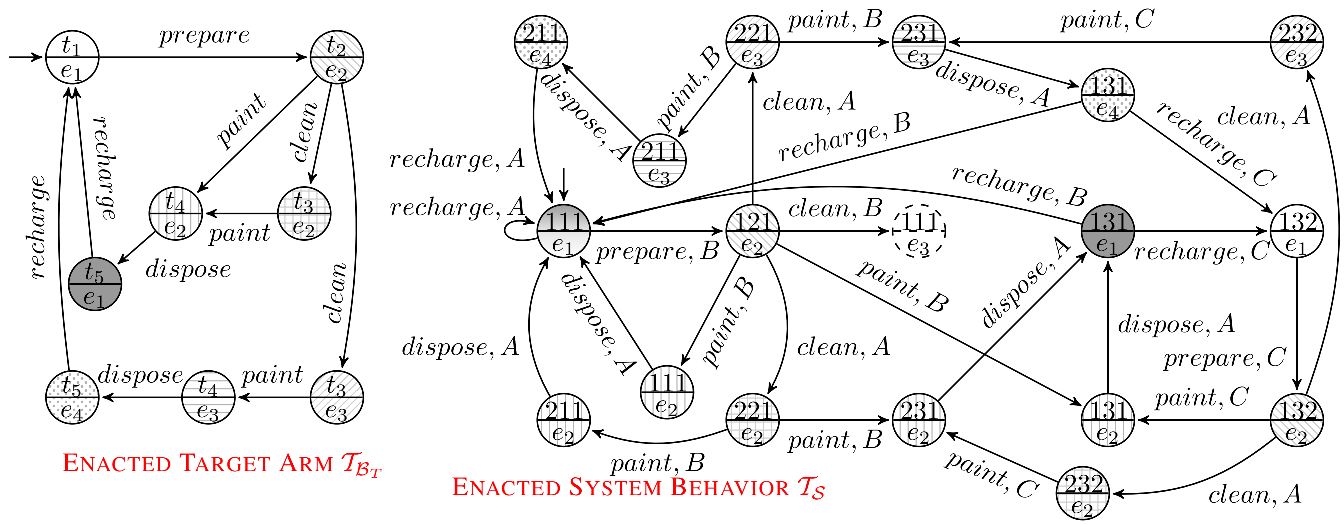


Figure 2: The largest ND-simulation relation between the enacted target behavior $\mathcal{T}_{\mathcal{B}_T}$ and (a part of) the enacted system behavior $\mathcal{T}_{\mathcal{S}}$ is shown using patterns. A state in $\mathcal{T}_{\mathcal{S}}$ ND-simulates the states in $\mathcal{T}_{\mathcal{B}_T}$ that shares its pattern, e.g., $\langle\langle a_1, b_3, c_1\rangle, e_2\rangle$ in $\mathcal{T}_{\mathcal{S}}$ ND-simulates state $\langle t_4, e_2\rangle$ in $\mathcal{T}_{\mathcal{B}_T}$. Dashed states in $\mathcal{T}_{\mathcal{S}}$ ND-simulate no state in $\mathcal{T}_{\mathcal{B}_T}$ (e.g., state $\langle\langle a_1, b_1, c_1\rangle, e_3\rangle$).

Algorithm 1 *NDS*$(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}})$ – Largest ND-Simulation

$\mathcal{R} := S_t \times S_{\mathcal{S}} \setminus \{\langle s_t, s_{\mathcal{S}}\rangle \mid env(s_t) \neq env(s_{\mathcal{S}})\}$
repeat
  $\mathcal{R} := (\mathcal{R} \setminus \mathcal{C})$, where $\mathcal{C}$ is the set of $\langle s_t, s_{\mathcal{S}}\rangle \in \mathcal{R}$ such that there exists $a \in \mathcal{A}$ for which for each k there is a transition $s_t \xrightarrow{a} s'_t$ in $\mathcal{T}_t$ such that either:
  (a) there is no transition $s_{\mathcal{S}} \xrightarrow{a,k} s'_{\mathcal{S}}$ in $\mathcal{T}_{\mathcal{S}}$ such that $env(s'_t) = env(s'_{\mathcal{S}})$; or
  (b) there exists a transition $s_{\mathcal{S}} \xrightarrow{a,k} s'_{\mathcal{S}}$ in $\mathcal{T}_{\mathcal{S}}$ such that $env(s'_t) = env(s'_{\mathcal{S}})$ but $\langle s'_t, s'_{\mathcal{S}}\rangle \notin \mathcal{R}$.
until $(\mathcal{C} = \emptyset)$
return $\mathcal{R}$

The controller generator (CG), with the largest ND-simulation at hand, can decide how to delegate actions as the target agent's requests come in. For instance, if a *clean* action is requested after a block has been prepared, the CG knows it ought to delegate such request to arm $\mathcal{B}_A$ so as to stay within the ND-simulation. While physically possible, delegating the cleaning action to arm $\mathcal{B}_A$ would bring the enacted system into state $\langle\langle a_1, b_1, c_1\rangle, e_3\rangle$ which is known not to be in ND-simulation with the target. ■

The next result shows that checking for the existence of a composition can be reduced to checking whether there exists an ND-simulation between the enacted target and the enacted system that includes their respective initial states.

Theorem 1. *Let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E}\rangle$ be a system and $\mathcal{B}_t$ a target behavior over $\mathcal{E}$. Let $\mathcal{T}_t = \langle S_t, \mathcal{A}, s_{t_0}, \delta_t\rangle$ and $\mathcal{T}_{\mathcal{S}} = \langle S_{\mathcal{S}}, \mathcal{A}, \{1, \ldots, n\}, s_{\mathcal{S}_0}, \delta_{\mathcal{S}}\rangle$ be the enacted target behavior and enacted system behavior for $\mathcal{B}_t$ and $\mathcal{S}$, respectively. A controller P for a system $\mathcal{S}$ that is a composition of the target behavior $\mathcal{B}_t$ over $\mathcal{E}$ exists iff $s_{t_0} \preceq s_{\mathcal{S}_0}$.*

Proof (sketch). We prove the two directions separately.

If. Given $s_{t_0} \preceq s_{\mathcal{S}_0}$ we show how to build a controller P that is a composition. We proceed as follows. We observe that given a history h, we can extract the resulting state of the enacted system $s_{\mathcal{S}}$ as $last(h)$. Moreover, we can extract the sequence of actions performed in h and the resulting environment states, and hence the state of the enacted target behavior, say s_t. Now, if tuple $\langle s_t, s_{\mathcal{S}}\rangle$ is in the largest ND-simulation, that is $s_t \preceq s_{\mathcal{S}}$, then for every action $a \in \mathcal{A}$ that the target may execute in s_t, there is some index k_a which mantains the ND-simulation. We then define $P(h, a) = k_a$. If, instead $s_{t_0} \not\preceq s_{\mathcal{S}_0}$, then function $P(h, a)$ can assume *any* value, in particular, $P(h, a) = undef$. It can be shown that such controller P is indeed a composition.

Only-if. We assume there exists a controller P that is a composition. Let us define relation R as the set of tuples $\langle s_t, s_{\mathcal{S}}\rangle$ for which there exists a history h obtained by running a controller P from the initial state $s_{\mathcal{S}_0}$ such that the resulting states of the enacted target and the enacted system after history h are s_t and $s_{\mathcal{S}}$, respectivley. It can be shown that such relation R is indeed an ND-simulation of $\mathcal{T}_t$ by $\mathcal{T}_{\mathcal{S}}$ and therefore $R \subseteq \preceq$. As a result, considering that $\langle s_{t_0}, s_{\mathcal{S}_0}\rangle \in R$ (by just taking h to be the initial history where no action has yet been performed), it follows that $s_{t_0} \preceq s_{\mathcal{S}_0}$, hence the thesis holds. □

Theorem 1 gives us a straightforward method to check for the existence of a composition. Namely: *(i)* compute the largest ND-simulation relation of $\mathcal{T}_t$ by $\mathcal{T}_{\mathcal{S}}$; and *(ii)* check whether $\langle s_{t0}, s_{\mathcal{S}0}\rangle$ is in this relation.

From the computational point of view, the algorithm *NDS* above computes the largest ND-simulation relation $\preceq$ between $\mathcal{T}_t$ and $\mathcal{T}_{\mathcal{S}}$ in polynomial time in the size of $\mathcal{T}_t$ and $\mathcal{T}_{\mathcal{S}}$. Since in our case the number of states of $\mathcal{T}_{\mathcal{S}}$ is exponential in the number of available behaviors $\mathcal{B}_1, \ldots, \mathcal{B}_n$, we get that we can compute the largest ND-simulation relation $\preceq$ in exponential time in the *number of available behaviors*. As a result, the new technique is a notable improvement with respect to the ones based on reduction to PDL (De Giacomo & Sardina 2007; Sardina, Patrizi, & De Giacomo 2007), which are exponential in the *number of states* of the behaviors and of the environment.

Theorem 2. *Checking for the existence of compositions by computing the largest ND-simulation relation $\preceq$ can be done in polynomial time in the number of states of the available behaviors, of the environment, and of the target behavior, and in exponential time in the number of available behaviors.*

Considering that the composition problem itself is EXPTIME-hard (Muscholl & Walukiewicz 2007), this is the best we can hope for.

Once we have computed the ND-simulation, *synthesizing* a controller becomes an easy task. In fact, there is a well-defined procedure that, given an ND-simulation, builds a finite state program that returns, at each point, the set of available behaviors capable of performing a target-conformant action. We call such a program *controller generator*.

Formally, let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E}\rangle$ be a system, $\mathcal{B}_t$ a target behavior over $\mathcal{E}$, and let $\mathcal{T}_\mathcal{S} = \langle S_\mathcal{S}, \mathcal{A}, \{1, \ldots, n\}, s_{\mathcal{S}0}, \delta_\mathcal{S}\rangle$ and $\mathcal{T}_t = \langle S_t, \mathcal{A}, s_{t0}, \delta_t\rangle$ be the enacted system behavior and the enacted target behavior corresponding, respectively, to $\mathcal{S}$ and $\mathcal{B}_t$. The <u>*controller generator (CG)*</u> of $\mathcal{S}$ for $\mathcal{B}_t$ is a tuple *CG* $= \langle \Sigma, \mathcal{A}, \{1, \ldots, n\}, \partial, \omega\rangle$, where:

1. $\Sigma = \{\langle s_t, s_\mathcal{S}\rangle \in S_t \times S_\mathcal{S} \mid s_t \preceq s_\mathcal{S}\}$ is the set of states of *CG*, formed by those pairs of $\mathcal{T}_t$'s and $\mathcal{T}_\mathcal{S}$'s states that are in the largest ND-simulation relation; given a state $\sigma = \langle s_t, s_\mathcal{S}\rangle$ we denote s_t by $com_t(\sigma)$ and $s_\mathcal{S}$ by $com_\mathcal{S}(\sigma)$.
2. $\mathcal{A}$ is the finite set of shared actions.
3. $\{1, \ldots, n\}$ is the finite set of available behavior indexes.
4. $\partial \subseteq \Sigma \times \mathcal{A} \times \{1, \ldots, n\} \times \Sigma$ is the *transition relation*, where $\langle \sigma, a, k, \sigma'\rangle \in \partial$, or $\sigma \xrightarrow{a,k} \sigma'$ in *CG*, iff
   - $com_t(\sigma) \xrightarrow{a} com_t(\sigma')$ in $\mathcal{T}_t$;
   - $com_\mathcal{S}(\sigma) \xrightarrow{a,k} com_\mathcal{S}(\sigma')$ in $\mathcal{T}_\mathcal{S}$;
   - for all $com_\mathcal{S}(\sigma) \xrightarrow{a,k} s'_\mathcal{S}$ in $\mathcal{T}_\mathcal{S}$, $\langle com_t(\sigma'), s'_\mathcal{S}\rangle \in \Sigma$.
5. $\omega : \Sigma \times A \mapsto 2^{\{1,\ldots,n\}}$ is the *output function*, where $\omega(\sigma, a) = \{k \mid \exists\, \sigma' \text{ s.t. } \sigma \xrightarrow{a,k} \sigma' \text{ in } CG\}$.

Thus, *CG* is a finite state transducer that, given an action a (compliant with the target behavior), outputs, through function ω, the set of *all* available behaviors that can perform a next according to the largest ND-simulation $\preceq$. Observe that computing *CG* from the relation $\preceq$ is easy, since it involves checking *local* conditions only.

If there exists a composition of $\mathcal{B}_t$ by $\mathcal{S}$, then $s_{t0} \preceq s_{\mathcal{S}0}$ and *CG* does include state $\sigma_0 = \langle s_{t0}, s_{\mathcal{S}0}\rangle$. In such cases, we get actual controllers, called *generated controllers*, that are compositions of $\mathcal{B}_t$ by $\mathcal{S}$ by picking up, at each step, one service among those returned by ω in *CG*.

Formally we proceed as follows. A <u>*trace for CG*</u> starting from σ^0 is a finite or infinite sequence of the form $\sigma^0 \xrightarrow{a^1,k^1} \sigma^1 \xrightarrow{a^2,k^2} \cdots$, such that $\sigma_j \xrightarrow{a^{j+1},k^{j+1}} \sigma_{j+1}$ in *CG*, for all j. A <u>*history for CG*</u> starting from state σ^0 is a prefix of a trace starting from state σ^0. By using histories, one can introduce <u>*CG-controllers*</u>, which are functions $CGP_{\text{CHOOSE}} : \mathcal{H}_{CG} \times \mathcal{A} \to \{1, \ldots, n, u\}$, where $\mathcal{H}_{CG}$ is the set of *CG* histories starting from any state in Σ, and defined as follows: $CGP_{\text{CHOOSE}}(h_{CG}, a) = \text{CHOOSE}(\omega(last(h_{CG}), a))$, for all $h_{CG} \in \mathcal{H}_{CG}$, where <u>CHOOSE</u> stands for a choice function that chooses one element among those returned by $\omega(last(h_{CG}), a))$. Let us assume that the controller generator *CG* of $\mathcal{S}$ for $\mathcal{B}_t$ includes state $\sigma_0 = \langle s_{t0}, s_{\mathcal{S}0}\rangle$. Then, for each *CG*'s history $h_{CG} = \sigma^0 \xrightarrow{a^1,k^1} \cdots \xrightarrow{a^\ell,k^\ell} \sigma^\ell$ starting from $\sigma^0 = \sigma_0$, we can obtain its corresponding system history $proj_\mathcal{S}(h_{CG})$, called the <u>*projected system history*</u>, as follows: $proj_\mathcal{S}(h_{CG}) = com_\mathcal{S}(\sigma^0) \xrightarrow{a^1,k^1} \cdots \xrightarrow{a^\ell,k^\ell} com_\mathcal{S}(\sigma^\ell)$, i.e., we take the "system" component of each *CG* state σ^i in the history. Moreover, from a *CG*-controller CGP_{CHOOSE}, we obtain the corresponding <u>*generated controller*</u> as the function $P_{\text{CHOOSE}} : \mathcal{H} \times \mathcal{A} \to \{1, \ldots, n, u\}$, where $\mathcal{H}$ is the set of system histories starting from $s_{\mathcal{S}0}$, defined as follows. For each system history h and action a: *(i)* if $h = proj_\mathcal{S}(h_{CG})$ for some *CG* history h_{CG}, then $P_{\text{CHOOSE}}(h, a) = CGP_{\text{CHOOSE}}(h_{CG}, a)$; else *(ii)* $P_{\text{CHOOSE}}(h, a) = u$.

Through generated controllers, we can relate *CG*s to compositions and show that, one gets *all* controllers that are compositions by considering all choice functions for CHOOSE. Notably, while each specific composition may be an infinite state program, the controller generator *CG*, which in fact includes them all, is always finite.

Theorem 3. *If CG includes the state $\sigma_0 = \langle s_{t0}, s_{\mathcal{S}0}\rangle$, then every controller generated by CG is a composition of the target behavior $\mathcal{B}_t$ by system $\mathcal{S}$.*

Theorem 4. *Every controller that is a composition of the target behavior $\mathcal{B}_t$ by system $\mathcal{S}$ can be generated by CG.*

In other words *CG* is analogous to a sort of "meta-plan" or a stateful nondeterministic "complete universal plan," which keeps all the existing plans at its disposal and decides which one to follow for the next action, possibly with contingent decisions.

Reactive Adaptability

Next we show that Theorems 3 and 4 give us a sound and complete technique for dealing with failure cases (a), (b), and (c) without any re-planning. As a matter of fact, once we have the controller generator *CG*, actual compositions can be generated "*just-in-time*," as (target compliant) actions are requested. What is particularly interesting about *CG*-controllers is that one can *delay the choice* performed by CHOOSE until run-time, where one can take into account contingent information, e.g., about availability of behaviors. This gives a great flexibility to the controller, which, in a sense, can "switch" compositions on the go as needed. We call such *CG*-controller, <u>*just-in-time CG-controller*</u>, and denote it by CGP_{jit}.

Freezing of behaviors CGP_{jit} already addresses temporary freezing of behaviors, i.e., failure case (a). In particular, if a behavior is temporarily frozen, then CGP_{jit} simply avoids choosing it, and continues with one of the other possible choices.[2] Obviously, if no other choices are possible, then CGP_{jit} shall wait for the behavior to come back.

State change of behaviors and environment CGP_{jit} also addresses unexpected changes in the internal state of behaviors and/or of the environment, that is, failure cases (b) and (c).[3] To understand this, let us denote by $\mathcal{T}_{\mathcal{S}}(z_{\mathcal{S}})$ the variant of the enacted system behavior whose initial state is $z_{\mathcal{S}}$ instead of $s_{\mathcal{S}0}$. Similarly, let us denote by $\mathcal{T}_t(z_t)$ the enacted target behavior whose initial state is z_t instead of s_{t0}. Now suppose that the state of the enacted system behavior changes, unexpectedly, to state $\hat{s}_{\mathcal{S}}$, due to a change of the state of a behavior (or a set of behaviors) and/or of the environment. Then, if s_t is the state of the target when the failure happened, one should recompute the composition with the system starting from $\hat{s}_{\mathcal{S}}$ and the target starting from $\hat{s}_t$, where $\hat{s}_t$ is just s_t with its environment state replaced by the one in $\hat{s}_{\mathcal{S}}$ (note $\hat{s}_t = s_t$ for failures of type (b)). Observe, though, that the ND-simulation is *independent* from the initial states of both the target and the system. Therefore, the ND-simulation between $\mathcal{T}_t(\hat{s}_t)$ and $\mathcal{T}_{\mathcal{S}}(\hat{s}_{\mathcal{S}})$ is the ND-simulation $\preceq$ we already have. This implies that we can still use the very same controller generator *CG* (and the same just-in-time *CG*-controller CGP_{jit} as well), with the guarantee that all compositions of the system variant for the target variant, if any, are still captured by *CG* (and CGP_{jit} too). Put it all together, we only need to check whether $\hat{s}_t \preceq \hat{s}_{\mathcal{S}}$, and, if so, continue to use CGP_{jit} (now from the *CG* history of length 0: $\langle \hat{s}_t, \hat{s}_{\mathcal{S}} \rangle$).

Computing reactive compositions on-the-fly We close the section with a notable observation: CGP_{jit}, that is CGP_{CHOOSE} with CHOOSE resolved at run-time, (and *CG* for the matter) can be computed *on-the-fly* by storing only the ND-simulation $\preceq$. In fact, at each point, the only information required for the next choice is $\omega(\sigma, a)$, where $\sigma \in \Sigma$ (recall $\Sigma = \preceq$) is formed by the current state of the enacted target behavior and that of the enacted system behavior. Now, in order to compute $\omega(\sigma, a)$ we only need to know $\preceq$.

Example 5. Upon an unexpected change in the system, in the environment or any available behavior, the CG can react/adapt to the change immediately. For instance, suppose the target is in state t_3, the environment in state e_3 and the available behaviors $\mathcal{B}_A$, $\mathcal{B}_B$, and $\mathcal{B}_C$ are in their states a_2, b_2, and c_2, respectively. That is, $\mathcal{T}_{\mathcal{B}_T}$ is in state $\langle t_3, e_3 \rangle$ whereas $\mathcal{T}_{\mathcal{S}}$ is in state $\langle \langle a_2, b_2, c_1 \rangle, e_3 \rangle$. Suppose that, in an unexpected way, the environment happens to change to state e_2—someone has re-charged the water tank. All that is needed in such case is to check that the new states of $\mathcal{T}_{\mathcal{B}_T}$ and $\mathcal{T}_{\mathcal{S}}$, namely $\langle t_3, e_2 \rangle$ and $\langle \langle a_2, b_2, c_1 \rangle, e_2 \rangle$, are still in the ND-simulation. Since they are, the CG continues the realization of the target from such (new) enacted states. ■

[2]If more information is at hand, CGP_{jit} may use it to choose in an informed way, though this is out of the scope of this paper.

[3]Although hardly as meaningful as the ones above, unforeseen changes in the target's state can be accounted for in a similar way.

Parsimonious Refinement

When considering failure cases (d) and (e), a simple reactive approach is not sufficient and more complex refinement techniques are required. We show then how to do the composition refinement in an intelligent manner. Let us start by defining a parametric version of the algorithm for computing the ND-simulation. Such a version, called *NDSP*$(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}, \mathcal{R}_{init}, \mathcal{R}_{sure})$, takes two extra parameters: $\mathcal{R}_{init}$, the starting relation from which the largest ND-simulation is extracted; and $\mathcal{R}_{sure}$, a relation containing tuples already known to be in the ND-simulation to be computed.

Algorithm 2 *NDSP*$(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}, \mathcal{R}_{init}, \mathcal{R}_{sure})$

$\mathcal{R} := \mathcal{R}_{init} \setminus \mathcal{R}_{sure}$
$\mathcal{R} := \mathcal{R} \setminus \{\langle s_t, s_{\mathcal{S}} \rangle \mid env(s_t) \neq env(s_{\mathcal{S}})\}$
repeat
  $\mathcal{R} := (\mathcal{R} \setminus \mathcal{C})$, where $\mathcal{C}$ is the set of $\langle s_t, s_{\mathcal{S}} \rangle \in \mathcal{R}$ such that there exists $a \in \mathcal{A}$ for which for each k there is a transition $s_t \xrightarrow{a} s'_t$ in $\mathcal{T}_t$ such that either:
  (a) there is no transition $s_{\mathcal{S}} \xrightarrow{a,k} s'_{\mathcal{S}}$ in $\mathcal{T}_{\mathcal{S}}$ such that $env(s'_t) = env(s'_{\mathcal{S}})$; or
  (b) there exists a transition $s_{\mathcal{S}} \xrightarrow{a,k} s'_{\mathcal{S}}$ in $\mathcal{T}_{\mathcal{S}}$ such that $env(s'_t) = env(s'_{\mathcal{S}})$ but $\langle s'_t, s'_{\mathcal{S}} \rangle \notin \mathcal{R} \cup \mathcal{R}_{sure}$.
until $(\mathcal{C} = \emptyset)$
return $\mathcal{R} \cup \mathcal{R}_{sure}$

Algorithm *NDSP* is correct (that is, it coincides with *NDS*), provided its two new parameters are used adequately.

Theorem 5. *Let $\mathcal{S}$ be a system and $\mathcal{B}_t$ a target behavior. If $\mathcal{R}_{sure} \subseteq NDS(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}) \subseteq \mathcal{R}_{init}$, then $NDSP(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}, \mathcal{R}_{init}, \mathcal{R}_{sure}) = NDS(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}})$.*

Proof (sketch). Let $\mathcal{R}^i_1$ and $\mathcal{R}^i_2$ be the sets representing $\mathcal{R}$ in algorithms *NDS* and *NDSP*, respectively, after i repeat-loop iteration. It can be shown, by induction on i, that $\mathcal{R}^i_2 \cup \mathcal{R}_{sure} \subseteq \mathcal{R}^i_1 \subseteq NDS(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}})$ and that $NDS(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}) \subseteq \mathcal{R}^i_2 \cup \mathcal{R}_{sure}$. Hence, since at the limit $R^i \cup \mathcal{R}_{sure} = NDS(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}, \mathcal{R}_{init}, \mathcal{R}_{sure})$, the thesis follows. □

Next, we introduce convenient notations to shrink and expand systems and ND-simulation relations. Consider a system $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E} \rangle$ and a set of behavior indexes $W \subseteq \{1, \ldots, n\}$. The set $\mathcal{S}(W)$ denotes the system derived from $\mathcal{S}$ by considering only (i.e., projecting on) all behaviors $\mathcal{B}_i$ such that $i \in W$ (note $\mathcal{S} = \mathcal{S}([1 \ldots n])$). Let $\mathcal{T}_t$ be an enacted target behavior over $\mathcal{E}$. We denote by $\preceq_W$ the *largest* ND-simulation relation of $\mathcal{T}_t$ by $\mathcal{T}_{\mathcal{S}(W)}$. Let $U \subseteq \{1, \ldots, n\}$ such that $W \cap U = \emptyset$. We denote by $\preceq_W \otimes U$, the relation obtained from $\preceq_W$ by (trivially) putting all behaviors $\mathcal{B}_i$, with $i \in U$, back into the system. Formally, we can define such operation as follows (without loss of generality, assume

$W = \{1, \ldots, \ell\}$ and $U = \{\ell+1, \ldots, m\}$):

$$\begin{aligned}\preceq_W \otimes U = \\ \{\langle s_t, s'\rangle \mid s' = \langle b^1, \ldots, b^\ell, b^{\ell+1}, \ldots, b^m, e\rangle \\ \text{such that } \langle s_t, \langle b^1, \ldots, b^\ell, e\rangle\rangle \in \preceq_W \text{ and} \\ b^i \text{ is a state of } \mathcal{B}_i, \text{ for } i \in \{\ell+1, \ldots, m\} \}.\end{aligned}$$

When "putting back" a set of behaviors into the system in this way, we are guaranteed to (already) get an ND-simulation for the (expanded) system $\mathcal{S}(W \cup U)$. Observe, however, that it may not necessarily be the largest one.

Lemma 6. *Let $W, U \subseteq \{1, \ldots, n\}$ such that $W \cap U = \emptyset$. Then,*

- $\preceq_W \otimes U \subseteq \preceq_{W \cup U}$*;*
- $\preceq_W \otimes U$ *is an ND-simulation of* $\mathcal{T}_t$ *by* $\mathcal{T}_{\mathcal{S}(W \cup U)}$.

Proof. Without loss of generality, take $W = \{1, \ldots, \ell\}$, and $U = \{\ell+1, \ldots, m\}$. Suppose that $\langle\langle t, e\rangle, \langle b^1, \ldots, b^\ell, b^{\ell+1}, \ldots, b^m, e'\rangle\rangle \in \preceq_W \otimes \{r\}$. Due to the definition of $\otimes$, it is the case that $\langle t, e\rangle \preceq_W \langle b^1, \ldots, b^\ell, e', e'\rangle$. This means that $e' = e$ and that for each $a \in \mathcal{A}$, there exists index $k_a \in W$ satisfying the requirements of the ND-simulation definition for system $\mathcal{S}(W)$. Clearly then $\langle t, e\rangle \preceq_{W \cup U} \langle b^1, \ldots, b^\ell, b^{\ell+1}, \ldots, b^m, e'\rangle$. Indeed, $e = e'$, and for every $a \in \mathcal{A}$, the same index k_a would also satisfy the requirements of the ND-simulation definition for system $\mathcal{S}(W \cup U)$—the new behaviors are not used and they cannot remove capabilities of the other behaviors. This shows that $\preceq_W \otimes U$ is an ND-simulation of $\mathcal{T}_t$ by $\mathcal{T}_{\mathcal{S}(W \cup U)}$, and hence, $\preceq_W \otimes U \subseteq \preceq_{W \cup U}$, as $\preceq_{W \cup U}$ is the largest ND-simulation of $\mathcal{T}_t$ by $\mathcal{T}_{\mathcal{S}(W \cup U)}$. $\square$

Finally, when $F \subseteq W$, we denote by $\preceq_W|_F$ the relation obtained from $\preceq_W$ by *projecting out* all (failed) behaviors $\mathcal{B}_i$ such that $i \in F$—F stands for the indexes of the behaviors that happen to fail. Surprisingly, the new largest ND-simulation after failure is in fact *contained* in the relation obtained by merely projecting out the failed components from the ND-simulation at hand right before the failure.

Lemma 7. *Let $W, F \subseteq \{1, \ldots, n\}$ such that $F \subseteq W$. Then,*

- $\preceq_{W \setminus F} \subseteq \preceq_W|_F$*;*
- $\preceq_W|_F$ *may not be an ND-simulation of* $\mathcal{T}_t$ *by* $\mathcal{T}_{\mathcal{S}(W \setminus F)}$.

Proof. By Lemma 6, $\preceq_{(W \setminus F)} \otimes F \subseteq \preceq_{(W \setminus F) \cup F}$, that is, $\preceq_{(W \setminus F)} \otimes F \subseteq \preceq_W$. By projecting out F on both relations, we get $\preceq_{(W \setminus F)} \otimes F|_F \subseteq \preceq_W|_F$. Then, since $\preceq \otimes X|_X = \preceq$ for any $\preceq$ and X, $\preceq_{(W \setminus F)} \subseteq \preceq_W|_F$ follows.

It is immediate to find cases where the containment is proper, and hence the second part follows. $\square$

Notice that despite $\preceq_W$ being the largest ND-simulation when the behaviors in W are active, the projected relation $\preceq_W|_F$ is *not* necessarily even an ND-simulation relation for (contracted) system $\mathcal{S}(W \setminus F)$.

Permanent unavailability When a behavior becomes permanently unavailable (cf. case (d)), one cannot rely on waiting for it to resume when the composition really needs it. Instead, one can either continue the composition and just "hope for the best," that is, hope that the failed behavior will not be required, or one can "refine" the current composition to continue guaranteeing the full realization of the target.

The following theorem guides such a refinement. Due to Lemma 7, it is enough just to start the *NDSP* algorithm from the relation obtained by merely projecting out the failed behaviors, generally resulting in substantially less algorithm iterations. Indeed, as behaviors become unavailable, the effort to obtain the new largest ND-simulation relation is *systematic* and *incremental* in that no tuples that were previously discarded will be considered.

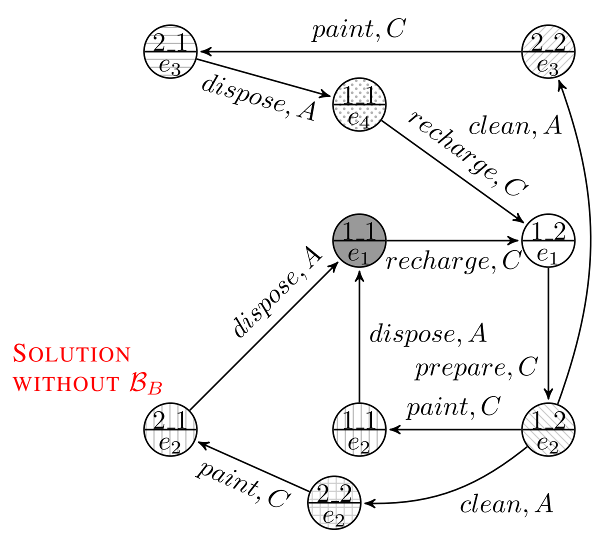
Theorem 8. *Let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E}\rangle$ be a system and $\mathcal{B}_t$ a target behavior over $\mathcal{E}$. Let $W \subseteq \{1, \ldots, n\}$ be the (indexes of the) behaviors currently working in $\mathcal{S}$, and let $F \subseteq \{1, \ldots, n\}$, with $F \subseteq W$, be the (indexes of the) behaviors that become permanently unavailable. Then,*

$$\preceq_{(W \setminus F)} = NDSP(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}(W \setminus F)}, \preceq_W|_F, \beta),$$

for every β such that $\beta \subseteq \preceq_{(W \setminus F)}$.

Proof. It follows from Lemma 7 and Theorem 5. $\square$

Example 6. Suppose that arm $\mathcal{B}_T$ is being successfully realized by means of controller P_1. At some point, however, arm $\mathcal{B}_B$ suddenly breaks down in state b_3, just after painting a block. With $\mathcal{B}_B$ out, controller P_1 cannot guarantee the target anymore. Interestingly, though, controller P_2 can now (keep) realizing $\mathcal{B}_T$ from the new (unexpected) sub-system. To handle such failure case, first behavior $\mathcal{B}_B$ is projected out from the ND-simulation relation $\preceq_{\{A,B,C\}}$, thus getting $\preceq_{\{A,B,C\}}|_{\{B\}}$. Then, starting relation $\preceq_{\{A,B,C\}}|_{\{B\}}$, the new ND-simulation relation is computed using *NDSP*, getting $\preceq_{\{A,C\}}$, see picture below.



Observe that tuple $\langle\langle t_3, e_3\rangle, \langle\langle a_2, c_1\rangle, e_3\rangle\rangle$ would indeed be in relation $\preceq_{\{A,B,C\}}|_{\{B\}}$, but it would later be filtered out by the *NDSP* algorithm. Indeed, the original tuple $\langle\langle t_3, e_3\rangle, \langle\langle a_2, b_2, c_1\rangle, e_3\rangle\rangle \in \preceq_{\{A,B,C\}}$ relied on $\mathcal{B}_B$ for mantaining the ND-simulation. Finally, if arm $\mathcal{B}_B$ happens to resume, the CG comes back to the ND-simulation of Figure 2. ■

Resumed behaviors Consider now the case in which while behaviors with indexes in W are currently operating, a set of behaviors surprisingly comes back again into the system, cf. case (e). Let the indexes of such behaviors be U, with $U \cap W = \emptyset$. Obviously this would never reduce the capabilities of the whole system, but it could enhance it with more choices. To exploit them, one needs to compute the new largest ND-simulation $\preceq_{(W \cup U)}$. In doing so, one can leverage on the fact that $\preceq_{(W \cup U)}$ *contains* the ND-simulation $\preceq_W \otimes U$ (cf. Lemma 6) by completely avoiding consideration (for potential filtering) of those tuples in $\preceq_W \otimes U$, i.e., we pass those tuples as the "sure set" to the *NDSP* algorithm.

Theorem 9. *Let $\mathcal{S} = \langle \mathcal{B}_1, \ldots, \mathcal{B}_n, \mathcal{E}\rangle$ be a system and $\mathcal{B}_t$ a target behavior over $\mathcal{E}$. Let $W \subseteq \{1, \ldots, n\}$ be the (indexes of the) behaviors currently working in $\mathcal{S}$, and $U \subseteq \{1, \ldots, n\}$, with $W \cap U = \emptyset$, be the (indexes of the) resumed behaviors. Then,*

$$\preceq_{(W \cup U)} \;=\; NDSP(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}(W \cup U)}, \alpha, \preceq_W \otimes U),$$

for every α such that $\preceq_{(W \cup U)} \subseteq \alpha$.

Proof. It follows from Theorem 5 and Lemma 6. □

Observe that U could even include new behaviors not included in $\{1, \ldots, n\}$—the thesis of Lemma 6 would still hold.

Reusing previous computed ND-simulations Suppose that we have already computed and stored the ND-simulations for the sets of indexes in $\mathcal{W}$ (obviously $\{1, \ldots, n\} \in \mathcal{W}$), and suppose we are to compute the ND-simulation $\preceq_W$ for $W \notin \mathcal{W}$. Let us then define:

$$\bar{\alpha} = \bigcap_{\{W' \in \Supset^{\mathcal{W}}_{W}\}} \preceq_{W'}|_{(W' \setminus W)};$$

$$\bar{\beta} = \bigcup_{\{W' \in \Subset^{\mathcal{W}}_{W}\}} \preceq_{W'} \otimes (W \setminus W');$$

where $\Supset^{\mathcal{W}}_{W}$, resp. $\Subset^{\mathcal{W}}_{W}$, stands for for set of *tightest* supersets, resp. subsets, of W in $\mathcal{W}$, namely:

$$\Supset^{\mathcal{W}}_{W} = \{W' \in \mathcal{W} \mid W \subseteq W' \wedge \forall V \in \mathcal{W}. W \subseteq V \rightarrow V \not\subset W'\};$$

$$\Subset^{\mathcal{W}}_{W} = \{W' \in \mathcal{W} \mid W' \subseteq W \wedge \forall V \in \mathcal{W}. V \subseteq W \rightarrow W' \not\subset V'\}.$$

Then, by using the above Theorems 8 and 9 we get that:

$$\preceq_W \;=\; NDSP(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}, \bar{\alpha}, \bar{\beta}).$$

Notice that by using $NDSP(\mathcal{T}_t, \mathcal{T}_{\mathcal{S}}, \bar{\alpha}, \bar{\beta})$ to compute $\preceq_W$, we *maximally reuse the computations already done* to devise other ND-simulations. Obviously, once we have computed $\preceq_W$, we can immediately compute CGP_{jit} on-the-fly as before.

Conclusions

In this paper, we presented a simulation-based technique for the behavior composition (De Giacomo & Sardina 2007), radically departing from previous approaches. Such a technique is a substantial improvement over the previous ones from the complexity-theoretic perspective (it is exponential in the number, and not the size, of the available behaviors). More importantly, it produces flexible solutions that are ready to handle exceptional circumstances unforeseen at specification time, avoiding re-planning altogether in significant cases and bounding it in others.

We remark that the proposed technique is quite suitable for optimized implementations. First, optimized techniques exist for computing simulation, such as those in (Henzinger, Henzinger, & Kopke 1995; Tan & Cleaveland 2001; Gentilini, Piazza, & Policriti 2003), and implemented in systems such as CWB-NC (http://www.cs.sunysb.edu/∼cwb/). Second, it is known that a relationships exists between simulation and checking invariance properties in temporal-logic-based model checkers and synthesis systems, see e.g., (Vardi & Fisler 1999; Asarin *et al.* 1998). In fact, we are currently implementing the technique proposed in this paper using the synthesis system TLV (http://www.cs.nyu.edu/acsys/tlv/), see e.g., (Piterman, Pnueli, & Sa'ar 2006). Another option would be to exploit ATL-based verifiers, such as Mocha (http://www.cis.upenn.edu/∼mocha/), which can check game-structures for properties such as invariants, and extract winning strategies for them, see e.g., (Alura, Henzinger, & Kupferman 2002).

The kind of failures we have considered here can be seen as core forms of breach-of-contract with respect to the specification. Of course other forms of failures are possible (Tripathi & Miller 2001; Pettersson 2005; Marin, Bertier, & Sens 2003), but they essentially assume more information at hand upon a failure, e.g., a module may state unavailability duration and/or the state, or possible states, it will join back. Moreover, such additional information may be of statistical or probabilistic nature. Exploiting such information for failure reaction opens interesting directions for future work.

Acknowledgments

The authors would also like to thank the anonymous reviewers for their interesting comments. The first author was supported by the Australian Research Council and Agent Oriented Software (grant LP0560702), and the National Science and Engineering Research Council of Canada under a PDF fellowship. The other authors were partially supported by the the European FET basic research project FP6-7603 Thinking Ontologies (TONES).

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