Building Virtual Behaviors from Partially Controllable Available Behaviors in Nondeterministic Environments

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Abstract

The composition problem involves how to coordinate a set of available modules (e.g., concrete devices installed in a smart house, such as video cameras, lights, blinds, etc.) so as to implement a desired but non-existent target complex component (e.g., a complex entertainment house system). This paper summarizes the results in (De Giacomo, Patrizi, and Sardina 2013), by formally defining the problem within an AI context, characterizing its complexity, and identifying effective techniques to solve it. Related results are also briefly discussed.

Introduction

With computers now embedded in everyday devices and environments like mobile phones, cars and planes, houses, offices, and factories, the trend is to build complex systems from a collection of simple components. For example, complex entertainment systems within a smart house can be “realised” (i.e., implemented) by suitably coordinating the behaviour of a plethora of simple devices and artifacts—lights, phones, game consoles, TVs, music systems, etc.—installed in the house. Such embedded systems can provide services that range from simple tasks, such as “turn on the lights in the bedroom,” to more complex ones, such as “bring me a cup of coffee” or “handle house intruder” (by tracking and taking pictures of the intruder, toggling lights rapidly, and alerting the owner by email or phone).

The problem of automatically synthesizing such a controller-coordinator for a desired target (complex) system is called the behaviour composition problem. Informally, the problem amounts to realizing an abstract desired target behavior module (e.g., a smart house system or complex web-service) by reusing and re-purposing a set of accessible modules implementing certain concrete behaviors (e.g., installed artifacts in the house or available web-services). The question then is whether it is possible, and if so synthesise a controller, to coordinate and execute the existing available behavior modules so that it appears as if the target module is being run. Behaviours here refer to the operational logic of a system (e.g., a vacuum cleaner, microwave, or web-service) and are generally represented using transition systems.

This paper summarizes the results on behavior composition presented in (De Giacomo, Patrizi, and Sardina 2013) and discusses further related developments. Such work formally defines the composition problem in an AI context, characterizes its complexity, develops effective techniques to solve it, and identifies links with several areas of Computer Science and AI. When looking at behavior composition from an AI perspective, actual controllability of available behaviors becomes a prominent issue. While one can instruct a behavior module to carry out an action, the actual outcome of the action may not always be foreseen a priori, though it can possibly be observed after execution. While the work presented here is based on revisiting a certain stream of work in service composition (Berardi et al. 2005), the issue of dealing with partial controllability (of behaviors) becomes central one.

Behavior composition is strongly related to several forms of (advanced) automated planning, in particular, to planning for temporally extended goals (Bacchus and Kabanza 1998) as well as fully-observable non-deterministic (FOND) planning (Danielie, Traverso, and Vardi 2000). The former investigates techniques for building finite or infinite plans that satisfy linear- or branching-time specifications, while the latter studies the planning problem in the context of actions whose effects cannot be fully determined a priori. Indeed, the composition problem requires an advanced conditional plan (with loops) that always guarantees all possible target requests to be “served,” which is, ultimately, a (temporal) invariant property. What is more, as later proved by (Ramirez, Yadav, and Sardina 2013), such plans amount to strong-cyclic policies, the general solution concepts for FOND planning. Even more, the solutions obtained via the simulation technique developed in this work are akin to the so-called universal plans (Schoppers 1987), that is, plans representing every possible solution.

We shall first present the formal definition of the problem and its computational complexity. We then provide our technique based on the formal notion of simulation for synthesizing the most general kind of solutions, called controller generators, and show how these can deal with behavior failures. After that, we demonstrate how we can resort, in practice, to existing platforms for synthesis via model checking by recasting the composition task as a safety game. We close by discussing recent developments and open challenges.
The Problem

We explain the behavior composition problem using the painting arms scenario depicted in Figure 1. The overall aim of the system is to process blocks, one at a time, by first preparing a block, then optionally cleaning it if necessary (by using paint from a special tank), then painting the block (by using paint from another tank), and finally disposing the end product. This desired process is represented by target behavior $T$. Importantly, after the block is disposed for collection, the process always makes sure the water and paint tanks are recharged before processing the next block.

Unfortunately, the desired arm $T$ does not exist in reality. Nonetheless, there are three different actual arms available: a cleaning-disposing arm $B_1$ able to clean and dispose blocks; an arm $B_2$ capable of preparing, cleaning, and painting blocks; and an arm $B_3$ that can paint and prepare blocks. All three arms are able to trigger the tanks' recharge operation. Notice that arm $B_2$ behaves non-deterministically when it comes to painting a block. This captures the modeler's incomplete information about $B_2$'s internal logic.

All modules are meant to execute on a shared non-deterministic environment $E$ capturing the dynamics of the domain. For example, blocks can be painted or cleaned only after they have been prepared, and the water tank can contain water (states $e_1$ and $e_2$) or be empty (states $e_3$ and $e_4$). Observe that $B_1$ uses a cleaning action implementation which requires water available, though clean can still be performed by other means—as done by arm $B_2$—and hence it is still legal from environment state $e_3$.

Formally, a behavior over an environment $E$ with set of states $E$ is a tuple $B = \langle B, b_0, G, F, g \rangle$, where:

- $B$ is the finite set of behavior states;
- $b_0 \in B$ is the behavior initial state;
- $G \subseteq E$ is a set of guards over $E$;
- $F \subseteq B$ is the set of final states (where $B$ can be stopped);
- $g \subseteq B \times G \times A \times B$ is the behavior transition relation.

We write $b \xrightarrow{g,a} b'$ in $B$ to denote $\langle b, g, a, b' \rangle \in g$: action $a$ can be executed by $B$ in state $b$ when the environment is in a state $e$ such that $e \in g$, which may lead the behavior to successor state $b'$. A behavior $B$ is deterministic if there are no two transitions $b \xrightarrow{g_1,a} b'$ and $b \xrightarrow{g_2,a} b''$ in $B$ such that $b' \neq b''$ and $g_1 \cap g_2 \neq \emptyset$. Behaviors $B_2$ and $B_3$ are deterministic, but not $B_1$ due to the paint transition in $b_2$.

An available system is a tuple $S = \langle B_1, \ldots, B_n, E \rangle$, where $B_i$'s are all the available behaviors over the shared environment $E$. Available behaviors and environment could be non-deterministic, and hence partially controllable. Informally, the behavior composition task is stated as follows:

Given a system $S$ and a deterministic target behavior $T$, is it possible to (partially) control the available behaviors in $S$ in a step-by-step manner—by instructing them on which action to execute next and observing, afterwards, the outcome in the behavior used—so as to “realize” the desired target behavior?

In other words, can we adequately control the system so that it appears as if one was actually executing the target module?

Formally, a controller for target $T$ on system $S$ is a partial function $C : H_S \times A \mapsto \{1, \ldots, n\}$, which, given a history $h \in H_S$ of the available system (where $H_S$ is, basically, the set of all finite traces of the asynchronous product of the available behaviors) and a requested (target-compatible) action, returns the index of an available behavior to which the action in question is delegated for execution. Intuitively, a controller (fully) realizes a target behavior if for every trace (i.e., run) of the target, at every step, the controller returns the index of an available behavior that can perform the requested action. Formally, one first defines when a controller $C$ realizes a trace of the target $T$. Then, a controller $C$ realizes the target behavior $T$ iff it realizes all its traces. In that case, $C$ is said to be a composition for target $T$ on system $S$. Being a sort of conditional planning problem, it is not surprising that deciding whether there is a composition of a target module in an available system, even when the system is fully deterministic, is EXPTIME-complete.

Composition via Simulation

One of the most significant results is that one can rely on the notion of simulation relation (Milner 1971) as a formal tool for solution characterization. Intuitively, a transition system $S_1$ simulates another transition system $S_2$, if $S_1$ is able to
The search for a system’s winning strategy (in fact, all such strategies) is performed through a fixpoint computation which isolates the fragment of state space where the system can force the game to stay in the safe area. Through a reduction, this procedure can be exploited to compute an ND-simulation relation (in fact, the largest one).

4. It supports the systematic handling of several types of failures (Section 4). Firstly, controller generators can be used to generate just-in-time composition controllers, that is, controllers generated on-the-fly as the target and system are executed. Such controllers provide reactive adaptability to temporary unavailability of available behaviors and unexpected state change of behaviors and environment. Secondly, when one or more available behaviors become permanently unavailable or a new available behavior is added to the available system $S$, a parsimonious refinement of the solution (i.e., controller generator) at hand can be performed (Theorems 7 and 8), thus avoiding a (re)computation of a new solution from scratch.

**Composition as a Safety Game**

The task of computing an ND-simulation relation, and thus that of synthesizing a composition, can be cast as that of checking whether a winning strategy exists in a so-called safety game. The benefit of this approach is the availability of actual systems (e.g., TLV (Pnueli and Shahar 1996), JTLV (Bloem et al. 2011)) capable of computing, in a space-efficient manner, the winning strategy of a given game.

A safety-game is a game played by two opponents, system and environment, controlling the values assigned to a finite set of variables ranging over finite domains. The set $X$ of variables is partitioned into the subsets $X_s$ and $X_e$, controlled, respectively, by the system and the environment. The game starts with a fixed initial assignment to all variables and every turn consists of an environment’s move followed by a move of the system. The moves available at each step to the system and environment players are governed by two transition relations, $p_s$ and $p_e$, respectively. Since such moves depend, in general, on the (current) values of all variables (including those not controlled by the acting player) a player can affect, via its move, the options available next to the other player. The goal of the system is to keep the game inside a “safe” area, that is, a set of states where the assignments to variables satisfy a certain criterion, while that of the environment is to prevent this. In other words, the system’s objective is to enforce an invariant. The safe area is represented by the so-called safety-goal formula. For instance, to guarantee that the values assigned to variables $v_1$ and $v_2$ are always different, one can use the formula $v_1 \neq v_2$.

A game is said to be winning for the system if the system has a strategy—a function from the history of visited states to the next system’s move—which guarantees the game to stay in the safe area, no matter how the environment plays.

The search for a system’s winning strategy (in fact, all such strategies) is performed through a fixpoint computation which isolates the fragment of state space where the system can force the game to stay in the safe area. Through a reduction, this procedure can be exploited to compute an ND-simulation relation (in fact, the largest one).
The idea of the reduction is to encode in the environment player the enacted available system as well as the enacted target behavior, and in the system player the behavior delegation mechanism. So, the environment player encodes (a) the enacted target behavior, which selects, at runtime, the action to perform next according to internal logic; and (b) the asynchronous execution of the available behaviors, synchronously combined with the shared environment. This approach is motivated by the fact that both the action request and the actual evolution of the available system are not under the system player’s control. Technically, the environment player is able to control a “requested action” variable ranging over all actions available to the target and a set of variables capturing the state of all behaviors and the shared environment. The transition relation $\rho_e$ imposes the rules on such control to mimic the enacted target and the available system. In turn, the system player is able to control a distinguished delegation variable ranging over the available behaviors and stating which behavior is to be activated at a given point (to fulfill the active request). Formally, the transition relation $\rho_s$ allows the delegation of the current requested action to any behavior, even one that is not able, in its current state, to perform the action.

Finally, the goal formula expresses the fact that it is always the case that the action currently selected by the environment is actually executable by the behavior that the system player has delegated the action to. That is, the goal requires that all actions requested by the target behavior, according to its transition relation, can be delegated to some available behavior so that all possible future requests can be successfully delegated.

Discussion

The framework summarized in this paper can be seen as a core account for behavior composition, that can be extended in a number of directions. Several extensions, including distributed composition, multiple target composition, composition under partial observability, or composition with data or high-level programs were proposed (see Section 7).

An important recent development concerns the settings in which there are no composition solutions. For example, removing any of the three processing arms in Figure 1 or just removing state $b_1$ from module $B_2$ would render the target arm $T$ unrealizable. In those cases, a mere “no solution” answer may be highly unsatisfactory: one would prefer accounts for the “best” possible approach to the composition instance. Again relying on the ND-simulation notion, (Yadav and Sardina 2012; Yadav et al. 2013) proposed a solution concept, and a corresponding effective technique, as the alternative target module that is closest to, though probably less powerful than, the original target and is fully realizable. Importantly, such alternative target is provably unique.

We close by noting that besides automated planning, and synthesis in general, the behavior composition problem is of interest for several other areas of CS and AI, including intelligent multi-agents (e.g., coordination of agents’ teams or plans), robot-ecologies and ambient intelligence (Bordignon et al. 2007) (e.g., to achieve advanced functionalities from a plethora of simple devices), and web-service composition (Berardi et al. 2005).

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References


