Runtime Interchange for Adaptive Re-use of Intelligent Cyber-Physical System Controllers

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Abstract—Cyber-Physical Systems (CPSs) such as those found within autonomous vehicles are increasingly adopting Artificial Neural Network (ANN)-based controllers. To ensure the safety of these controllers, there is a spate of recent activity to formally verify the ANN-based designs. There are two challenges with these approaches: (1) The verification of such systems is difficult and time consuming. (2) These verified controllers are not able to adapt to frequent requirements changes, which are typical in situations like autonomous driving. This raises the question: how can trained and verified controllers, which have gone through expensive training and verification processes, be re-used to deal with requirement changes?

This paper addresses this challenge for the first time by proposing a new framework that is capable of dealing with requirement changes at runtime through a mechanism we term runtime interchange (RI). Our approach functions via a continual exchange and selection process of multiple pre-verified controllers. It represents a key step on the way to component-oriented engineering for intelligent designs, as it preserves the behaviours of the original controllers while introducing additional functionality. To demonstrate the efficacy of our approach we utilise an existing autonomous driving case study as well as a set of smaller benchmarks. These show that introduced overheads are extremely minimal and that the approach is very scalable.

Index Terms—Cyber-physical systems, runtime enforcement, formal methods, artificial neural networks (ANNs).

I. INTRODUCTION

Cyber-Physical Systems (CPSs) [1] intertwine distributed controllers, which are used for controlling physical processes. Traditionally, these used model-driven approaches to ensure safety. The model driven approaches are no longer suitable with the introduction of tasks such as machine vision in industrial CPS and autonomous vehicles. These tasks are primarily handled by machine intelligence functionality programmed using data-driven methods such as Artificial Neural Networks (ANNs). This is leading to the need for new system design paradigm where model-driven and data-driven approaches need to be considered in an unified fashion [2], [3].

Considering this, several approaches inspired by formal methods [4] have been developed for the verification of safety properties of ANNs. Seshia et al. [5] discuss some of the challenges for such formal analysis. There have been several attempts at developing scalable formal verification techniques such as AI² [6]. Also, there have been attempts at verified autonomy [7] using a neural network controller of an autonomous toy racing car called F1/10. This feed-forward neural network controller is mapped to hybrid automata [8]. This is then analysed by the Flow* model checker to ensure that the vehicle will not collide with the adjoining obstacles, which are static.

These attempts at formally verified controllers are laudable for ensuring safety. However, some key challenges remain. Specifically, both the training of complex ANNs and the subsequent static verification of these controllers are time consuming processes with scalability concerns. Finally, it is becoming clear that complex CPS such as autonomous vehicles require adaptive controllers which can cope with requirements changes at runtime (see the recent survey [9]). This poses the question: how to re-use trained and verified ANN-based controllers, which have been developed with considerable effort, so as to deal with frequent requirement changes?

Here we present a formal methodology to address this issue. Our work falls into runtime assurance [10], where system behaviours are augmented at runtime by supervisory systems. The purpose of our framework, which we term “Runtime Interchange (RI)”, is to provide an environment where re-usable controller components can be composed and interchanged at runtime in order to achieve goals outside each component’s original scope. RI is capable of reusing controllers developed using traditional model-driven approach with new types of data-driven controllers such as neural networks. We motivate the approach using the following case study.

A. Motivating Example: F1/10 autonomous vehicle

We use as an example an F1/10 racing car that drives around a square track (Figure1). The car is controlled using a Multi-layer Perceptron (MLP) (a type of neural network) trained using LiDAR data to avoid crashing [8].

This original verified controller only manages the steering of the vehicle and is trained only to avoid collision with the

Figure 1. Autonomous F1/10 driving course
The overall system diagram for RI is depicted in Figure 4. Here, the RI Manager is an automatically generated component responsible for the interchange of the different controller

normal, where the car is driving as in the original case study [8], stopping, where the car must stop in reaction to an object on the track, and cautious, which is where the car needs to slow down either to follow the kinematics of a vehicle in front of it or in preparation for stopping for an object on the track.

Each of these modes will have groups of controllers that are specialised for their operation. For instance, we adopt the MLP steering controller from [8] as well as their “full throttle” speed controller for the normal mode. However, if a pedestrian walks onto the road, different controllers, such as a swerving heuristic as well as a linear braking model are adopted.

Controllers may be utilised by more than one group — for instance, the steering MLP is used in both the normal and cautious modes. In the following section we formalise how we can define the limits of these controllers, compose them, and safely switch between them at runtime.

A. Overview of Runtime Interchange (RI)

Inspired by synchronous programming languages [13], we consider compositions of CPS controllers (including ANNs) as modular black-box components which run in iterations called ticks. During each tick, the overall system first reads sensory input, then processes the inputs using one or more controllers, then finally emits outputs before restarting the loop.

Each of these controller components are structured into groups, and each group has a policy defining the situations where it may be used. For instance, the normal driving group composes the “Steering MLP” with a constant full throttle, whereas the stopping driving group combines the “Swerving Heuristic” and “Linear Braking” controllers. These groups are then associated with policies, defining when they may be used.

II. RUNTIME INTERCHANGE FOR INTELLIGENT CONTROLLERS

Three distinct modes are necessary to meet the runtime requirement changes in the F1/10 course in Figure 2 —

Figure 2. Other vehicles and pedestrians on the driving course

walls. However, real-world environments are often chaotic and unpredictable. Consider the case where a bystander unexpectedly walks onto the car’s track, or the case where a second car attempts to follow behind the first car. These are not a contingencies that the autonomous network was trained for, and as such it will not react appropriately, and the following car may crash into the leading car. We depict these two situations as Figure 2.

In these scenarios it is possible that the original MLP may still be suitable to control the steering of the autonomous cars, as it was designed to handle noisy data. However, additional functionality is required to control the throttle of the vehicle. Intuitively, if an obstacle is detected, the vehicle needs to apply brakes and slow down to avoid collision. Then, if the obstacle leaves, the vehicle can return to its original speed. In order to detect the obstacles, we can utilise the existing LiDAR, scanning for the minimum distance in the central 41.5 degrees of each scan, as represented in Figure 3.

This leads us to the main contributions of the paper. (1) We present a formal approach, called Runtime Interchange (RI), for combining pre-verified controllers developed using model-driven and data-driven approaches. RI significantly extends existing techniques based on runtime enforcement of reactive systems [11], [12], which deal only with single controllers. (2) We present a demonstration of our system, analysing scalability and overhead, and demonstrate the enforcement of timed policies to deal with runtime requirement changes for the first time (to the best of our knowledge).

The rest of the paper is organised as follows: § II introduces RI. § III then presents our methodology for automatically synthesizing our RI code. § IV presents benchmarking results. Finally, § V presents an overview of the related work in this area, and § VI concludes the paper.

II. RUNTIME INTERCHANGE FOR INTELLIGENT CONTROLLERS

Three distinct modes are necessary to meet the runtime requirement changes in the F1/10 course in Figure 2 —
groups at runtime. It does this based upon the aforementioned policies using controller suspension \([13]\), a technique adopted from synchronous languages. Suspension freezes a statefulcontroller’s state when it should not advance, for instance if it would receive data not suitable for it. In our case, the only controller that would need suspension is the “Distance PID”, as if it is not currently reading a distance to a car in front the internal state of the PID may become corrupt.

B. Preliminaries and Notations for Runtime Interchange

We consider Intelligent Cyber-Physical Systems to have finite ordered sets of valued input channels \(I = \{i_1, i_2, \ldots, i_n\}\) and valued output channels \(O = \{o_1, o_2, \ldots, o_n\}\). For a variable (resp. channel) \(\nu\), \(\mathcal{V}(\nu)\) denotes its domain, and for a finite ordered set of variables \(V = \{v_1, \ldots, v_n\}\), \(\mathcal{V}(V)\) is the product domain \(\mathcal{V}(v_1) \times \cdots \times \mathcal{V}(v_n)\).

Consider \(n \in \mathbb{N}\), \(\mathbb{B}_n\) denotes the domain of the finite ordered set of Boolean \(\{b_1, \ldots, b_n\}\). A valuation of the variables in \(V\) is a mapping \(\nu\) which maps every variable \(v \in V\) to a value \(\nu(v)\) in \(\mathcal{V}(v)\).

A finite (resp. infinite) word over \(\mathcal{V}_C\) (where \(C = I \cup O\)) is a finite sequence \(\sigma = \eta_1 \cdot \eta_2 \cdot \cdots \cdot \eta_n\) where \(\forall i \in [1, n] : \eta_i\) is a tuple of values of variables in \(C = I \cup O\). For convenience where necessary, each element \(\eta_i\) is considered to be a pair \((\eta_i, \eta_o)\), where \(\eta_1\) is a valuation of all the variables in \(I\), and \(\eta_o\) is a valuation of all the variables in \(O\). The set of finite (resp. infinite) words over \(\mathcal{V}_C\) is denoted by \(\mathcal{V}^*_C\) (resp. \(\mathcal{V}_C^\omega\)).

The length of a finite word \(\sigma\) is \(n\), denoted \(|\sigma|\). The empty word over \(\mathcal{V}_C\) is denoted by \(\varepsilon_C\), or \(\varepsilon\) when clear from the context. \(\mathcal{V}_C^+\) denotes \(\mathcal{V}_C^\omega \setminus \{\varepsilon\}\). The concatenation of two words \(\sigma\) and \(\sigma'\) is denoted by \(\sigma \cdot \sigma'\). A word \(\sigma'\) is a prefix of a word \(\sigma\), denoted as \(\sigma' \preceq \sigma\), whenever there exists a word \(\sigma''\) such that \(\sigma = \sigma' \cdot \sigma''\); conversely \(\sigma\) is said to be an extension of \(\sigma'\).

Given an input-output word \(\sigma = (x_1, y_1) \cdot (x_2, y_2) \cdots (x_n, y_n) \in \mathcal{V}_C^\omega\), the input word obtained from \(\sigma\) is \(\sigma_I\) where \(\sigma_I = x_1 \cdot x_2 \cdots x_n \in \mathcal{V}_I^\omega\) is the projection on inputs ignoring outputs. Similarly, the output word obtained from \(\sigma\) is \(\sigma_O\) where \(\sigma_O = y_1 \cdot y_2 \cdots y_n \in \mathcal{V}_O^\omega\) is the projection on outputs.

Given a word \(\sigma\) and \(i \in [1, |\sigma|]\), \(\sigma_i\) denotes the element at index \(i\) in \(\sigma\). Given a word \(\sigma\) and two integers \(i, j\) s.t. \(1 \leq i \leq j \leq |\sigma|\), the subword of \(\sigma\) from index \(i\) to \(j\) is denoted as \(\sigma_{[i..j]}\). Given an \(n\)-tuple of symbols \(e = (e_1, \ldots, e_n)\), for \(i \in [1, n]\), \(\pi_i(e) = e_i\) denotes the projection of \(e\) on its \(i\)-th element. The operator \(\pi_i\) is naturally extended to words of \(n\)-tuples of symbols to produce the word formed by the concatenation of the projections on the \(i\)-th element of each tuple.

In every tick, the RI manager first examines the input from the environment, and later the output from the controller. The overall output of the RI manager in every tick is an input-output event. We introduce function IO which is used to treat an input word \(\sigma_I \in \mathcal{V}_I^\omega\), and an output word \(\sigma_O \in \mathcal{V}_O^\omega\) as an input-output word in \((\mathcal{V}_I \times \mathcal{V}_O)^\ast\).

Function IO: Given an input word \(\sigma_I = x_1 \cdot x_2 \cdots x_n \in \mathcal{V}_I^\omega\) and an output word \(\sigma_O = y_1 \cdot y_2 \cdots y_n \in \mathcal{V}_O^\omega\) s.t. \(|\sigma_I| = |\sigma_O|\), \(\text{IO}(\sigma_I, \sigma_O) = (x_1, y_1) \cdot (x_2, y_2) \cdots (x_n, y_n)\).

A property \(\varphi\) over \(C\) defines a set \(L(\varphi) \subseteq \mathcal{V}_C^\omega\). A program \(\mathcal{P} \models \varphi\) iff \(L(\mathcal{P}) \subseteq L(\varphi)\). In this paper, properties are formally defined as VDTA.

C. Policy Specification

We adopt Valued Discrete Timed Automata (VDTA), a language for expressing policies over industrial and cyber-physical systems \([14]\). A VDTA can be seen as an automaton with a finite set of locations, a finite set of discrete clocks used to represent time evolution, and external input (resp. output channels) called “external variables” which are used for representing system data. They model the data from the monitored system (resp. environment) read from the input (resp.) channels in every tick. In a VDTA, time evolves synchronously: that is, the system executes as a series of discrete logical ticks where each tick takes exactly one transition \([13]\).

In the semantics of VDTA, each transition will be associated with values of external variables.

Example II.1. Let us consider the required behaviour for the RI system as depicted in Figure 2 for the autonomous vehicle. In order to safely move through the environment in Figure 2, this system describes three control groups (modes): normal, stopping, and cautious. Each of these modes will need an associated policy to describe when it should and should not be used. If one mode is active, and it becomes unsuitable for use, the system should automatically change to another mode.

Firstly, let us examine the normal mode. This represents the original control scheme from \([5]\), and is made from just the “Steering MLP” controller, with the acceleration control simply set to maximum at all times (taking the car to its maximum speed). This mode can be considered safe for use until an object is detected on the track in front of the vehicle. To test for this, we define a function min(R) which returns the minimum distance in the middle 41.5° of the LiDAR rays (e.g. Figure 3). If min(R) ever returns a distance less than or equal to 1.2 units, we say this is “unsafe”, and this group is no longer suitable for use. In addition, for it to become “safe” again, we require six consecutive readings where min(R) is greater than 1.2 units. This requirement prevents sensor noise accidentally changing our system from “unsafe” to “safe”.

We can encode these two rules as the VDTA policy \(\mathcal{A}_\text{norm}\) depicted in Figure 4a. Here, the policy begins in the “safe”, accepting location \(l_\text{drive}\), denoted as safe by its blue colour. While the policy remains in this location the policy is itself considered accepting, meaning that while it stays in this location, the associated controller group \(f_\text{norm}\) is accepting (i.e. suitable for use at this time).

The controller group may only stay in this location when the function min(R) returns a distance > 1.2. Should a reading ever be <= 1.2, meaning an object is within 1.2 units of the front of the car, the policy moves to the non-accepting \(l_\text{warn}\) location, denoted as non-accepting by its red colouring. While the policy remains in this location, the associated controller group f\text{norm} is considered non-accepting (i.e. unsuitable for use at this time). Note also the timer reset \(t := 0\) on the transition from \(l_\text{drive}\) to \(l_\text{warn}\). This sets a timer, \(t\), to zero.
There are three options for transitions in this location. Firstly, the distance \( \min(R) \) may continue to return \( \leq 1.2 \), which continues to cause timer \( x \) to reset and the location to stay set as \( l_{\text{warn}} \). Secondly, the distance \( \min(R) \) may return \( > 1.2 \), meaning that the system could be considered safe. However, if timer \( x \) is not \( \geq 6 \) the self loop transition will be taken, meaning that the policy continues to be considered non-accepting. The self loop transition, as it does not feature a timer reset, will advance the timer. Finally, if the distance \( \min(R) \) has returned \( > 1.2 \) six times in a row, the timer \( x \) will be \( \geq 6 \), and as such, the transition from \( l_{\text{warn}} \) back to \( l_{\text{drive}} \) may be taken, indicating that the normal mode may be considered accepting once more.

Let us now consider the interaction with other policies. The stopping mode policy is described in Figure 5b as \( A_{\text{stop}} \). This policy’s control group is the “Swerving Heuristic” paired with “Linear Braking”, are needed to safely bring the car to a complete halt. This policy describes the exact inverse of the normal policy. It says that if any reading \( \min(R) \) is less than 1.2, we move to the accepting location \( l_{\text{detect}} \) from non-accepting location \( l_{\text{absent}} \). Like with \( A_{\text{norm}} \), if this location observes six consecutive readings where the minimum distance is greater than 1.2 then the policy moves to the original location. This would render this policy non-accepting once more.

Intuitively, when \( A_{\text{norm}} \) is accepting, \( A_{\text{stop}} \) is non-accepting, and vice versa. This means that when one of these control modes is suitable for use, the other may be considered unsuitable. Should the normal mode be active, and a reading \( \min(R) \) be \( \leq 1.2 \), then the two policies will switch, and the RI Manager should select the outputs from the other control group.

Let us now consider the need for a third control mode.

While all situations are covered by the first two control modes, and even though is safe to do so in this environment, quality of service is degraded if the car must always come to a halt if any object is detected. We mitigate this with the cautious control mode \( A_{\text{caut}} \), which operates using the “Distance PID” controller to manage speed and the “Steering MLP” to manage steering of the vehicle. To quantify when this control group is suitable for use we must first define a function \( \text{kin}(\text{distance}, \text{speed}) \) which, given the distance to an object and the current speed of the vehicle returns the minimum safe deceleration to prevent the car crashing into that object. We now define the third mode as accepting when the distance \( \min(R) \) is between 1.2 and 0.6 units. If the distance reads lower than 0.6 units we must receive 6 consecutive readings where it is greater than 0.6 before returning to an accepting location. We also define that the third mode as non-accepting if it outputs an acceleration which is not safe according to function \( \text{kin}(\text{distance}, \text{speed}) \). Finally, as large distances have the potential to corrupt the internal state of the PID, we also define that should the distance to the next object \( \min(R) \) be greater than 1.2 units during operation, we do not allow for any return to operation. We encode these rules as the VDTA in Figure 5c. Note the “trap” location \( l_{\text{alone}} \), which has no pathways back to any accepting locations once it has been entered.

D. VDTA Syntax and Semantics

Let \( X = \{x_1, \ldots, x_k\} \) be a finite set of integer variables representing discrete clocks. A valuation for a clock variable \( x \) of \( X \) is an element of \( \mathbb{N} \), that is a function from \( x \) to \( \mathbb{N} \). The set of valuations for the set of clocks \( X \) is denoted by \( \chi \). For \( \chi \in \mathbb{N}^X, \chi + 1 \) (which captures the ticking of the digital clock) is the valuation assigning \( \chi(x) + 1 \) to each clock variable \( x \) of \( X \). Given a set of clock variables \( X' \subseteq X \), \( \chi[X' \leftarrow 0] \) is the valuation of clock variables \( \chi \) where all the clock variables in \( X' \) are assigned to 0.

**Definition II.2** (Syntax of VDTAs). An VDTA is a tuple \( \mathcal{A} = (L, l_0, F, X, I, O, \Delta) \) where:

- \( L \) is a finite non-empty set of locations, with \( l_0 \in L \) the initial location, and \( F \subseteq L \) the set of accepting locations;
- \( X \) is a finite set of discrete clocks;
- \( I \) is the set of input channels;
- \( O \) is the set of output channels;
- \( \Delta \) is a finite set of transitions, and each transition \( \tau \in \Delta \) is a tuple \( (l, G, A^X, l') \) also written \( l \xrightarrow{G, A^X} l' \) such that,
  - \( l, l' \in L \) are respectively the origin and target locations of the transition;
  - \( G = G^I \land G^O \) is the guard where
    - \( G^I = G^I \land G^O \) where
      - \( G^I \) is a computable predicate over inputs i.e., conjunction of constraints of the form \( f_1(l) \land f_2(l) \), where \( f_1 \) and \( f_2 \) are computable functions over input variables, and \( \in \{<,\leq,=,\geq,>,\neq\} \);
      - \( G^O \) is a computable predicate over inputs and outputs i.e., conjunction of constraints of the form

\( f_1(I \cup O) \nmid f_2(I \cup O) \), where \( f_1 \) and \( f_2 \) are computable functions over input and output variables (but requiring at least one of the output variables as an argument), and \( \varepsilon \in \{<,\leq,=,\geq,>,\neq\} \);

- \( G^\times \) is a clock constraint over \( X \) defined as conjunctions of constraints of the form \( x^t_c, x^f_c(I) \), \( x^t_f(I \cup O) \) where \( x \in X \) and \( c \in \chi \). \( f_1(I) \) is a computable predicate over input variables, \( f_2(I \cup O) \) (requiring at least one of the output variables as an argument) is a computable predicate over input and output variables, and \( \varepsilon \in \{<,\leq,=,\geq,>,\neq\} \);

\( A^\times \subseteq X \) is the set of clocks to be reset.

Example II.3. The VDTA \( A_{\text{norm}} \) for Figure 5a has a set of locations \( L = \{ l_{\text{drive}}, l_{\text{warn}} \} \), with accepting locations \( F = \{ l_{\text{drive}} \} \). \( l_{\text{drive}} \) is also the initial location. The VDTA has the set of input variables \( I = \{ R, v \} \) and the set of outputs \( O = \{ d, s \} \).

\( A_{\text{norm}} \) features one function, \( \min(R) \), introduced in Example II.2.

In an VDTA, a transition can have guards involving variables, clocks, and functions. For example, the transition from \( l_{\text{caution}} \) to \( l_{\text{drive}} \) happens when both \( \min(R) < 1.3 \) and the value of clock \( x > 2 \). This implies that there has been three consecutive readings where the minimum distance is greater than 1.3 units.

Clock values can be reset upon transitions. For example, upon transition from \( l_{\text{drive}} \) to \( l_{\text{caution}} \), the value of clock \( x \) is reset to 0.

1) Semantics for VDTA: Let \( A = (L, I_0, F, X, I, O, \Delta) \) be a VDTA. The semantics of \( A \) is a timed transition system, where a state consists of a location, and valuations of clocks \( X \). Each transition is associated with values of external variables in \( C \).

Definition II.4 (Semantics of VDTAs). The semantics of \( A \) is a timed transition system \( [A] = (Q, q_0, Q_F, \Gamma, \rightarrow) \), defined as follows:

- \( Q = L \times \mathbb{N}^X \) is the set of states of the form \( q = (l, \chi) \) where \( l \in L \) is a location, \( \chi \) is a valuation of clocks;

- \( Q_0 = \{(l_0, \chi_{X = 0})\} \) is the set of initial states;

- \( Q_F = F \times \mathbb{N}^X \) is the set of accepting states;

- \( \Gamma = \{ \eta \mid \eta \in \mathcal{D}_C \} \) is the set of transition labels;

- \( \rightarrow \subseteq Q \times \Gamma \times Q \) is the smallest set of transitions of the form \( (l, \chi) \rightarrow (l', \chi') \) such that \( \exists (l, G, A^\times, l') \in \Delta \), with \( G^\times \chi + 1, \eta \) and \( G^D \) evaluating to true, and \( \chi' = (\chi + 1)A^\times \cdot 0 \).

A run \( \rho \) of \( [A] \) from a state \( q \in Q \) over a trace \( w = q_1 \cdots q_{n-1} \eta \eta_n \eta_n \cdots \) is a sequence of moves in \( [A] \): \( \rho = q \xrightarrow{\eta} q_1 \cdots q_{n-1} \eta_n \eta_n \cdots \) for some \( n \in \mathbb{N} \). A run is accepted if it starts from the initial state \( q_0 \in Q \) and ends in an accepted state \( q_n \in Q_F \).

Definition II.5 (Deterministic (complete) VDTA). A VDTA \( A = (L, I_0, F, X, I, O, \Delta) \) with its semantics \( [A] \) is said to be a deterministic VDTA whenever for any location \( l \) and any two distinct transitions \( (l, g_1, A^\times, l') \in \Delta \) and \( (l, g_2, A^\times, l'_2) \in \Delta \) with same source \( l \), the conjunction of guards \( g_1 \land g_2 \) is unsatisfiable. \( A \) is complete whenever for any location \( l \in L \) the disjunction of the guards of the transitions leaving \( l \) evaluates to true.

E. Controller Component Suspension

While in the simple case all controller components would execute every tick, in reality not all controller designs are suitable to be executed over all possible inputs. Consider the policy in Figure 5c with the “trap” location \( l_{\text{alone}} \), representing the situation where the internal state of the “Distance PID” may have become corrupted by a reading of \( \min(R) \) being too large. This is a “trap” location as it is a non-accepting location with no possible path leading back to an accepting location.

Due to the presence of the “trap” location, we can detect that this scenario will occur should we present the large \( \min(R) \) input to the controller. As a result, instead of presenting the input, we instead suspend the associated policy and controller, freezing their state and preventing corruption. In other words, if a policy is guaranteed to advance to a trap location given the input to the RI network, we suspend operation of that policy and its associated controllers. Consequently, the trap location is never entered in any policy due to the associated suspension. This is further elaborated using Remark II.7.

To achieve this, we must compare inputs from the environment over control group policies in the absence of controller outputs. We thus need to consider the input property that we obtain from \( A_0 \) by projecting on inputs \( [12], [14] \).

Remark II.6 (Input VDTA \( A_i \)). Given a property defined as VDTA \( A = (L, I_0, F, X, I, O, \Delta) \), input VDTA \( A_i = (L, I_0, F, X, I, \Delta_i) \) is obtained from \( A \) by ignoring outputs channels on the transitions. The structure of the input automaton \( A_i \) that we obtain will be exactly identical to the automaton \( A \). For every transition \( t \in \Delta \) there will be a transition \( t' \in \Delta_i \) where \( t' = (l, G', A^\times, l') \) is obtained from \( t = (l, G, A^\times, l) \) (with \( G = G^D \land G^\times \) where \( G^D = G^D \land G^O \)), by discarding \( G^O \) in \( G^\times \) and discarding clock constraints in \( G^\times \) with the function on the right-hand side requiring an output channel as an input parameter. Input VDTAs may be non-deterministic.

Input VDTA \( A_i \) described in remark II.6 is a property of inputs (only) that we obtain from a VDTA \( A \) that expresses a property over both inputs and outputs. Once obtained, we can first compare an input value to the input VDTA for a given group. If that group would move into a “trap” location, i.e. a location which guarantees non-acceptance forever, we suspend the controllers associated with this group and we do not update the policy this tick. This process is discussed further in the next section.

Remark II.7. As discussed, controller groups are suspended if an input would advance it to a trap location. Here we describe the mechanims for this. Let \( \varphi_i \) be the policy (defined as \( A_{\varphi_i} \)) corresponding to the controller group \( i \). Let \( x \in D_i \) denote the input in a particular tick.

- If the controller group \( i \) will not be suspended in that particular tick, the state of the policy \( A_{\varphi_i} \) will be updated by consuming the event \((x, y) \in D_{CE} \) where \( y \) is the output produced by that controller group in that tick.
• If the controller group \( i \) will be suspended in a given tick, for the updation of the policy \( \mathcal{A}_\phi \), w.r.t. the input \( x \in \mathcal{D}_I \) that is observed in that tick, the output of the controller group \( i \) in that tick is considered to be invalid/empty (denoted as \( \bot \)). For every location in \( \mathcal{A}_\phi \), for all \( x \in \mathcal{D}_I \) we consider implicit self transitions with event \((x, \bot)\), allowing the policy to remain in the same location when the controller group is suspended.

Thus, the output domain \( \mathcal{D}_O \) will be considered as \( \mathcal{D}_O \cup \{\bot\} \). An example of this is presented in Figure 6. If the policy is in location \( l_{pad} \), and \( \min(R) > 1.2 \), then the RI Manager emits \( \bot \) for this policy and suspends the associated “Distance PID” controller. As a result, the self loop \( l_{pad} \) is taken instead of advancing to location \( l_{alone} \).

![Figure 6. Suspendable policy for cautious group \( \mathcal{A}_{\text{caut}} \)](image)

### III. RI MANAGER SYNTHESIS

#### A. Problem Definition

We consider the system (controller) as a grey-box, since the RI Manager takes into account the number of controller groups present within the controller, though the internals of each controller is considered to be unknown. The context of the RI Manager is illustrated in Figure 7. For the synthesis of the RI Manager, the user (designer) provides a set of policies, one policy per controller group defined as VDTA.

Given a set of policies denoted as \( \mathcal{P}_\phi = \{\phi_1, \ldots, \phi_n\} \) where \( n \) is the number of controller groups, \( \forall i \in 1 \ldots n : \phi_i \subseteq \mathcal{D}_C \) is the policy corresponding to controller group \( i \).

![Figure 7. Context of RI Manager](image)

It every reaction (tick), the input-output to the RI Manager is a pair \((x, (y_1, \ldots, y_n))\), where \( x \in \mathcal{D}_I \) is the input and \((y_1, \ldots, y_n) \in \mathcal{D}_O \times \mathcal{D}_O \times \ldots \times \mathcal{D}_O \) is an ordered \( n \)-tuple where \( y_i \in \mathcal{D}_O \) is the output from controller group \( i \). Upon consuming an event \((x, (y_1, \ldots, y_n))\) as input, the RI Manager produces an input-output event \((x, y_i) \in \mathcal{D}_C\) as output, where \( y_i \in \{y_1, \ldots, y_n\} \) and \( y_i \neq \bot \).

In every tick, the RI Manager first processes the input \( x \) (i.e., input from the environment), then forwards both this input and an \( n \)-tuple of Boolean values (one Boolean value per controller group) indicating to the controller groups which groups should be executed in that tick and which should be suspended.

After the controller groups have finished, it then receives their \( n \)-tuple of outputs \((y_1, \ldots, y_n)\) where \( y_i \in \mathcal{D}_O \cup \{\bot\} \), where \( y_i \) corresponds to the output produced by controller group \( i \). The symbol \( \bot \) is used to denote invalid output (used when a controller group is suspended and will not produce any output in a particular tick). The RI Manager finally selects one output \( y_i \) from \((y_1, \ldots, y_n)\), and the final input-output event from the RI manager in a tick is \((x, y_i) \in \mathcal{D}_C\).

**Definition III.1** (RI Manager for \( \mathcal{P}_\phi = \{\phi_1, \ldots, \phi_n\} \)). Given a set of policies \( \mathcal{P}_\phi = \{\phi_1, \ldots, \phi_n\} \), where \( \phi_i \subseteq \mathcal{D}_C \), an RI manager for \( \mathcal{P}_\phi \) is a function \( M : (\mathcal{D}_I \times (\mathcal{D}_O \times \mathcal{D}_O \times \ldots \times \mathcal{D}_O))^* \rightarrow (\mathcal{D}_I \times \mathcal{D}_O)^* \) satisfying the following constraints

**Soundness**

\[ \forall \sigma \in (\mathcal{D}_I \times (\mathcal{D}_O \times \mathcal{D}_O \times \ldots \times \mathcal{D}_O))^*, \exists w \in (\mathcal{D}_I \times \mathcal{D}_O)^*, \exists i \in [1, n] : |w| = |M(\sigma)| - 1 \land \pi_1(\sigma|_{[\cdot, \cdot, \cdot, \cdot, i]} \land \pi_2(\sigma|M(\sigma)|) \neq \bot \land w \cdot M(\sigma|M(\sigma)|) \in \mathcal{P}_\phi. \]  

(Snd)

**Monotonicity**

\[ \forall \sigma, \sigma' \in (\mathcal{D}_I \times (\mathcal{D}_O \times \mathcal{D}_O \times \ldots \times \mathcal{D}_O))^* : \sigma \leq \sigma' \Rightarrow M(\sigma) \leq M(\sigma'). \]  

(Mono)

**Instantaneity**

\[ \forall \sigma \in (\mathcal{D}_I \times (\mathcal{D}_O \times \mathcal{D}_O \times \ldots \times \mathcal{D}_O))^* : |\sigma| = |M(\sigma)|. \]  

(Inst)

**Causality**

\[ \forall x \in \mathcal{D}_I, \forall (y_1, \ldots, y_n) \in (\mathcal{D}_O \times \mathcal{D}_O \times \ldots \times \mathcal{D}_O) : \exists i \in [1, n] : \mathcal{C}_i \cdot x \in \mathcal{P}_\phi \land y_i \neq \bot \land I(\mathcal{C}_i, \mathcal{P}_\phi) \cdot (x, y_i) = \phi_i. \]  

(Ca)

\( a) \text{ Soundness:} \) This constraint demands that the output released in each tick should be sound w.r.t. one of the policies, and the policy that is satisfied by the final output of the RI manager in each tick may be different (permitting interchanging the controller groups).

(Snd): For any input word \( \sigma \), the output of the RI Manager is \( M(\sigma) \), and the last event in the output is \( M(\sigma)|_{[M(\sigma)]} \).

The output in the input-output event \( M(\sigma)|_{[M(\sigma)]} \) should not be \( \bot \) (i.e., \( \pi_2(M(\sigma)|_{[M(\sigma)]}) \neq \bot \)).

The last event that is released as output \( M(\sigma)|_{[M(\sigma)]} \) should be sound w.r.t. one of the policies \( i \in [1, n] \). Let \( w \in (\mathcal{D}_I \times \mathcal{D}_O)^* \) denote the input-output of controller group \( i \) in the previous ticks.

- The length of \( w \) should be \( |M(\sigma)| - 1 \).
- The inputs in \( w \) should match with the inputs in \( \sigma \) (i.e., \( \pi_1(\sigma|_{[\cdot, \cdot, \cdot, \cdot, i]} = \pi_1(w) \)). In the previous ticks, the outputs in \( w \) may be different from the outputs in \( M(\sigma) \) because

1Note that the output domain of each controller group is \( \mathcal{D}_O \) (i.e., \( \forall i \in [1, n], \mathcal{D}_O \subseteq \mathcal{D}_O \)).
the outputs in $M(\sigma)$ may be sound w.r.t policy different from $i$ in the previous ticks.

- The word that is obtained by concatenating $w$ with the last event that is released as output should satisfy policy $\varphi_i$ (i.e., $w \cdot M(\sigma)|_{M(\sigma)} \in \varphi_i$).

b) Monotonicity: The monotonicity constraint expresses that what is already released as output by the RI manager cannot undone. \textbf{(Mono)} defines that the output of the RI manager for an extended input word $\sigma'$ of an input word $\sigma$, extends the output produced by the RI manager for $\sigma$.

c) Instantaneity: The instantaneity constraint means that the RI manager cannot suppress, delay and insert events. \textbf{[Inst]} expresses that for any given input sequence $\sigma$, the output of the RI manager $M(\sigma)$ should contain exactly the same number of events that are in $\sigma$ (i.e., $|\sigma| = |M(\sigma)|$). This means that, in every tick, RI manager receives a new event, and it must react instantaneously and produce an output event immediately. This requirement is essential for CPSs, which are reactive in nature.

d) Causality: \textbf{[Ca]} expresses that for every new event $(x, (y_1, \ldots, y_n))$ the RI manager first processes the input part $x$, to produce Boolean signals which will be sent to the controller along with the input $x$ indicating the controller regarding which controller groups have to be executed. There should be at least one non-suspended controller group policy $i \in [1, n]$, such that the input word obtained by concatenating the new input event $x$ to $\sigma_i$ (previous input) will satisfy the input property corresponding to policy $\varphi_i$. Moreover, the output produced by controller group $i$ should not be $\perp$ (controller group should not be suspended), and the input-output word of the controller group $i$ for $\sigma$ (which is $IO(\sigma_i, \sigma_O(i))$) followed by $(x, y_i)$ (which is the new input-output of controller group $i$) should satisfy the policy $\varphi_i$.

B. Functional Definition

We now provide a definition of a RI Manager for a given set of policies $\varphi_S = \{\varphi_1, \ldots, \varphi_n\}$.

**Definition III.2 (RI Manager Function).** Given a set of properties $\varphi_S = \{\varphi_1, \ldots, \varphi_n\}$, where $\varphi_i \in D_\varphi$ defined as VDTA $A_\varphi$, the RI Manager function $M : (D_I^x \times (D_{O1} \times \cdots \times D_{On}))^* \rightarrow (D_I \times D_O)^*$ is defined as:

$$M(\sigma_i, (\sigma_{O1}, \ldots, \sigma_{On})) = \gamma(\kappa(\sigma_i), (\sigma_{O1}, \ldots, \sigma_{On}))$$

where $\kappa : D_I^x \rightarrow (D_I \times D_B)^*$ is defined as:

$$\kappa(\epsilon_{D_I^y}) = (\epsilon_{D_I^y}, \epsilon_{D_B^x})$$

$$\kappa(\sigma_i \cdot x) = \begin{cases} \kappa(\sigma_i) \cdot (x, (b_1, \ldots, b_n)) & \text{s.t. } \forall i \in [1, n] : ((b_i == true) \Rightarrow (\exists \sigma' \in D_I^y : \sigma_i \cdot x \cdot \sigma' \in \varphi_i)) \end{cases}$$

$\gamma : (D_I \times D_B)^* \times (D_{O1} \times \cdots \times D_{On})^* \rightarrow (D_I \times D_O)^*$ is defined as:

$$\gamma((\epsilon_I, \epsilon_{D_B^x}), (\epsilon_{O1}, \ldots, \epsilon_{On})) = (\epsilon_I, \epsilon_O)$$

$$\gamma(\sigma_{IB} \cdot (x, (b_1, \ldots, b_n)), \sigma_O \cdot (y_1, \ldots, y_n)) = \gamma(\sigma_{IB}, \sigma_O) \cdot (x, y_i)$$

s.t. $b_i == true \land y_i \neq \perp \land IO(\pi_1(\sigma_{IB}), \pi_i(\sigma_O)) \cdot (x, y_i) \in \varphi_i$.

Let us understand Definition III.2 further. Function $M$ (RI Manager) takes a word over $(D_I \times (D_{O1} \times \cdots \times D_{On}))^*$ and returns a word over $(D_I \times D_O)^*$ as output. Here $\sigma_i \in D_I^y$, and $\forall i \in \mathbb{N} : \sigma_{oi} \in D_O \cup \{\perp\}$.

Function $M$ is defined as a composition of two functions $\kappa$ and $\gamma$, where the function $\kappa$ is to check each policy w.r.t. the input received from the environment and to indicate the controller of which controller groups have to be executed. Function $\gamma$ takes the output from all the controller groups and selects one among them to be forwarded to the environment as the final output of the RI system.

a) Function $\kappa$: Function $\kappa$ takes a word $\sigma_i \in D_I^y$ as input and returns a word in $(\Sigma_\ell \times \mathbb{B}_n)^*$ as output. Function $\kappa$ is defined inductively. It returns $(\epsilon_{D_I^y}, \epsilon_{D_B^x})$ when the input $\sigma_i = \epsilon_{D_I^y}$. If $\sigma_i$ is read as input $\gamma(\sigma_i)$ is returned as output, and when another new input $x \in D_I$ is observed, a new event $(x, (b_1, \ldots, b_n))$ will be appended to the output of the function $\gamma$ where, $b_i$ corresponding to policy $i$ will be true if the input word $\sigma_i \cdot x$ can be extended to a word that will satisfy the input property corresponding to $\varphi_i$, and will be false otherwise.

When the controller receives the event $(x, (b_1, \ldots, b_n))$, controller group $i$ will be executing only if the Boolean signal $b_i$ will be true, and will be suspended if $b_i$ is false.

b) Function $\gamma$: Function $\gamma$ takes an input word belonging to $(D_I \times \mathbb{B}_n)^*$ and an output word belonging to $(D_{O1} \times \cdots \times D_{On})^*$ as input, and it returns an input-output word belonging to $(D_I \times D_O)^*$ which is a sequence of tuples, where each event contains an input and an output. $\sigma_{IB}$ is used to denote a word belonging to $(D_I \times \mathbb{B}_n)^*$.

For a given input word $\sigma_i \in D_I^y$, the input word fed as input to $\gamma$ is the output of function $\kappa$ (i.e., $\kappa(\sigma_i)$).

Function $\gamma$ is defined inductively. When both input and output words are empty, the output of $\gamma$ is $\epsilon$. If $\sigma_{IB} \in (D_I \times \mathbb{B}_n)^*$, and $\sigma_O \in (D_{O1} \times \cdots \times D_{On})^*$ is read as input, its output will be $\gamma(\sigma_{IB}, \sigma_O)$, and when another new input event $(x, (b_1, \ldots, b_n))$ and output event $(y_1, \ldots, y_n)$ is observed, the output of function $\gamma$ will be appended with a new event $(x, y_i)$ where

- $b_i$ is true and
- $y_i \in (y_1, \ldots, y_n)$ is a valid output (i.e., output different from $\perp$), and
- the input-output word obtained from $\pi_1(\sigma_{IB})$ and $\pi_i(\sigma_O)$ (i.e., $IO(\pi_1(\sigma_{IB}), \pi_i(\sigma_O))$) followed by the event $(x, y_i)$ will satisfy the policy $\varphi_i$.

**Proposition 1.** Given a set of properties $\varphi_S = \{\varphi_1, \ldots, \varphi_n\}$, if an RI manager as per Definition III.2 exists for $\varphi_S$, then its RI manager function $M$ as per Definition III.2 satisfies the Soundness, Monotonicity, Instantaneity and Causality constraints as per Definition III.7.

Note that an RI Manager does not modify the outputs of the controller groups. So, the existence of an RI Manager for a given set of policies depends on the presence of statically verified controller groups (i.e., each group individually satisfies its policies). Given such policies and controller groups,
an RI Manager will exist. The synthesized RI Manager allows the system to dynamically switch among a set of controller groups based on the situation/observed input.

C. Algorithm

In Section III-B we provided an abstract view of our RI Manager defining it as a function $M$. For a given set of policies $\varphi_S = \{\varphi_1, \cdots, \varphi_n\}$, this function $M$ is defined as a composition of two functions, $\kappa$ and $\gamma$, where function $\kappa$ examines the input from the environment and decides which controller groups should be suspended, and function $\gamma$ examines outputs from all the controller groups, and checks if they are acceptable w.r.t. their corresponding policies, finally emitting one output amongst those that were acceptable as the final output to the environment.

In this section we provide an online algorithmic view of our RI Manager defined in Section III-B, which further illustrates how functions $\kappa$ and $\gamma$ and the overall enforcement function $M$ are implemented.

The algorithm requires a set of policies $\varphi_S = \{\varphi_1, \cdots, \varphi_n\}$, (where each policy $i \in [1, n]$ is formally defined as a VDTA $A_{\varphi_i} = (Q, \delta, \Gamma, I, O, \delta, \Gamma)$) with semantics $[A_{\varphi_i}] = (Q, q_0, Q, \Gamma, \rightarrow)$ as input. Let us recall that for any given property $\varphi_i$ defined as VDTA $A_{\varphi_i}$, the input automaton corresponding to $A_{\varphi_i}$ (denoted as $A_i$) is obtained from $A$ by projecting on inputs.

**Algorithm 1 RI Manager for $\varphi_S = \{\varphi_1, \cdots, \varphi_n\}$**

1: $t \leftarrow 0$
2: for all $i \in [1, n]$ do
3: $A_{\varphi_i} \xleftarrow{} A_{\varphi_i} \cdot q_0$
4: end for
5: while true do
6: $\eta_t \leftarrow \text{read\_in\_chan}()$
7: for all $i \in [1, n]$ do
8: $b_i \leftarrow (\exists q_f' \in Q_f. \exists \sigma' \in D_f' \Leftarrow A_{\varphi_i} (\eta_{o_t} \sigma' \rightarrow A_{\varphi_i} q_f'))$
9: end for
10: call\_controllers($\eta_t, (b_1, \cdots, b_n)$)
11: $(\eta_{o_{t+1}}, \cdots, \eta_{o_{t+1}}) \leftarrow \text{read\_out\_chan}()$
12: for all $i \in [1, n]$ do
13: $b'_i \leftarrow (b_i \land \exists q_f' \in Q_f \Leftarrow A_{\varphi_i} (\eta_{o_{t+1}} \rightarrow A_{\varphi_i} q_f'))$
14: end for
15: $\eta_{o_t} \leftarrow \text{sel} - \text{NonDet}((b'_1, \cdots, b'_n), (\eta_{o_{t+1}}, \cdots, \eta_{o_{t+1}}))$
16: release((\eta_t, \eta_{o_t}))
17: for all $i \in [1, n]$ do
18: $A_{\varphi_i} q_t \xleftarrow{} A_{\varphi_i} q'_f$ where $A_{\varphi_i} q_t (\eta_{o_t} \rightarrow A_{\varphi_i} q'_f)$
19: end for
20: $t \leftarrow t + 1$
21: end while

Algorithm 1 is an infinite loop, and an iteration of the algorithm is triggered at every time step. We join this algorithm to the controller groups through a reactive interface. The runtime algorithm passes data to and from the controller by calling the function call\_controller($\eta_{o_t}, (b_1, \cdots, b_n)$). Here, $\eta_{o_t}$ is the observed input, and $\forall i \in [1, n], b_i$ is a Boolean which indicates the controller group $i$ should be executed with input $\eta_{o_t}$ if $b_i$ is true, and should be suspended otherwise.

In Algorithm 1, $t$ keeps track of the time-step (i.e., tick), and is initialized at 0. For every controller group $i \in [1, n]$, $A_{\varphi_i} \cdot q$ keeps track of the state of its policy $\varphi_i$ (i.e., state of both automata $A_{\varphi_i}$ and $A_{\varphi_i}$). Note that $q$ contains information about the current location $l$, the current valuations of internal variables $v$, and the current valuations of the clocks $\chi$. Lines 2 to 3 deals with initializing the state of each policy $A_{\varphi_i}$.

Functions read\_in\_chan() and read\_out\_chan() read the input and output channels respectively, and release() takes an input-output event and emits it from the RI system. Function $\kappa$ in Definition III.2 (which decides which controller groups have to be executed in a tick w.r.t. the observed input) corresponds with lines 7 to 9 in Algorithm 1. For each controller group $i \in [1, n]$, a Boolean value $b_i$ is computed, which will be true if it is possible to reach an accepting state in the input automaton now or in the future (corresponding to $\varphi_i$ from the state reached from its current state upon the observed input event $\eta_{o_t}$).

Function $\gamma$ in Definition III.2 corresponds to lines 12 to 15 in Algorithm 1. The for-loop (lines 13 to 14) computes a Boolean $b'_i$ for each controller group $i$, where $b'_i$ will be true if the controller group $i$ is not suspended and if it is possible to reach an accepting state $q'_f$ from the current state $q$ in $A_{\varphi_i}$ upon the event $(\eta_{o_t}, \eta_{o_{t+1}})$ where $\eta_{o_t}$ is the observed input and $\eta_{o_{t+1}}$ is the output produced by controller group $i$.

Function sel – NonDet() takes an n-tuple of Boolean signals and an n-tuple of outputs, and non-deterministically selects one output at some index $i \in [1, n]$ for which the corresponding value in the n-tuple of Boolean signals at index $i$ is true.

Finally, the current state of each policy is updated (using the input observed and the output produced by the controller group) before proceeding with the next tick (lines 17 to 19).

IV. RESULTS

To evaluate the efficacy of the RI framework we analyse the performance of the F1/10 case study introduced in Section I-A with the controller and manager network depicted in Figure 2. We first measured the crash rate of the original Steering MLP from [8] in the original setting, i.e. a single car driving around an empty course. We then extend the environment, adding pedestrians that may randomly appear on the track at any time, and measure the new crash rate. Finally we add a second and third car, introduced 15 and 30 time units after the first car respectively, and performed measurements again. The averaged values across 1,000 trials for each setting are presented in Table I (where multiple cars are in a setting, the crash rate is the average of all cars across all trials).

As expected, the original MLP is not suitable for control of the autonomous F1/10 in this new environment, with a very high crash rate with the random pedestrians. We then combine the original Steering MLP with our own custom controllers (the Swerving Heuristic, the Linear Braking model, and the Follower PID) according to the policies laid out in Section I and synthesise a RI Manager according to the methodology in Section III. For implementation purposes, we compile the control network to C. We then run these modified vehicles in...
these same environments, again for 1,000 trials per scenario, and present our results in Table II.

Table II

| No. Cars | No. Peds | Normal Mode Change Rate | Stopping Mode Change Rate | Cautious Mode Change Rate | Crash Rate |
|----------|----------|-------------------------|---------------------------|--------------------------|------------|
| 1        | 0        | 0.8 %                   | 0.8 %                     | 0.8 %                    | 0.6 %      |
| 1        | 1        | 8 %                     | 1.5 %                     | 1.5 %                    | 0.6 %      |
| 2        | 0        | 0.8 %                   | 0.8 %                     | 0.8 %                    | 0.8 %      |
| 2        | 1        | 1.5 %                   | 1.5 %                     | 1.5 %                    | 0.6 %      |
| 3        | 2        | 1.5 %                   | 1.5 %                     | 1.5 %                    | 0.6 %      |

Firstly, we note that the RI controllers are orders of magnitude safer than the original controllers in the chaotic environment. No accidents were recorded for the 1- or 2-car scenarios, and while accidents were recorded for the 3-car 2-pedestrian situation, these were rare, and upon examination were caused by pedestrians colliding with the cars the majority of the time. That said, given that some crashes were caused by the cars, this environment is too 'busy' for the controllers as designed in Figure 4 and further controllers with additional policies are required for ensuring safety under all circumstances (except when pedestrians hit cars intentionally).

Table II also presents the time the RI manager selected each mode. Given no pedestrians, the cars remained in normal, and used the pure control scheme, giving the same performance as the pure results in Table I (i.e. no crashes). Once we add pedestrians, the cars begin switching modes. The normal mode remains active most of the time, but the cautious mode, where cars will slow down according to the “Distance PID”, is also selected for use up to 16 % of the time. Finally, the stopping mode, which brings the cars to a complete halt, is active up to 3 % of the time. These controller mode selection ratios largely track one another from scenario to scenario given the same number of pedestrians. This is because it is most common for the leading car to detect a pedestrian and change mode/slow down, which then causes any following cars to also change mode and slow down. It is only in rare cases where the leading car(s) are able to avoid a pedestrian without stopping (e.g. via swerving) leaving follower car(s) to stop without the leader.

Finally, in Table II the Change Rate column refers to the percentage of operation cycles that resulted in a mode change from one mode to another. As can be seen, mode changes are relatively uncommon, happening only in up to 1.6 % of cycles, meaning that operation according to the policies laid out in Figure 5 is largely stable.

A. Overhead of RI

To examine the overhead of our approach, we measured the execution in CPU cycles (using C's `time.h`) of the RI Manager code compared to the combined execution cycles of the controller components. We averaged this across all execution scenarios across all sets of 1,000 trials, and found an average introduced overhead of 2.2 %.

B. Scalability of RI

Given that Algorithm 1 has operations structured over four “for” loops which iterate over the set of policies, the algorithm will scale in O(n) time where n is the number of policies. To verify this we modify the implementation of the RI manager to feature 1 \times 10^5, 2 \times 10^5, 3 \times 10^5, and 4 \times 10^5 copies of the three policies, and repeat the 1 car 1 pedestrian experiment. Compared to 1 \times 10^5, 2 \times 10^5 executed 2.4 times slower; 3 \times 10^5 executed 3.3 times slower; and 4 \times 10^5 executed 4.0 times slower, confirming the O(n) nature of the RI system.

V. RELATED WORK

With the advent of autonomous systems, which may be classed as intelligent CPS [11], there is a need to consider alternative design approaches that are amenable to both model-driven and data-driven techniques [2, 3]. The challenges posed by such systems include the need for ensuring safe operation of the system at all times, including when the environment is non-static. There has been a recent resurgence of research efforts based on formal methods (which are especially suited to model-driven development) being combined with data-driven approaches such as neural networks [5]. Some approaches have suggested encoding networks which are themselves adaptable to their environment (e.g. using Petri Nets [3]). In the adaptive Petri Net model proposed, in [3], adaptation in the model is achieved by considering special transitions with neural network algorithms, and the approach also requires modeling the environment. Likewise [15] demonstrates using a single neural network for adaptive fault-tolerant control of a model helicopter. Other approaches consider static verification, where there has been considerable progress [6]. However, scalability remains a concern when considering extremely complex autonomous systems [3]. Hence, runtime based formal solutions are getting recent research traction [11].

Several formally based runtime enforcement approaches have been proposed [16–19], which are not suitable for autonomous systems as they are reactive in nature. Our work is related to the class of runtime enforcement techniques that are suitable for reactive systems [12, 20, 21]. These rely on low-overhead wrappers, which mediate between the environment and the controller of a reactive system, to ensure that the system operates safely at all times by ensuring that all user specified policies hold. Whenever the input and output of the system lead to non-compliance, the enforcer alters the input / output streams appropriately. Early enforcers for reactive systems [20] were uni-directional. More recently, bi-directional enforcement has been developed for both industrial processes [14] and medical devices [12]. Such enforcers have also been used to enforce timed policies over autonomous
systems [11]. However, the approach of runtime enforcement is not directly applicable in our setting as run-time adaptation to requirement changes is needed [9].

Our work being based on the re-use of several pre-designed and pre-verified controllers is similar in spirit to interface theories [22]. These are inspired by assume-guarantee reasoning for studying component compatibility in a formal setting. In [22] components are state-less and their interfaces describe the assumptions on the inputs and the associated guarantees on the output. These have been extended to synchronous components (which are stateful) in [23]. While these provide a formal framework for component-based system design, the interconnection between components is static, unlike in our setting, where we can dynamically create different configurations of the controllers to meet changing requirements.

Our work is likewise similar in spirit to that provided via control barrier functions [24], which seek to provide a method to synthesize safe controllers directly. However, control barrier functions differ significantly from RI, as they require open models (as opposed to our own black box compositions) and synthesize a single controller (as opposed to our manager that chooses between available controllers).

VI. CONCLUSIONS

There is recent research momentum in the direction of safe and adaptive autonomy [7], [9], including in designing the experimental F1/10 racing car [8]. While model-checking can be used to ensure that the racing car operates safely in a static environment, for safe autonomy to be practicable, we need to also consider uncertainties in the environment. In other words, autonomous systems need to be adaptive, able to cope with requirement changes. For this purpose we propose a method called Runtime Interchange (RI). We envision the requirements to be encoded as a set of control modes and we propose an approach to automatically synthesise a RI Manager, which switches between a set of controllers to keep the system safe at all times. Our approach is demonstrated to have low overheads and linear scalability. Our work is similar in spirit to recent work on the use of runtime enforcers with drones [11] which aim to keep a drone within a safe operating range. However, unlike their work, we are able to dynamically choose between multiple controllers.

While our work is towards safe autonomy, it is not devoid of limitations. First, we have to know all operating modes of the environment a-priori. What happens when a new mode is encountered, which was never seen before? Second, can we perform incremental design i.e. when new policies are introduced, could we use the old RI Manager with a new RI Manager? These are open problems still to pursue.

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