Unifying Model-based and Reactive Programming within a Model-based Executive

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Abstract
Real-time, model-based, deduction has recently emerged as a vital component in AI's tool box for developing highly autonomous reactive systems. Yet one of the current hurdles towards developing model-based reactive systems is the number of methods simultaneously employed, and their corresponding melange of programming and modeling languages. This paper offers an important step towards unification. We introduce RMPL, a rich modeling language that combines probabilistic, constraint-based modeling with reactive programming constructs, while offering a simple semantics in terms of hidden state Markov processes. We introduce probabilistic, hierarchical constraint automata (PHCA), which allow Markov processes to be expressed in a compact representation that preserves the modularity of RMPL programs. Finally, a model-based executive, called Reactive Burton is described that exploits this compact encoding to perform efficient simulation, belief state update and control sequence generation.

Introduction
Highly autonomous systems, such as NASA's Deep Space One spacecraft (Muscettola et al. 1999) and Rover prototypes, are being deployed that leverage many of the fruits of AI's work on automated reasoning - planning and scheduling, task decomposition execution, model-based reasoning and constraint satisfaction. Yet a likely show stopper to widely deploying this level of autonomy is the myriad of AI modeling languages employed, coupled to the programming and specification languages used to implement and verify the real-time system.

This paper concentrates on the part of this challenge that lies at the reactive layer - robotic execution, model-based monitoring and reactive programming. Key to this challenge is the development of a unified language that can express a rich set of mixed hardware and software behaviors (Reactive Model-based Programming Language - RMPL), a compact encoding of the underlying Markov process (hierarchical constraint automata - HCA), and an executive for this encoding that supports efficient state estimation, monitoring and control generation (Reactive Burton).

Reactive MPL achieves expressivity at both the software and hardware levels by merging key ideas from synchronous programming languages, qualitative modeling and Markov decision processes. Synchronous programming offers a class of languages (Halbwachs 1993) developed for writing control programs for reactive systems (Harel & Pnueli 1985; Berry 1989) — logical concurrency, preemption and executable specifications. Qualitative modeling and Markov decision processes together offer a rich language for describing continuous process and uncertainty.

Reactive Burton achieves efficient execution through a careful generalization of state enumeration algorithms that are successfully employed by the Sherlock (de Kleer & Williams 1989) and Livingstone (Williams & Nayak 1996) systems on simpler modeling languages.

We start with a sketch of R. Burton, set in the context of other work on robotic execution and reactive programming. The first half of the paper then introduces hierarchical constraint automata, their deterministic execution, and their expression using Reactive MPL. The direct mapping from RMPL combinators to HCA, coupled with HCA's hierarchical representation avoids the state explosion problem that frequently occurs while compiling large reactive programs.

The second half of the paper turns to model-based execution under uncertainty. First we generalize HCAs to a factored representation of partially observable Markov decision processes (POMDPs) with limited rewards. We then develop RBurton's stochastic monitoring and execution capabilities, while leveraging off the compact encoding offered by probabilistic HCA. Finally, we demonstrate RMPL on a simplified version of a navigation maneuver performed within the Remote Agent Autonomous Spacecraft Experiment. The paper concludes with an additional discussion of related work.

The Reactive Burton Executive
The robotic execution task consists of controlling a physical plant according to a stream of high-level commands (goals), in the face of unexpected behavior from the system. To accomplish this the executive controls...
some variables of the plant, and senses the values of
some sensors to determine the hidden state of the plant.

A schematic of Reactive Burton is shown below. The
physical testbeds being used to demonstrate aspects of
RBurton’s capabilities include a deep space probe en-
route to an asteroid, a Russian rover, a deep space interfer-
omete, r and a chemical plant that generates rocket fuel from the atmosphere.

<table>
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RBurton consists of two main components. The
state estimation module determines the current most
likely states of the plant from observed behavior using
a plant model. This generalizes mode identification
(MI), (Williams & Nayak 1996). The key difference is
the expressiveness of the modeling languages employed.
Reactive MPL allows a rich set of embedded software
behaviors to be modeled, hence RBurton’s state esti-

mator offers a powerful tool for monitoring mixed
software/hardware systems.

RBurton’s control sequencer executes a program for
controlling the plant that is also specified using RMPL.
Actions are conditioned on external goals and proper-
ties of the plant’s current most likely state. Given mul-
tiple feasible options, RBurton selects the course of ac-
tion that maximizes immediate reward. As a control
language RMPL offers the expressiveness of reactive
languages like Esterel(Berry & Gonthier 1992), along
with many of the goal-directed task decomposition and
monitoring capabilities supported by robotic execution
languages like RAPS(Firby 1995), TCA(Simmons 1994)
and ESL(Gat 1996).

What is particularly key is the fact that the plant
model used for reasoning and the control program used
for execution are written in the same language.

Hierarchic Constraint Automata
RMPL programs may be viewed as specifications of
POMDPs, that is probabilistic automata with partial
observability and rewards. While POMDPs offer a nat-
ural way of thinking about reactive systems, as a direct
encoding they are notoriously intractable. To develop
an expressive, yet compact encoding we introduce five
key attributes. First, transitions are probabilistic, with
associated costs. Second, the POMDP is factored into
a set of concurrently operating automata. Third, each
state is labeled with a constraint that holds whenever
the automaton marks that state. This allows an ef-
ficient, intentional encoding of co-temporal processes,
such as fluid flows. Fourth, automata are arranged in a
hierarchy – the state of an automaton may itself be an
automaton, which is invoked when marked by its par-
ent. This enables the initiation and termination of more
complex concurrent and sequential behaviors. Finally,
each transition may have multiple targets, allowing an
automaton to be in several states simultaneously. This
enables a compact representation for recursive behav-
iors like “always” and “do until”.

These attributes are a synthesis of representations
from several areas of computation. The first attribute
comes from the area of Markov processes, and is essen-
tial for tasks like stochastic control or failure analysis
and repair. The second and third attributes are prev-
lent in areas like digital systems and qualitative mod-
eling. The fourth and fifth are prevalent in the field of
synchronous programming, and form the basis for re-
active languages like Esterel(Berry & Gonthier 1992),
Lustre(Halbwachs, Caspi, & Pilaud 1991), Signal(Guer-
nic et al. 1991) and State Charts(Harel 1987). Together
they allow complex systems to be modeled that involve
software, digital hardware and continuous processes.

Hierarchic constraint automata (HCA) incorporate
each of these attributes. An HCA models physical pro-
cesses with changing interactions by enabling and dis-
abling constraints within a constraint store (e.g., a valve
opening causes fuel to flow to an engine). Transitions
between successive states are then conditioned on con-
straints entailed by that store (e.g., the presence or ab-

A constraint system $(D, \models)$ is a set of tokens $D$, closed under conjunction, together with an entailment
relation $\models \subseteq D \times D$. The relation $\models$ satisfies the stan-
dard rules for conjunction. *

R. Burton, uses propositional state logic as its con-
straint system. In state logic each proposition is an as-
signement $x_i = \nu_{ij}$, where variable $x_i$ ranges over a finite
domain $D(x_i)$. Propositions are composed into formula
using the standard logical connectives – and $(\land)$, or $(\lor)$
and not $(\neg)$. If a variable can take on multiple values,
then $x_i = \nu_{ij}$ is replaced with $\nu_{ij} \in x_i$.

A deterministic, hierarchical, constraint automaton
$\mathcal{S}$ is specified as a tuple $(\Sigma, \Theta, \Pi, C_P, T_P)$, where:

- $\Sigma$ is a set of states, partitioned into primitive states
  $\Sigma_p$ and composite states $\Sigma_c$. Each composite state
  denotes a hierarchical, constraint automaton.
- $\Theta \subset \Sigma$ is a set of start states.
- $\Pi$ is a set of variables with each $x_i \in \Pi$, ranging over a
  finite domain $D(x_i)$. $C[\Pi]$ denotes the set of all finite
  domain constraints over $\Pi$.
- $C_P : \Sigma_p \rightarrow C[\Pi]$, associates with each primitive state
  $s_i$ a finite domain constraint $C_P(s_i)$ that holds
  whenever $s_i$ is marked.

The standard rules for conjunction are 1) $a \equiv a$ (iden-
tity); 2) $a \land b \equiv a$ and $a \land b \equiv b$ $(\land$ elimination); 3) $a \equiv b$
and $b \land c \equiv d$ implies $a \land c \equiv d$ $(\land$ cut); and 4) $a \equiv b$ and
$a \equiv c$ implies $a \equiv b \land c$ $(\land$ introduction).
Simulating Deterministic HCA

First some preliminaries. Given automaton $A$, $\overline{T_P}(A)$ denotes a function that returns the relevant constraints that are associated with any primitive state contained in $A$ or one of its descendants. Formally, $\overline{T_P}(A) = C_P \cup \bigcup_{E \in \Sigma} \overline{T_P}(B)$. Similarly, $\overline{T_P}(A)$ returns the relevant transition function associated with any of these primitive states — $\overline{T_P}(A) = \overline{T_P}(A) \cup \bigcup_{E \in \Sigma} \overline{T_P}(B)$.

A full marking of an automaton is a subset of states of an automaton, together with the start states of any composite states in the marking. This is computed recursively from an initial set of states $M$ using $\mathcal{M}_F(M) = M \cup \bigcup_{s \in M} (\mathcal{M}_F(\Theta(s)))$.

Given a current marking $M$ on an automaton $A$, the function $\text{Step}(A, M)$ computes a new marking corresponding to the automaton transitioning one time step.

$\text{Step}(A, M)$:
1. $M_1 := \{s \in M \mid s \text{ primitive}\}$
2. $C := \bigwedge_{s \in M_1} \overline{T_P}(s)$
3. $M_2 := \bigcup_{s \in M_1} \overline{T_P}(s, C)$
4. return $\mathcal{M}_F(M_2)$

Step 1 throws away any composite marked states, they are uninteresting as they lack associated constraints or transitions. Step 2 computes the conjunction of the constraints implied by all the primitive states in $M$. Step 3 computes for each primitive state the set of states it transitions to after one time step. In step 4, applying $\mathcal{M}_F$ to the union of these states marks the start states of any composite state. The result is the full marking for the next time step.

A trajectory of an automaton $A$ is a finite or infinite sequence of markings $m_0, m_1, \ldots$, such that $m_0$ is the initial marking, and for each $i \geq 0$, $m_{i+1} = \text{Step}(A, m_i)$. The initial marking is $\mathcal{M}_F(\Theta)$.

Elaborating on step 3, we represent the transition function for each primitive state $T_P(s)$ as a set of pairs $(l_i, s_i)$, where $s_i \in \Sigma$, and $l_i$ is a set of labels of the form $c \in C[\Pi]$. This is the traditional representation of transitions, as a labeled arc in a graph. If the automaton is in state $s$, then at the next instant it will go to all states $s_i$, whose label $l_i$ is entailed by constraints $C$ that are associated with currently marked primitive states, as computed in the second step of the algorithm. $l_i$ is said to be entailed by $C$, written $C \models l_i$, if $\forall c \in l_i, c \in C$ holds, and if for each $c \not\in l_i, C \not\models c$. It is straightforward to translate this representation into our formal representation: $T_P(s, C) = \{s_i \mid C \models l_i\}$.

Two properties of these transitions are distinctive: Transitions are conditional on what can be deduced, not just what is explicitly assigned, and transitions are enabled based on lack of information.

Step provides a deterministic simulator for the plant, when applied to an HCA that specifies a plant model. Alternatively Step provides a deterministic version of the control sequencer for RBBurton, by placing appropriate restrictions on the control HCA. Constraints attached to primitive states on this HCA are restricted to control assignments, while transition labels are conditioned on the external goals and the estimated current state. The set of active constraints collected from marked states during step 2 of the algorithm is then the set of control actions to be output to the plant.

A Simple Example

We illustrate HCA with a simple automaton. $c$ represents a constraint, start states of an automaton are marked with arrows, and all transitions are labeled. For convenience we use $c$ to denote the label $\models c$, and $\not\models c$ to denote the label $\not\models c$. Circles represent primitive states, while rectangles represent composite states.

The automaton has two start states, both of which are composite. Every transition is labeled $\models d$, hence all transitions are disabled and the automaton is preempted whenever $d$ becomes true. The first state has one primitive state, which asserts the constraint $c$. If $d$ does not hold, then it goes back to itself — thus it repeatedly asserts $c$ until $d$ becomes true. The second automaton has a primitive start state. Once again, at anytime if $d$ becomes true, the entire automaton will immediately terminate. Otherwise $d$ waits until $a$ becomes true, and then goes to its second state, which is composite. This automaton has one start state, which it repeats at every time instant until $d$ holds. In addition, it starts another automaton, which checks if $e$ holds, and if true generates $b$ in the next state. Thus, the behavior of the overall automaton is as follows: it starts asserting $c$ at every time instant. If $a$ becomes true, then at every instant thereafter it checks if $e$ is true, and asserts $b$ in the succeeding instant. Throughout it watches for $d$ to become true, and if so halts. An RMPL program that produces an equivalent automaton is:

```plaintext
do
(always c, 
when a donext always if e thennext b) 
watching d
```

Reactive MPL: Primitive Combinators

We now present the syntax for the reactive model-based programming language. Our preferred approach is to introduce a minimum set of primitives, used to construct programs — each primitive that we add to the...
language is driven by a desired feature. We then define on top of these primitives a variety of program combinators, such as those used in the simple example, that make the language usable. The primitives are driven by the need to write reactive control software in the language, as well as to model physical systems. To write reactive control programs we require combinators for preemption, conditional branching and iteration. For modeling hardware, we require constructs for representing co-temporal interactions and uncertain effects. Finally we need logical concurrency to be able to compose models and programs together.

As we introduce each primitive we show how to construct its corresponding automata. In these definitions lower case letters, like c, denote constraints, while upper case letters, like A and B, denote automata. The term “theory” refers to the set of all constraints associated with marked primitive states at some time point.

**c.** This program asserts that constraint c is true at the initial instant of time. This construct is used to represent co-temporal interactions, such as a qualitative constraint between fluid flow and pressure. The automaton for it is:

```
  A
```

**if c thennext A.** This program starts behaving like A in the next instant if the current theory entails c. This is the basic conditional branch construct. Given the automaton for A, we construct an automaton for if c thennext A by adding a new start state, and going from this state to A if c is entailed.

```
  A

  if c thennext A
```

**unless c thennext A.** This program executes A in the next instant if the current theory does not entail c. The automaton for this is similar to the automaton for if c thennext A. This is the basic construct for building preemption constructs — it is the only one that introduces conditions $\neq c$. This introduces non-monotonicity, however since these non-monotonic conditions hold only in the next instant, the logic is stratified and monotonic in each state. This avoids the kinds of causal paradoxes possible in languages like Esterel.

```
  unless c thennext A
```

We also allow generalized sequences for if ... then and unless ... then, terminated with thennext.

**A, B.** This is the parallel composition of two automata, and is the basic construct for introducing concurrency. The composite automaton has two start states, given by the two automata for A and B.

```
  A, B
```

**always A.** This program starts a new copy of A at each instant of time — this is the only iteration construct needed. The automaton is produced by marking A as a start state and by introducing an additional new start state. This state has the responsibility of initiating A during every time step after the first. A transition back to itself ensures that this state is always marked. A second transition to A puts a new mark on the start state of A at every next step, each time invoking a virtual copy of A. The ability of an automaton to have multiple states marked simultaneously is key to this novel encoding, which avoids requiring explicit copies of A.

```
  always A
```

### Adding Uncertainty to RMPL

The presentation has concentrated thus far on an expressive language and an algorithm for deterministically executing hierarchical constraint automata. This can be used to simulate the plant or to generate deterministic plant control sequences. Uncertainty requires closing the controller’s loop. The plant’s observables are used to predict its internal state, and to determine when it deviates from the intended effect. Uncertain effects are modeled by introducing transition probabilities, turning the plant into a partially observable Markov process. The efficient estimation of these processes for complex systems is notoriously difficult.

An efficient estimate of the plant’s possible states (its belief state) is enabled through the compact encoding of the plant’s model in terms of hierarchical constraint automata. This estimate is used to guide the evaluation of the control program at each time tick. To express probabilistic knowledge into Reactive MPL we introduce the probabilistic combinator **choose**:

```
choose [A with p, B with q].
```

This combinator reduces to A with probability $p$, to B with probability $q$, and so on. In order to ensure that the current theory does not depend upon the probabilistic choices made...
in the current state, we make the following restriction — all assertions of constraints in A and B must be in the scope of a next. This restriction ensures that no constraints are associated with the start states of A and B (technically the attached constraint is “true”), and thus the probabilities are associated only with transitions. The corresponding automaton is encoded with a single probabilistic start transition, which allows us to choose between A and B.

To incorporate probabilistic transitions into HCA we change the definition of $T_P$. Recall for deterministic HCA that $T_P(s_i)$ denotes a single transition function. For probabilistic HCA $T_P(s_i)$ denotes a distribution over transition functions $T_P^j(s_i)$, whose probabilities $P(T_P^j(s_i))$ sum to 1.

$T_P(s_i)$ is encoded as a probabilistic, AND-OR tree. This supports a simple transformation of nested choose combinator to probabilistic HCA. Each leaf of this tree is labeled with a set of one or more target states in $\Sigma$, which the automaton transitions to in the next time tick.

The branches $a_i \rightarrow b_j$ of a probabilistic OR node $a_i$ represent a distribution over a disjoint set of alternatives, and are labeled with conditional probabilities $P[b_j | a_i]$. The probability of branches emanating from each $a_i$ sum to unity.

The branches of a deterministic AND node represent an inclusive set of choices. Each branch is labeled by a set of conditions $l_j$ of the form $\models \phi$ or $\nvdash \phi$, where $\phi$ is any formula in propositional state logic over variables $\Pi$. Every branch is taken whose conditions are satisfied by the current state (i.e., $P[l_j | a_i, l_j] = 1$).

Each AND-OR tree is compiled into a two level tree (shown above), with the root node being a probabilistic OR, and its children being deterministic ANDs. Compilation is performed using distributivity, as shown below, and commutativity. This allows adjacent AND nodes to be merged, by taking conjunctions of labels, and adjacent OR nodes to be merged, by taking products of probabilities.

This two level tree is a direct encoding of $T_P(s_i)$. Each AND node represents one of the transition functions $T_P^j(s_i)$, while the probability on the OR branch, terminating on this AND node, denotes $P(T_P^j(s_i))$.

**RBurton: State Estimation**

To implement belief state update recall that a probabilistic HCA encodes a POMDP. A POMDP can be described as a tuple $(\Sigma, M, O, P_T, P_O, R)$. $\Sigma$, $M$ and $O$ denote finite sets of feasible states $s_i$, control actions $\mu_i$, and observations $o_i$. The state transition function, $P_T[s_i(t), \mu_i(t) \rightarrow s_i(t+1)]$ denotes the probability that $s_i(t+1)$ is the next state, given current state $s_i(t)$ and control action $\mu_i(t)$ at time $t$. The observation function, $P_O[s_i(t) \rightarrow o_i(t)]$ denotes the probability that $o_i(t)$ is observed, given state $s_i(t)$ at time $t$. The reward function $R(s_i(t))$ specifies the immediate reward for taking each control action given state $s_i(t)$ at time $t$.

RBurton incrementally updates the plant belief state, conditioned on each control action sent and each observation received, respectively:

$$\sigma^{(t+1)}[s_i] \equiv P[s_i^{(t+1)} | o_i^{(0)}, \ldots, o_i^{(t)}, \mu_i^{(0)}, \ldots, \mu_i^{(t)}]$$

$$\sigma^{(t+1)}[s_i] \equiv P[s_i^{(t+1)} | o_i^{(0)}, \ldots, o_i^{(t)}, \mu_{i+1}^{(0)}, \ldots, \mu_i^{(t)}]$$

Exploiting the Markov property, the belief state at time $t+1$ is computed from the belief state and control actions at time $t$ and observations at $t+1$ using the standard equations:

$$\sigma^{(t+1)}[s_i] = \sum_{j=1}^{n} \sigma^{(t)}[s_j] P_T[s_i, \mu_i \rightarrow s_j]$$

$$\sigma^{(t+1)}[s_i] = \sigma^{(t+1)}[s_i] \frac{P_O[s_i \rightarrow o_k]}{\sum_{j=1}^{n} \sigma^{(t+1)}[s_j] P_O[s_j \rightarrow o_k]}$$

To calculate $P_T$ recall that a transition $T$ is composed of a set of primitive transitions, one for each marked primitive state. Assuming conditional independence of primitive transition probabilities, given the current marking, the combined probability of each set is the product of the primitive transition probabilities of the set. This is analogous to the various independence of failure assumptions exploited by systems like GDE(de Kleer & Williams 1987), Sherlock(de Kleer & Williams 1989) and Livingstone(Williams & Nayak 1996). However unlike these earlier systems, multiple sets of transitions may go to the same target marking. This is a consequence of the fact that in an HCA primitive states have multiple next states. Hence the transition probabilities for all transitions going to the same target must be summed according to the above equation for $\sigma^{(t+1)}[s_i]$.

Given $P_T$, the belief update algorithm for $\sigma^{(t+1)}[s_i]$ is a modified version of the Step algorithm presented earlier. This new version of Step returns a set of markings, each with its own probability. Step 3a builds the sets of possible primitive transitions. Step 3b computes the combined next state marking and transition probability of each set. Step 3c sums the probability of all composite transitions with the same target:
The first enumeration algorithm for Sherlock and Livingstone, is directly used by RBurton to generate the composite transitions in step 3a and b in order from most to least likely. However, since the correspondence between transitions and next states is many to one, there is no guarantee that the belief states are enumerated in decreasing order.

Instead we assume that most of the probability density resides in the few leading candidate transition sets. Hence a best first enumeration of the few leading transition sets will quickly lead to a reasonable approximation. We enumerate transitions in decreasing order until most of the probability density space is covered (e.g., 95%), and then perform step 3c to merge the results.

Computing \( \sigma^{(t+1)}[s_i] \) requires \( P_G(s_i, C) \) at each time tick this looks for oc-
The automaton for this is derived from the automaton for \( A \) by adding the label \( \neq c \) on all transitions in \( A \).

**suspend \( A \) on \( c \). reactivate on \( d \).** This is like the "Control - Z, fg" pair of Unix — it suspends the process when \( c \) becomes true, and restarts it from the same point when \( d \) becomes true.

**when \( c \) do \( A \).** This starts \( A \) at the instant after the first one in which \( c \) becomes true. It is a temporally extended version of \( \text{if } c \text{ then } next \ A \).

**when \( c \) do \( A \).** This temporally extends \( \text{if } c \text{ then } A \). Its automaton is similar to the automaton for \( \text{if } c \text{ then } A \), except for the fact that there is a transition from the start state to itself labeled \( \neq c \).

### DS1 Optical Navigation Example

To make RMPL's capability concrete we model the autonavigation system of the spacecraft Deep Space 1. This system is used on the spacecraft once a week to do small course corrections. It works by taking pictures of three asteroids, and by using the difference between their actual locations from their projected locations to determine the course error. This is then used by another system to determine a new course. The following is a greatly simplified version of the program. MICAS is a hardware model for the miniaturized camera, AutoNav is the top-level control program, and TakePicture and SnapStore are subroutines, the second including a repair procedure.

**AutoNav() ::**

- TurnMicasOn,
- if IPSon then next SwitchIPSStandBy,
- do when IPSstandby \( \land \) MICASon donext
  - TakePicture(1);
  - TakePicture(2);
  - TakePicture(3);
  - {TurnMicasOff,
    OpticalNavigation()}
  watching PictureError \( \lor \) OpticalNavError,
- when OpticalNavError doneext AutoNav(),
- when PictureError doneext AutoNavFailed

**TakePicture(n) ::**

- do {TurnToTarget(n),
  - when Turndone do SnapStore(0)
  } watching PictureError

**SnapStore(n) ::**

- if \( n=3 \) then PictureError,
- next {MICASStakePicture;
  - if MICASfail then

**Discussion and Related Work**

The RMPL compiler is written in C, and generates hierarchical constraint automata as its target. This supports all primitive combinators and a variety of defined combinators. RBurton is written in Lisp, and builds upon the best-first enumeration code at the heart of the Livingstone system. The optical navigation scenario and other simple but expressive examples have been encoded. In addition the language is sufficiently expressive and compact to support the full DS1 spacecraft models developed for Livingstone. RBurton's behavior is equivalent to Livingstone for those examples. Current working includes modeling for a Mars rover and JPL's Space Interferometer Mission.

Turning to related work, Reactive MPL synthesizes ideas underlying constraint-based modeling, synchronous programming languages and POMDPs. Synchronous programming languages (Halbwachs 1993; Berry & Gonthier 1992; Halbwachs, Caspi, & Pilaud 1991; Guernic et al. 1991; Harel 1987; Saraswat, Jagadeesan, & Gupta 1996) were developed for writing control code for reactive systems. They are based on the Perfect Synchrony Hypothesis — a program reacts instantaneously to its inputs. Synchronous programming languages exhibit logical concurrency, orthogonal preemption, multiform time and determinacy, which Berry has convincingly argued are necessary characteristics for reactive programming. Reactive MPL is a synchronous language, and satisfies all these characteristics.
In addition, Reactive MPL is distinguished by the adoption of MDPs as its underlying model, its treatment of partial observability and its extensive use of constraint modeling to observe hidden state. This provides a rich language for continuous process, failure, uncertainty and repair.

In the Esterel work, Berry emphasizes executable specifications — "What you prove is what you execute" — this is to eliminate the gap between the specifications about which we prove properties, and the programs that are supposed to implement them. We carry this one step further, by doing our reasoning on executable programs directly, in real time.

As previously discussed, RMPL and RBurton overlap substantially with AI robotic execution languages RAPS, ESL and TCA. For example, method selection, monitoring, preemption and concurrent execution are core elements of these languages, shared with RMPL.

One key difference is that RMPL's constructs fully cover synchronous programming, hence moving towards a unification of the executive with the underlying real-time language. In addition RBurton's deductive monitoring capability handles a rich set of software/hardware models that go well beyond those handled by systems like Livingstone. This moves execution languages towards a unification with model-based, deductive monitoring.

Finally, note that hierarchical state diagrams, like State Charts (Harel 1987), are becoming common tools for system engineers to write real-time specifications. These specifications are naturally expressed within RMPL, due to RMPL's simple correspondence with hierarchical constraint automata, which are closely related to state charts. Together this offers a four way unification between synchronous programming, robotic execution, model-based autonomy and real-time specification — a significant step towards our original goal.

Nevertheless substantial work remains. Many execution and control capabilities key to highly autonomous systems fall well outside the scope of RMPL and RBurton. For example, RMPL has no construct for expressing metric time. Hence RBurton cannot execute or monitor temporal plans without the aid of an executive like RAPS or Remote Agent's Exec. In addition, outside of monitoring, RBurton does not employ any deduction or planning during control sequence generation. Unifying the kinds of sequence generation capabilities that are the hallmark of systems like HSTS (Muscettola 1994) and Burton (Williams & Nayak 1997), requires significant research.

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