Reactive Synthesis for Cyber-Physical System Control

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Synthesis of reactive systems

Specification

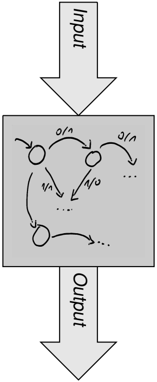
$+$

Input $= \{u, \ldots\}$
Output $= \{v, \ldots\}$

$\Rightarrow$

Realizable $\longrightarrow$

Not realizable



Synthesis of CPS controllers

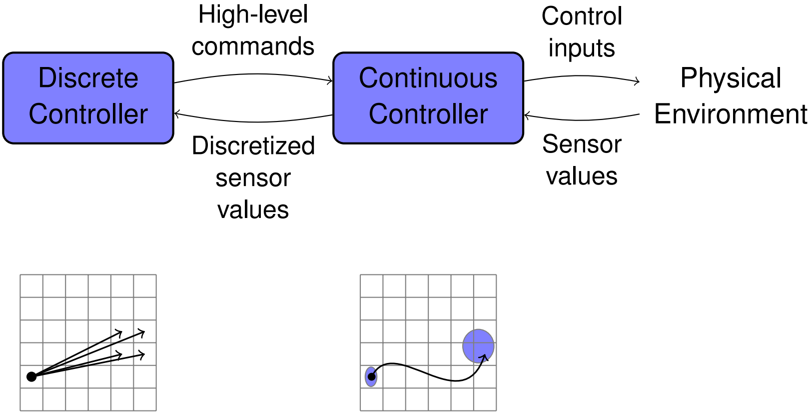
Main Question

How to deal with the **continuous** and **discrete** aspects of the problem at the same time?

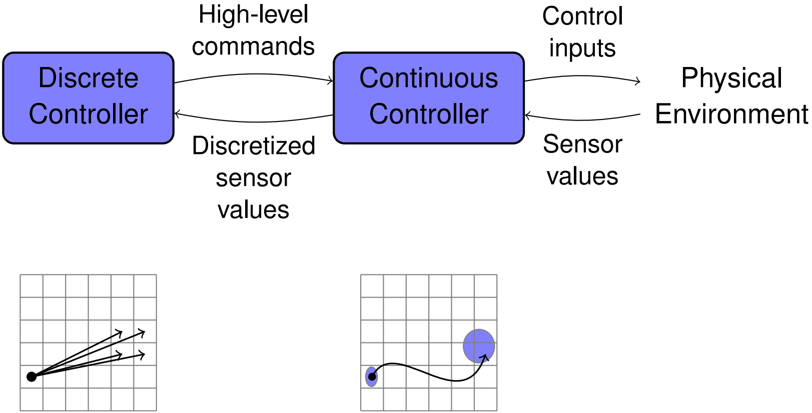
Approaches

1. Abstraction of the continuous world into the purely discrete world + discrete synthesis (e.g., Nilsson et al., 2016)
2. Simplifying the continuous parts (Linear hybrid automata / Timed automata) and using a specialized synthesis algorithm for the resulting mixed discrete/continuous model (e.g., Benerecetti et al., 2013; Papusha et al., 2016)
3. “Continuization” of the discrete parts and using purely continuous methods for controller computation

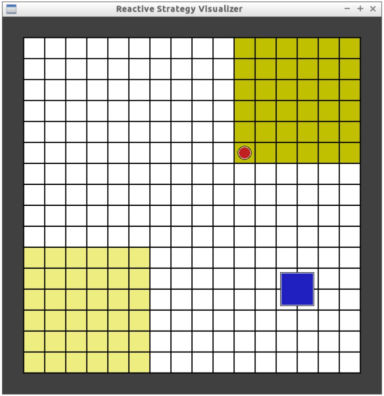
Using a discrete abstraction



Using a discrete abstraction



Discrete synthesis for CPS – Example



Based on joint work with Ufuk Topcu, HSCC 2014

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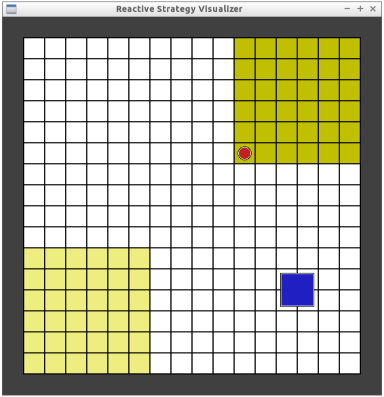


Input/Output

Input:

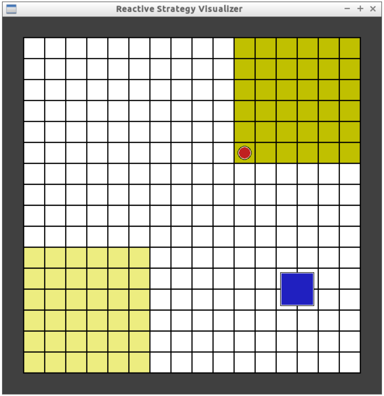
- (Sensed) positions of the robots
- Delivery requests

Output:

- Up/Left/Right/Down command of the red robot
- Pickup/drop actions of the red robot

Based on joint work with Ufuk Topcu, HSCC 2014

Discrete synthesis for CPS – Example

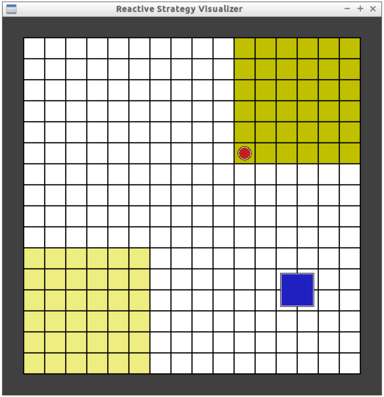


Guarantees

- Whenever a button is pressed, then the robot is eventually at the lower left region and performing a pick-up action, while later being in the top right region, performing a drop action, without performing a drop action in between.
- No crashes between the robots

Based on joint work with Ufuk Topcu, HSCC 2014

Discrete synthesis for CPS – Example

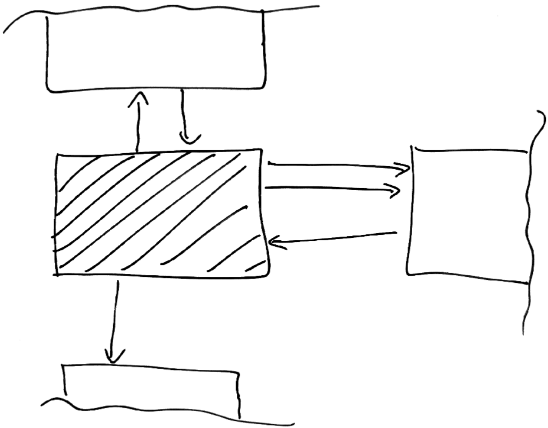


Assumptions

- Obstacle can only move in every second step
- Obstacle can only move by one cell per direction per step
- *x* position of the robot is updated according to its choice
- *y* position of the robot is updated according to its choice
- No robot jumps further that one cell are possible

Based on joint work with Ufuk Topcu, HSCC 2014

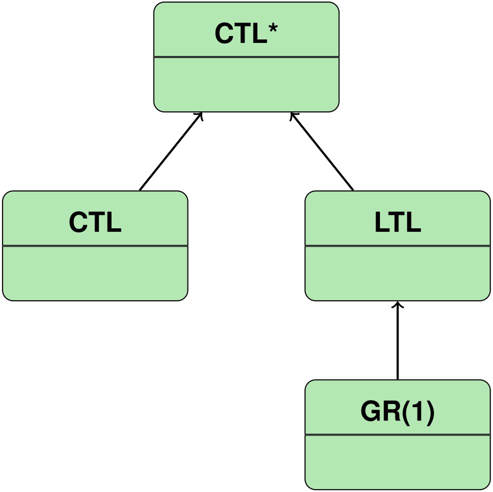
Assumptions and guarantees in specifications



Specification shape

$$\left(\bigwedge \text{Assumptions}\right) \rightarrow \left(\bigwedge \text{Guarantees}\right)$$

Reactive synthesis – Complexity vs. expressivity



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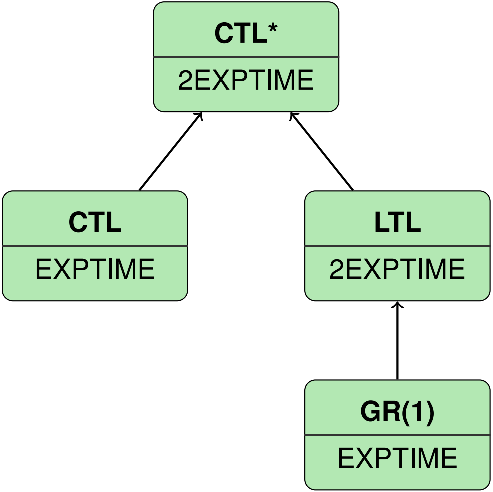

Reactive synthesis – Complexity vs. expressivity

GR(1) synthesis applications

- On-chip bus arbiter (Bloem et al., 2007b,a; Godhal et al., 2011)
- High-level robot control (Kress-Gazit et al., 2009; Raman et al., 2013; Jing et al., 2013)
- Vehicle power management (Ozay et al., 2011a)
- Camera network control (Ozay et al., 2011b)
- ...

GR(1)

EXPTIME

So is that the end of the story?

And everyone lived happily ever after...

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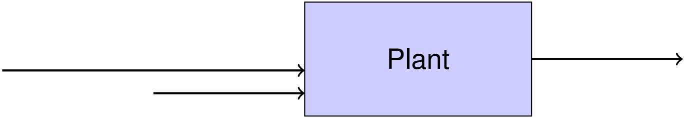
And everyone lived happily ever after...

...well, not quite. There is also:

- Noise
- Imprecise modelling of the environment
- Incomplete information
- Scalability
- Robustness / Error-resilience
- Quirks of the synthesis algorithm
- ...

Controlling (Cyber-)physical systems



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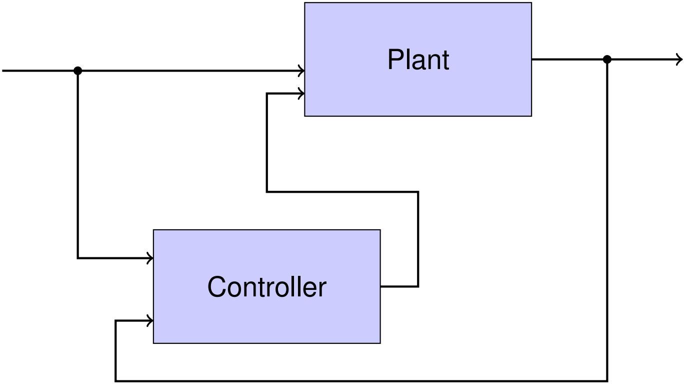

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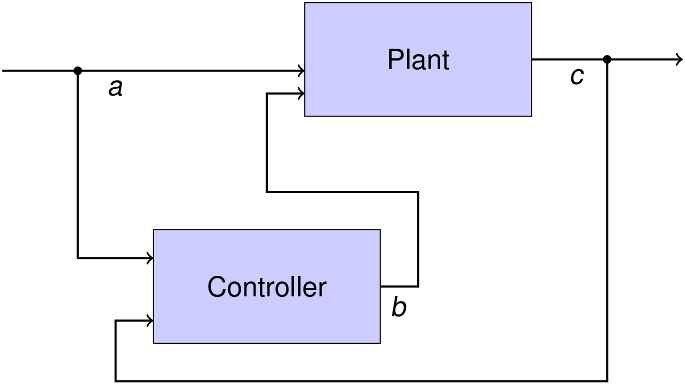

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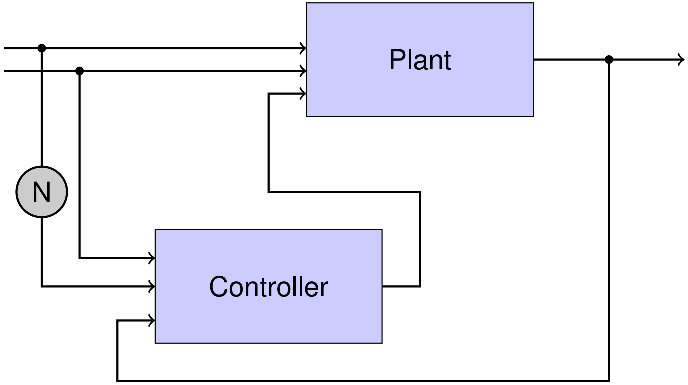

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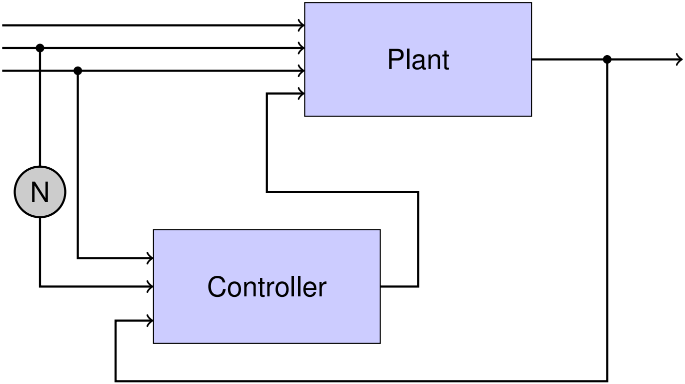

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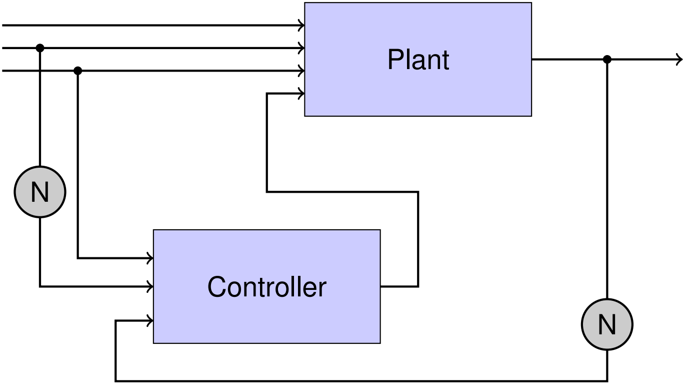

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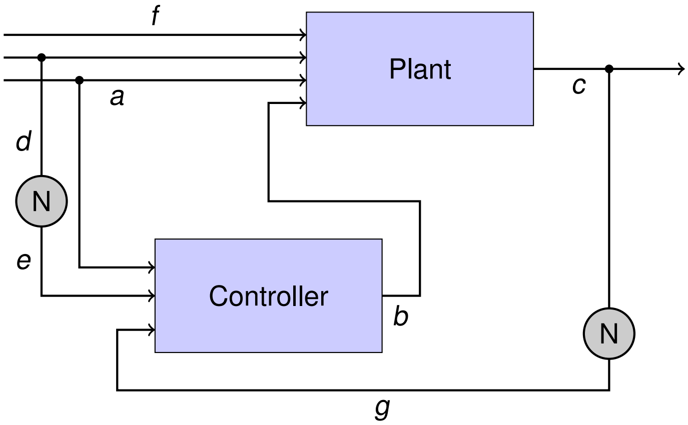
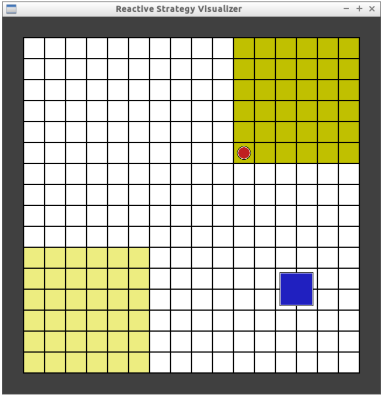


Example for error-resilience



Focus of this talk

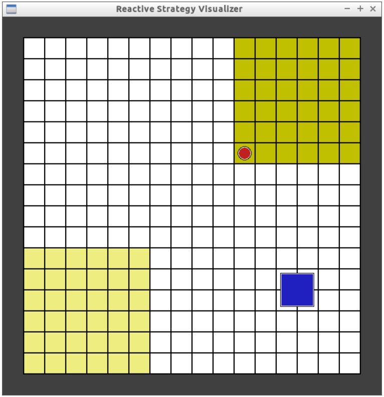
A few answers to how we can deal with...

- Noise
- Imprecise modelling of the environment
- Incomplete information
- Scalability
- Robustness / Error-resilience
- Quirks of the synthesis algorithm
- ...

Synthesizing *error-resilient* implementations

Based on joint work with Ufuk Topcu, HSCC 2014

Example for (discrete) robustness (revisited)



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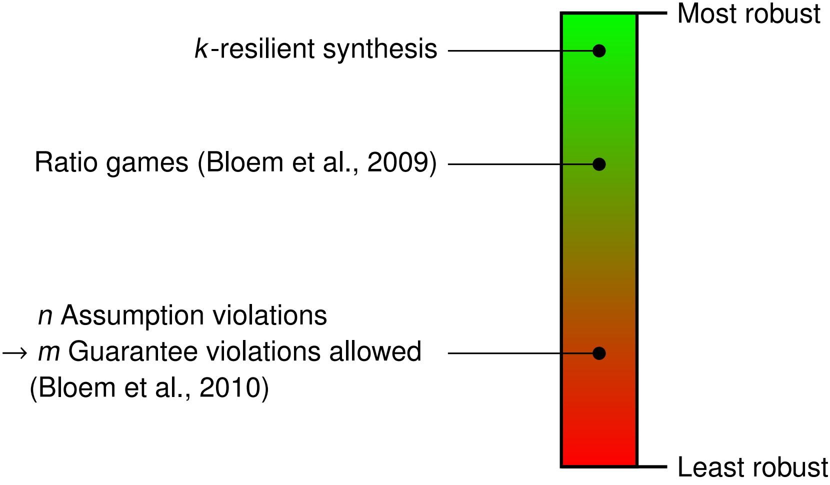
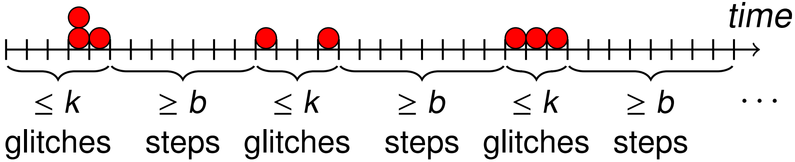
Spectrum of robustness (in discrete synthesis)



This figure is certainly not complete and only lists *some* approaches.

k-Resilient synthesis (Def.: Huang et al., 2012)



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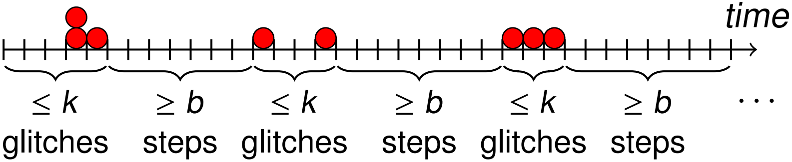


Algorithmic approach

Given a GR(1) specification ψ and k, we can encode the k-resilient synthesis problem of ψ by translating ψ to a modified GR(1) specification ψ' and perform GR(1) synthesis for ψ'.

The Reduction from GR(1) to GR(1) in a nutshell

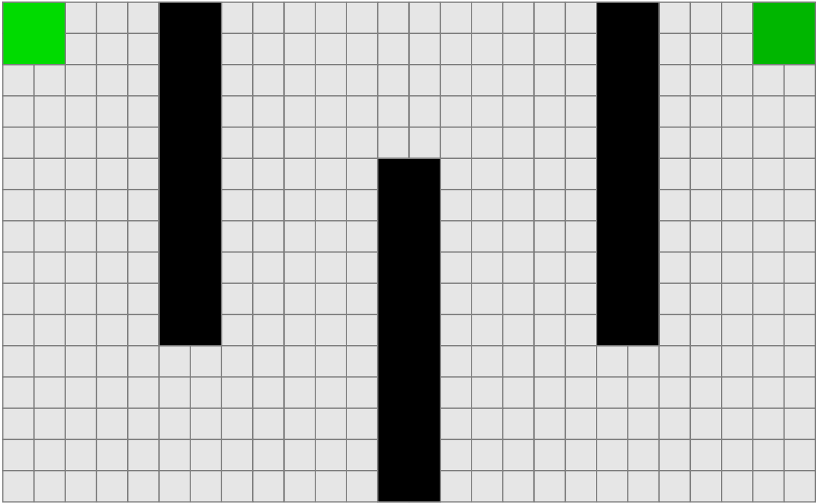
A counter for k

- We ask the system to be synthesized to output a **counter** that says how many *glitches* can be tolerated in the near future.
- If glitches stop occurring, then the system must eventually set the counter back to k.

Effect

- Quantification over b is abstracted by a liveness property
- Idea can be implemented by altering the specification.

Example: Robot patrolling



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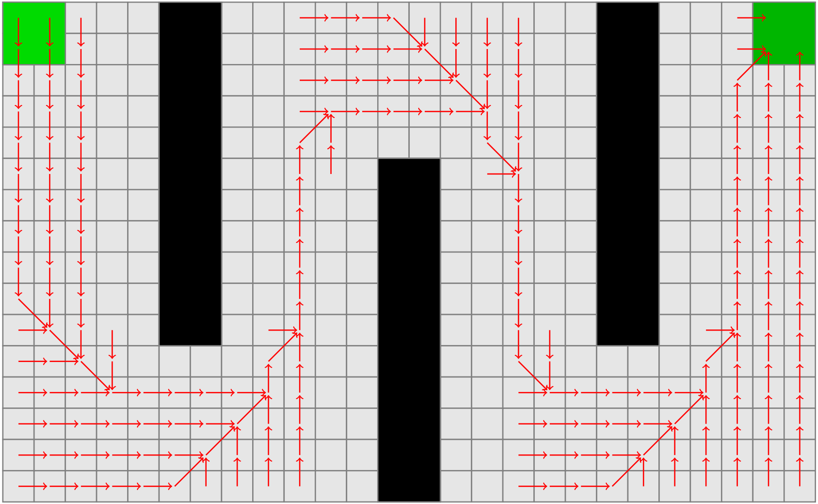

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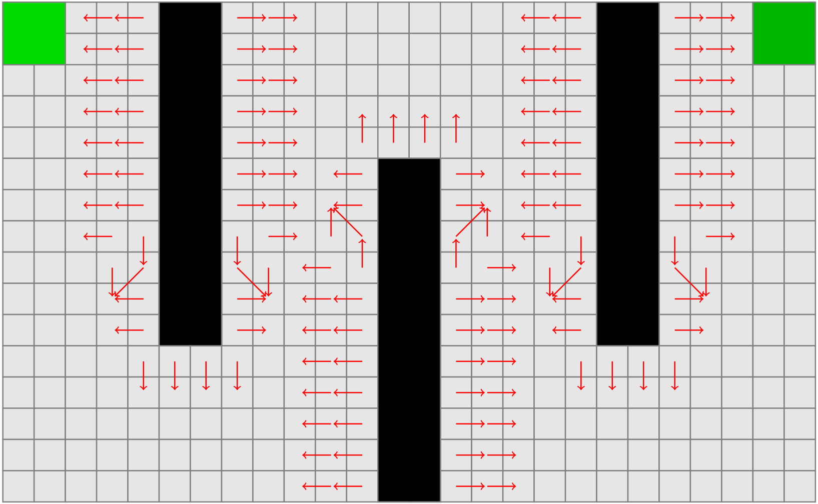
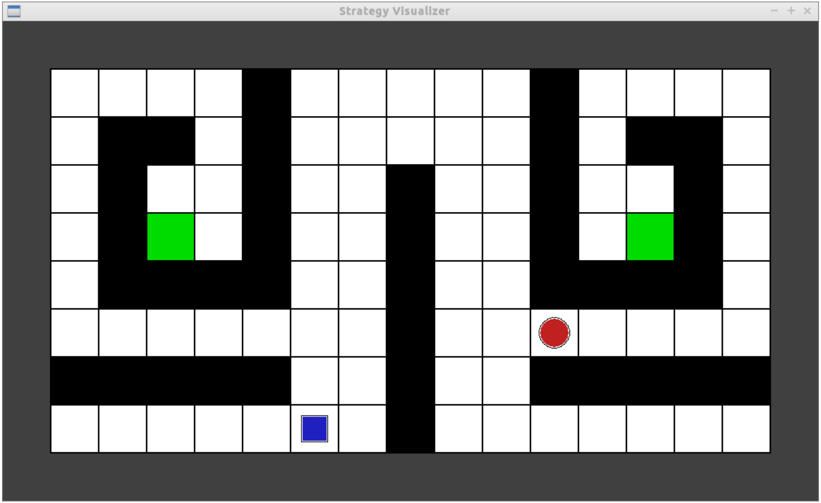


Synthesizing *cooperative* controllers

Based on joint work with Roderick Bloem and Robert Könighofer, IROS 2015

Demo



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How can we synthesize *cooperative* high-level robot controllers?

Naive approaches to solving this problem

- Require the system to satisfy the specification even if the environment is *naughty*

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Naive approaches to solving this problem

- Require the system to satisfy the specification even if the environment is *naughty* → assumptions are needed
- Change the specification to prevent uncooperative behavior → defeats the purpose of synthesis

Our approach

We modify the main generalized reactivity(1) synthesis approach to compute only *cooperative* controllers.

Making GR(1) synthesis cooperative

Synthesis objective

- All executions must be *correct*.
- From every state of the synthesized controller, there must always be an execution on which the assumptions are satisfied.

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Implementation: Safety

- Prevent the system from issuing a next output that *forces* the environment to subsequently violate its specification

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Implementation: Safety

- Prevent the system from issuing a next output that *forces* the environment to subsequently violate its specification

Implementation: Liveness

- Modify the GR(1) fixpoint computation

Standard GR(1) fixpoint equation

$$\nu Z. \bigwedge_{j \in \{1,\ldots,n\}} \mu Y. \bigvee_{i \in \{1,\ldots,m\}} \nu X. \mathrm{EnfPre}\Big((Z' \wedge \psi_j^g) \vee Y' \vee (\neg\psi_i^a \wedge X') \Big)$$

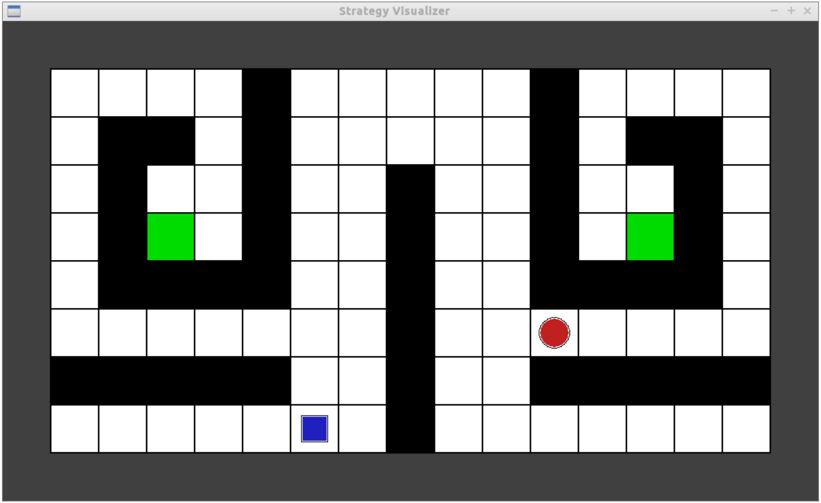
Cooperative GR(1) synthesis

$$\nu Z. \bigwedge_{j \in \{1,\ldots,n\}} \mu Y. \bigvee_{i \in \{1,\ldots,m\}} \nu X.\mathrm{EnfPre}\Big((Z' \wedge \psi_j^g) \vee Y' \vee (\neg \psi_i^a \wedge X')\Big)$$

$$\wedge\ \mu R.\mathrm{Reach}\Big((\psi_j^g \vee Y' \vee R') \wedge X\Big)$$

$$\wedge \bigwedge_{k \in \{1,\ldots,m\}} \mu R.\mathrm{Reach}\Big((\psi_k^a \vee R') \wedge Z\Big)$$

Demo



Optimal control in adversarial environments

Based on joint work with Gangyuan Jing and Hadas Kress-Gazit

(published at IROS 2013)

Adding an optimization criterion

Basic idea

In addition to the specification, we introduce a *cost function*.

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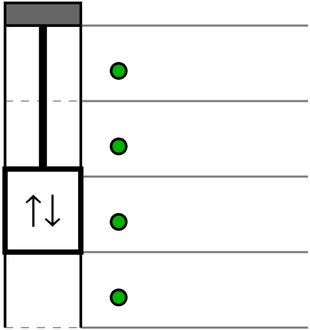

Example due to Chatterjee and Henzinger (2006)

Adding an optimization criterion

Specification parts

- The door can be open or closed.
- $\forall i \in \{1, 2, 3, 4\}$: If button i is pressed, floor i is eventually visited with the door open.
- At every step, the current floor number is not increased or decreased by more than one.
- The current floor number can only be changed if the door is closed.
- The “door close” command can fail or succeed, while the “open door” command always succeeds.

Optimization criterion / cost function

- Every operation has a (fixed) cost.
- We want to minimize the average cost per execution step.

What is an optimal strategy?

Optimal strategy (mean-payoff)

- Service requests for 1 step, then wait for 1 step, then
- service requests for 1 step, then wait for 2 steps, then
- service requests for 1 step, then wait for 3 steps, then
- ...

What is an optimal strategy?

Optimal strategy (mean-payoff)

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So what now?

We need to fix either:

- specification
- weigths/costs
- optimization objectives

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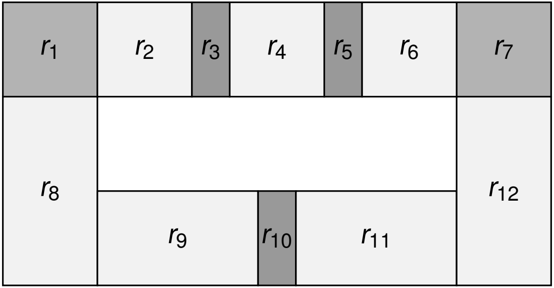
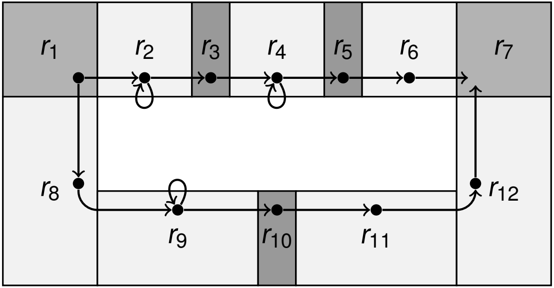
Example



Specification parts

Assumptions:	**Guarantees**	
$\mathbf{GF}(open_1)$	$\mathbf{G}(\neg open_1 \rightarrow \mathbf{X}(\neg r_3)))$	$\mathbf{F}r_7$
$\mathbf{GF}(open_2)$	$\mathbf{G}(\neg open_2 \rightarrow \mathbf{X}(\neg r_5)))$	
$\mathbf{GF}(open_3)$	$\mathbf{G}(\neg open_3 \rightarrow \mathbf{X}(\neg r_{10})))$	

Example



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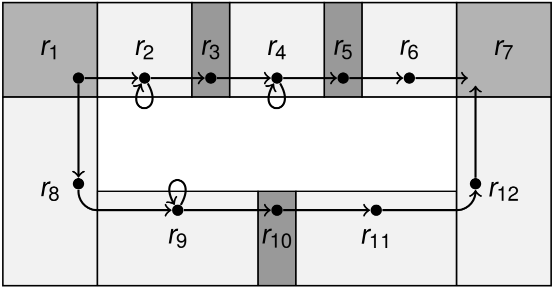
Introducing “action cost”



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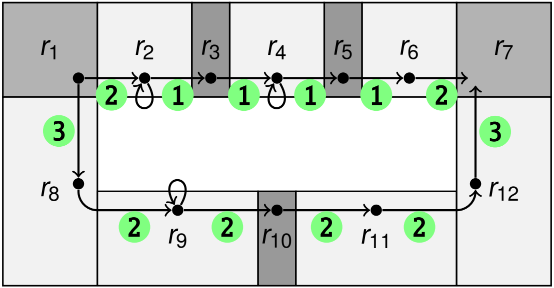

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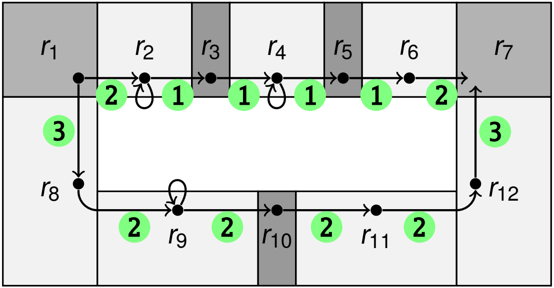


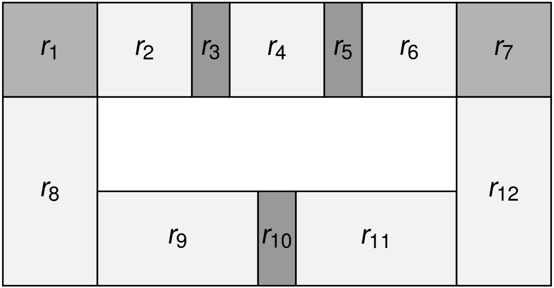
Computing *action cost* along a path

- Take the sum of costs until reaching the next goal

Characterizing waiting in strategies

Basic idea

Waiting in strategies can be detected by looking at the SCCs.



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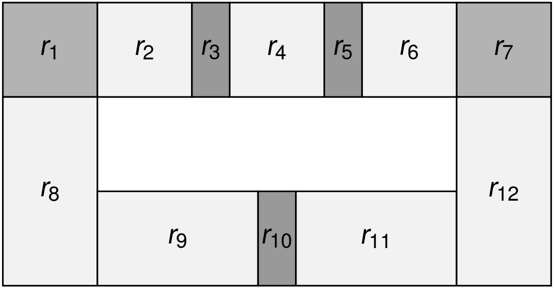
But what about repetitive tasks?

Here, we count SCCs up to the point of *reaching the next goal*.



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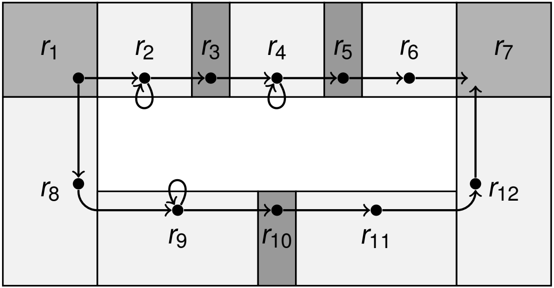

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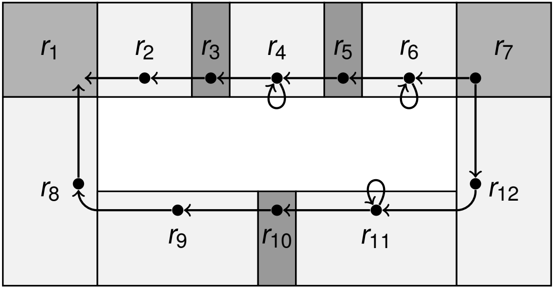


Conditions on the specification

Idea

- If the specification has a set of *goals* for the system, we can count the number of waiting cycles for reaching the respective *next* goal.
- After reaching the next goal, the counter resets.
- It is the aim of the system to reach the *next* goal cheaply.

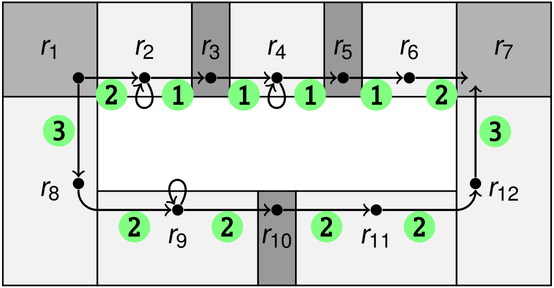
Using the idea for GR(1) specifications

- Still singly-exponential complexity
- Strategy shape is the same as for standard GR(1) synthesis: positional-per-goal

Combining action and waiting cost

Two-dimensional cost notion

From every state of a strategy, a strategy has a *cost tuple* that describes the cost to reach the next goal.



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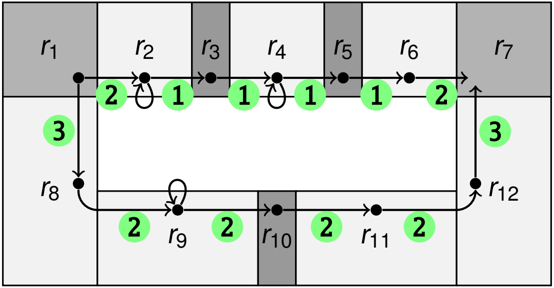

Example

Cost of path 1 from r_1: $(c_w, c_a) = (2, 8)$, cost of path 2: $(c_w, c_a) = (1, 14)$
Overall cost: depends on the **preference**

Preference relations

Preference relations

- We use a preference relation $\leq_P$ to choose which executions the strategy should prefer (e.g., $(1, 14) \leq_P (2, 8)$).
- The value of a strategy from some state is the **highest** combined cost (w.r.t. $\leq_P$) of all executions originating from the state.

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Using the idea for GR(1) specifications

For almost-linear preference relations, we can still compute optimal strategies in exponential time. They track:

- The current atomic proposition values
- The “current” liveness assumption **and** liveness guarantee
- Whether ∞ action cost can still be avoided

Risk-Averse Control of Markov Decision Processes with ω-regular Objectives

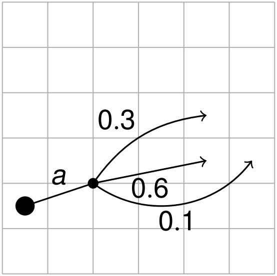
Based on joint work with Salar Moarref and Ufuk Topcu

(published at CDC 2016)

Basic problem setup

Basic Problem

- We want to control a Markov decision process (MDP) such that an ω-regular specification is satisfied...



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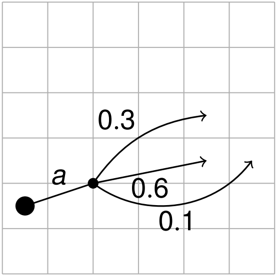
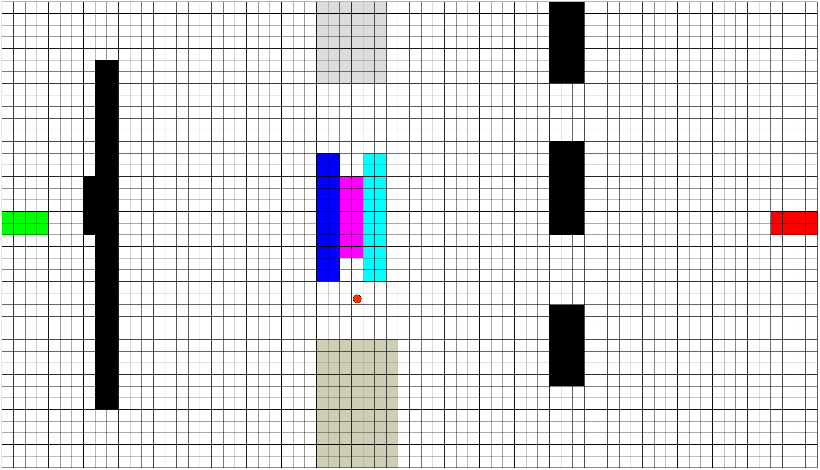
- We want to control a Markov decision process (MDP) such that an ω-regular specification is satisfied...
- ...but we want to do this in MDPs in which all policies have a probability of 0 for satisfying the specification.



Example problem



So how can we control the system?

Idea

We compute a controller that maximizes the probability to reach the next *goal*.

From every goal (or initially), A *p-risk averse controller* reaches the next goal with probability at least *p*.

So how can we control the system?

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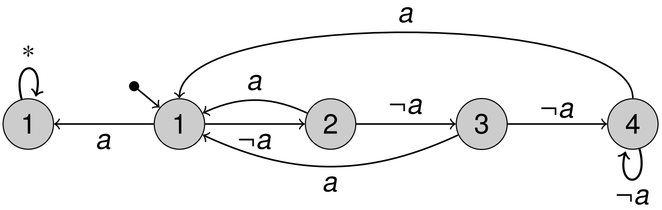
From every goal (or initially), A *p-risk averse controller* reaches the next goal with probability at least *p*.

But what *is* the next goal?

When working with general ω-regular specifications, this is not so easy to tell!

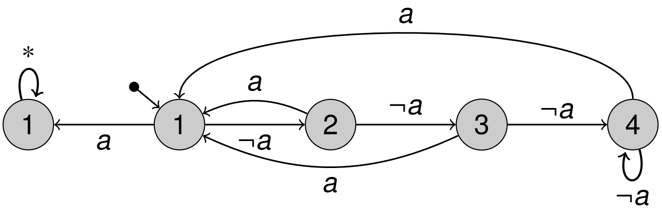
Deterministic Parity Automata



Acceptance

A deterministic parity automaton accepts all words that have a run on which the highest color occurring infinitely often is even.

Deterministic Parity Automata



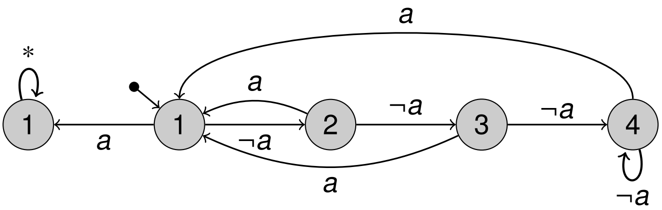
Acceptance

A deterministic parity automaton accepts all words that have a run on which the highest color occurring infinitely often is even.

Example (1)

$$\begin{array}{lcccccc} \vec{c} & = & 1 & 2 & 1 & 2 & \dots \\ w & = & \overline{a} & a & \overline{a} & a & \dots \end{array}$$

Deterministic Parity Automata



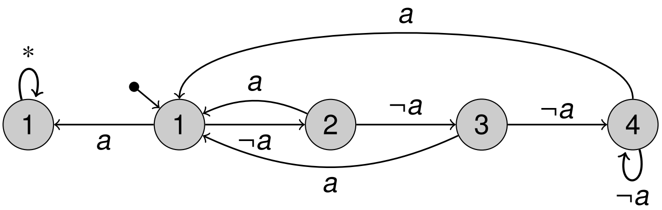
Acceptance

A deterministic parity automaton accepts all words that have a run on which the highest color occurring infinitely often is even.

Example (2)

$$\begin{array}{lllllll} \vec{c} & = & 1 & 2 & 1 & 1 & \ldots \\ w & = & \overline{a} & a & a & \overline{a} & \ldots \end{array}$$

Deterministic Parity Automata



Acceptance

A deterministic parity automaton accepts all words that have a run on which the highest color occurring infinitely often is even.

Example (3)

$$\begin{array}{ccccccccc} \vec{c} & = & 1 & 2 & 3 & 4 & 1 & 2 & \ldots \\ w & = & \overline{a} & \overline{a} & \overline{a} & a & \overline{a} & \overline{a} & \ldots \end{array}$$

Connecting Deterministic Parity Automata and MDP Control

Basic idea

We let the *controller* always tell the *current goal color* and when it just reached a goal.

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We let the *controller* always tell the *current goal color* and when it just reached a goal.

The controller may always *increase* the goal color, but *decrease* it only finitely a fixed number of times.

Connecting Deterministic Parity Automata and MDP Control

Basic idea

We let the *controller* always tell the *current goal color* and when it just reached a goal.

The controller may always *increase* the goal color, but *decrease* it only finitely a fixed number of times.

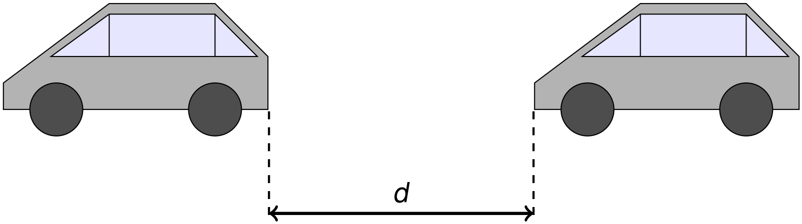
Finding p-risk averse policies

- For every $p \in [0, \ldots, 1]$, a p-risk averse control policy has a finite number of states
- Optimal strategies can be computed by solving a series of optimal reachability policy computations in MDPs.

Estimator-based synthesis

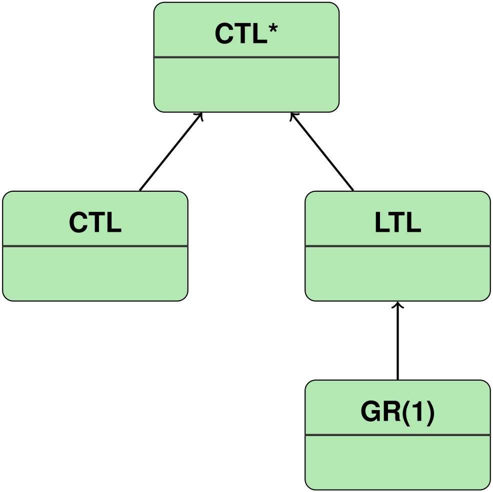
Based on joint work with Ufuk Topcu, HSCC 2015

Example application: Distance keeping assistant

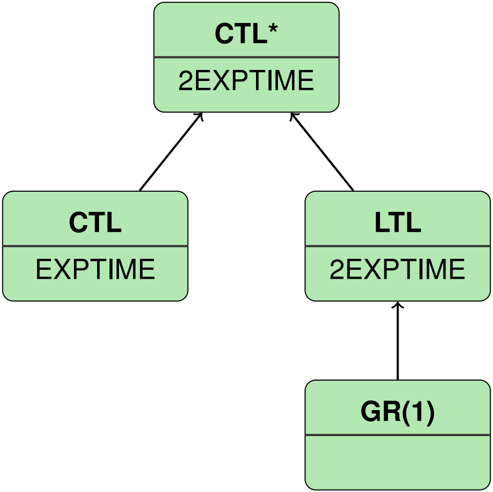


Observable:	Speed of the follower car
Noisily Measured:	Distance between cars
Unobserved:	Speed of the leader car
Controlled:	Acceleration (follower)

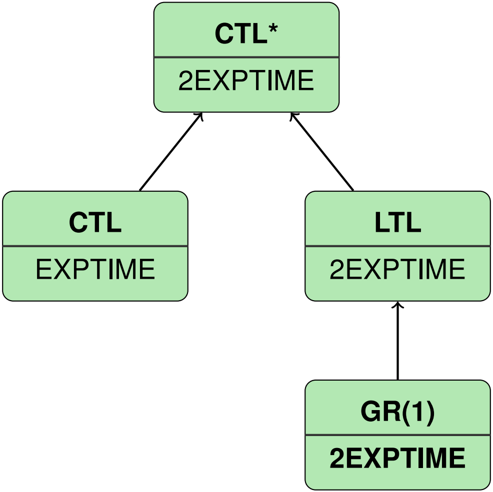
Synthesis – complexity vs. expressivity (incomplete inf.)



Synthesis – complexity vs. expressivity (incomplete inf.)



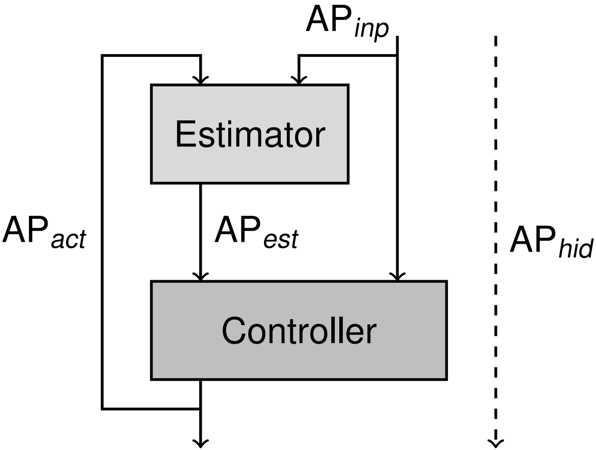
Synthesis – complexity vs. expressivity (incomplete inf.)



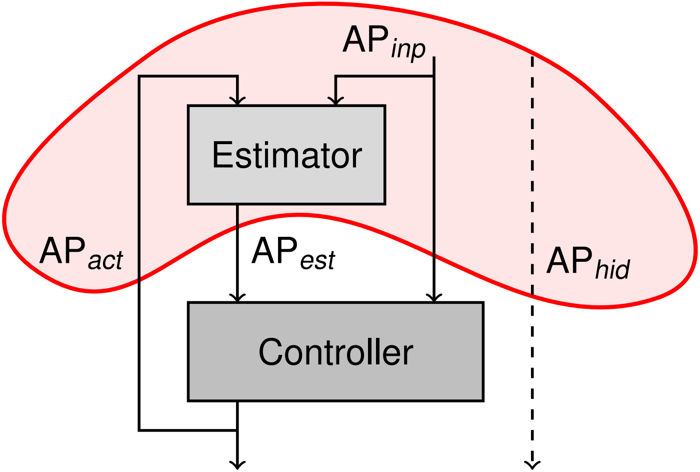
Synthesis with estimators (1/2)

Central question:
How to retain the
singly-exponential complexity of
GR(1) synthesis
under incomplete information?

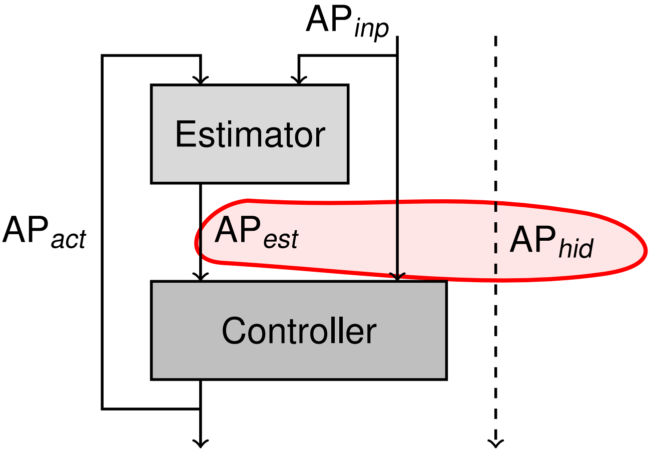
Synthesis with estimators (2/2)



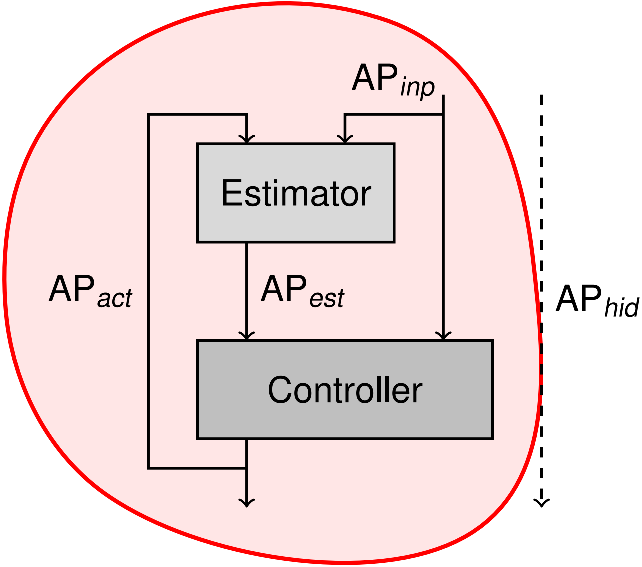
Synthesis with estimators (2/2)



Synthesis with estimators (2/2)



Synthesis with estimators (2/2)



Decoupling estimator computation from synthesis

Main ideas

- We decouple the **estimation** of the physical values and **reactive synthesis** using an **estimator specification** as glue.
- We modify the controller specification to only talk about observable variables.

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Example specification parts

Estimator specification	Controller Specification
$\mathbf{G}(minDistance \leq distance)$ $\mathbf{G}(maxDistance \geq distance)$	$\mathbf{G}(minDistance \geq 5)$

Main correctness proposition

We can soundly reduce the synthesis problem for φ under incomplete information to one over φ' over complete information if

$$(\varphi' \;\wedge\; \mathbf{G}\,\rho_e \;\wedge\; \mathbf{G}\,\rho_s) \;\rightarrow\; \varphi$$

holds.

Modified System Specification

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Environment Assumptions

Modified System Specification

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Environment Assumptions

Modified System Specification

Estimator Specification

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Environment Assumptions

Original System Specification

Modified System Specification

Estimator Specification

Scalable estimator computation

Problem

In general, estimator computation is still a doubly exponential problem

Scalable estimator computation

Our solution

We only consider **positional estimators**. These may only base their next estimates on:

- the last sensor values and the last estimates
- the current sensor values
- the possible evolutions of the environment

Properties of our approach

- fixed size of the estimators
- no “strategic planning” possible by the estimators
- unique optimal estimators exist for most estimate preference relations

Example: Discretized car following controller (1)

Properties

- $\mathit{distance} \in \{0, \ldots, 84, 85\}$
- $\mathit{speedLeader} \in \{0, \ldots, 15\}$
- $\mathit{speedFollower} \in \{0, \ldots, 15\}$
- $\mathit{accelerationLeader} \in \{-2, -1, 0, 1, 2\}$
- $\mathit{accelerationFollower} \in \{-2, -1, 0, 1, 2\}$
- Noisy distance update
- Approximate (± 2) distance measurement
- …

Specification parts

- The *distance* must always be at least 5.
- $\mathbf{G}(\mathit{distance} < 85 \vee \mathit{speedFollower} = 15)$

Example: Discretized car following controller (2)

$$\cdots \longrightarrow \left(\begin{array}{c} 84 \\ 14 \\ \hline 4 \\ 13 \\ 15 \\ 83 \\ 85 \end{array}\right) \longrightarrow \left(\begin{array}{c} 78 \\ 15 \\ \hline 0 \\ 11 \\ 12 \\ \\ \\ \end{array}\right)$$

Meaning of the encoding : $\left(\begin{array}{c} \mathit{observedDistance} \\ \mathit{speedFollower} \\ \hline \mathit{accFollower} \\ \mathit{minSpeedLeader} \\ \mathit{maxSpeedLeader} \\ \mathit{minDist} \\ \mathit{maxDist} \end{array}\right)$

Example: Discretized car following controller (2)

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Example: Discretized car following controller (3)

$$\cdots \longrightarrow \begin{pmatrix} 84 \\ 15 \\ \hline 2 \\ 13 \\ 15 \\ 82 \\ 83 \end{pmatrix} \rightarrow \begin{pmatrix} 84 \\ 15 \\ \hline 2 \\ 12 \\ 15 \\ 82 \\ 84 \end{pmatrix} \rightarrow \begin{pmatrix} 85 \\ 15 \\ \hline 2 \\ 12 \\ 15 \\ 83 \\ 85 \end{pmatrix} \rightarrow \begin{pmatrix} 85 \\ 15 \\ \hline 2 \\ 10 \\ 15 \\ 83 \\ 85 \end{pmatrix} \rightarrow \begin{pmatrix} 85 \\ 15 \\ \hline 2 \\ 8 \\ 15 \\ 83 \\ 85 \end{pmatrix} \rightarrow \begin{pmatrix} 85 \\ 15 \\ \hline 2 \\ 6 \\ 15 \\ 83 \\ 85 \end{pmatrix} \rightarrow \begin{pmatrix} 85 \\ 15 \\ \hline 2 \\ 4 \\ 15 \\ 83 \\ 85 \end{pmatrix} \rightarrow \begin{pmatrix} 85 \\ 15 \\ \hline 2 \\ 2 \\ 15 \\ 83 \\ 85 \end{pmatrix} \longrightarrow \cdots$$

Meaning of the encoding : $\begin{pmatrix} \mathit{observedDistance} \\ \mathit{speedFollower} \\ \hline \mathit{accFollower} \\ \mathit{minSpeedLeader} \\ \mathit{maxSpeedLeader} \\ \mathit{minDist} \\ \mathit{maxDist} \end{pmatrix}$

Computing positional estimators

1. Compute the reachable states of *any* estimator

$$R = \mu X.(\{x_0\} \cup \{x' \subseteq AP_{obs} \cup AP_{hid} \cup AP_{est} \mid \exists x \in X.$$
$$(x \setminus AP_{est}, x' \setminus AP_{est}) \in \rho_e, (x, x') \in \rho_s\})$$

2. Compute which estimates are admissible

$$\rho_u = \{(x, x') \in (2^{AP_{obs} \cup AP_{est}})^2 \mid \forall y, y' \subseteq 2^{AP_{hid}} :$$
$$((x \cup y) \in R \wedge ((x \setminus AP_{est} \cup y),$$
$$(x' \setminus AP_{est} \cup y'))) \in \rho_e \rightarrow ((x \cup y), (x' \cup y')) \in \rho_s\}.$$

3. Restriction to optimal estimates

$$\hat{\rho}_u = \{(x, x') \in \rho_u : x'|_{AP_{est}} = \min\{x''|_{AP_{est}} : (x, x'') \in \rho_u,$$
$$x' \setminus AP_{est} = x'' \setminus AP_{est}\}\}$$

Discretized car following controller (cont'd)

Computation times with `slugs` (BDD-based)

- Basic scenario: 22+28 minutes
- *Cruise mode scenario:* 22+460 minutes (6 realizability checks)

Without estimator-based synthesis

Belief space: $2^{16 \cdot 86}$ states – **beyond tractability**

Conclusion

“Spicing up CPS controller synthesis”

In this talk...

...we discussed a few approaches to make the concept of *reactive synthesis* more applicable to CPS controller computation.

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But can they be combined?

Apart from the *error-resilient synthesis* part, they all require modifications of the synthesis process. → **So no!**

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In this talk...

...we discussed a few approaches to make the concept of *reactive synthesis* more applicable to CPS controller computation.

But can they be combined?

Apart from the *error-resilient synthesis* part, they all require modifications of the synthesis process. → **So no!**

Ok, so what now?

We will need to research methods to combine the considerations presented in this talk in a larger framework that still allows for scalable synthesis!

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