A Framework for Simulation-Based Online Planning

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Modellierung Dynamischer und Adaptiver Systeme
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Autonomous Systems

- Autonomous systems have to adapt to
  - environmental conditions and
  - new requirements at runtime even if they are defined at design time

- ASCENS project
  - 2010-2015, EU-funded Integrated Project
  - 15 partners from 7 countries
  - Developed systematic approach for engineering autonomous ensembles including
    - SW process, formal modeling, verification,
    - monitoring, adaptation, awareness
  - Case studies on robotics, cloud computing, e-mobility
Decision Making under Uncertainty

- Very large state spaces ($|S| > 10^{10}$)
- Probabilistic effects
- Partially uncontrolled environment
- Incomplete design time knowledge
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1. Online Planning
Online Planning

- Real Situation
- observe
- build State Model and plan
- execute

Image sources:
thegrid.soup.io/post/312159914
mobots.epfl.ch/marxbot.html
Online Planning

Real Situation

observe

execute

build State Model and plan

Image sources:
thegrid.soup.io/post/312159914
mobots.epfl.ch/marxbot.html
Online Planning (Informally, Sequential)

\[
\textbf{while} \ \text{true} \ \textbf{do} \\
\quad \text{observe state} \\
\quad \text{plan} \\
\quad \text{execute action w.r.t. plan} \\
\textbf{end while}
\]
Online Planning (Informally, Concurrent)

while true do
    observe state
    execute || plan
end while
Online Planning: Parameters

- **State space** $S$
- **Action space** $A$
  - Attribute `actionRequired : Agent → Bool`
  - Operation `observe : Agent → S`
- **Operation** `execute : RealAction → ()`

**Planning**
- Reward function $R : S → \mathbb{R}$  
  => `getReward`
- Strategy $P_{Action}(A | S)$  
  => `sampleAction`
- Planning refines initial strategy according to $R$

**Online planning**
- Iterated execution and planning
Online Planning (Refined)

Agent || Planner

Agent

while true do
state ← observe()
planner.state ← state
when actionRequired do
  actionRequired ← false
  action ← planner.strategy.sampleAction(state)
end when
action.real.execute()
end while

Planner

while true do
  plan()
end while
while true do
  state ← observe()
  planner.state ← state
  when actionRequired do
    actionRequired ← false
    action ← planner.strategy.sampleAction(state)
  end when
  action.real.execute()
end while

while true do
  plan()
end while
Plug Points

Agent $\parallel$ Planner

```plaintext
while true do
  state ← observe()
  planner.state ← state
  when actionRequired do
    actionRequired ← false
    action ← planner.strategy.sampleAction(state)
  end when
  action.real.execute()
end while
```

Planner

```plaintext
while true do
  plan()
end while
```
A Framework for Online Planning
A Framework for Online Planning

Observation

Real Situation

Interaction

Operates w.r.t. state and strategy

\[ P_{Action}(A|S) \]
A Framework for Online Planning

Changes strategy w.r.t. reward function

$P_{Action}(A|S)$
3. Simulation-Based Online Planning
Three Types of State

Real Situation

State Model

Simulation
Approach

- Refine strategy $P_{Action}(A|S)$ by Simulation-Based Planning
  - Provide agent with simulation of itself and domain

- Generate simulations of future episodes
- Evaluate simulation episodes wrt. reward function
- Use estimates to refine simulations
- Finally: Execute a real action that performed well in simulation
- Repeat
3.1 The Framework for Simulation-Based Planning
The Framework for Simulation-Based Planning

$P_{\text{Action}}(A|S)$

$P_{\text{Sim}}(S|S \times A)$
The Framework for Simulation-Based Planning

\[ P_{Action}(A|S) \]

\[ P_{Sim}(S|S \times A) \]
The Framework for Simulation-Based Planning

\[ P_{Action}(A|S) \]

Simulate wrt. strategy and domain dynamics

\[ P_{Sim}(S|S \times A) \]
The Framework for Simulation-Based Planning

\[ P_{Action}(A|S) \]

Simulation result refines strategy

Weighted by episode reward

\[ P_{Sim}(S|S \times A) \]
SBP Parameters

- **Simulation** \( P_{Sim}(S | S \times A) \)
  - Agent’s model/knowledge of domain dynamics
  - Can be changed at runtime
  - May differ from real domain dynamics
  - Can be learned/refined from observations

- **Maximum search depth** \( h_{max} \)
  - Impacts simulation effort
  - Less simulation steps: Fast but shallow planning
  - Can be dynamically adapted
Simulation-Based Planning Algorithm

\textbf{op} plan()
\begin{verbatim}
vars s, r, episode, a
s ← state
r ← rewardFct.getReward(s)
episode ← nil
for 0 .. h_{max} do
    a ← strategy.sampleAction(s)
    s ← simulation.sampleSuccessor(s, a)
    episode ← episode::(s, a)
    r ← r + rewardFct.getReward(s)
end for
strategy ← updateStrategy(episode, r)
end op
\end{verbatim}
Simulation-Based Planning: Plug Points

```plaintext
op plan()
    vars s, r, episode, a
    s ← state
    r ← rewardFct.getReward(s)
    episode ← nil
    for 0 .. h_max do
        a ← strategy.sampleAction(s)
        s ← simulation.sampleSuccessor(s, a)
        episode ← episode::(s, a)
        r ← r + rewardFct.getReward(s)
    end for
    strategy ← updateStrategy(episode, r)
end op
```
Simulation-Based Planning: Variants

- Variants define `updateStrategy(Episode, Real)`
  - Vanilla Monte Carlo
  - Genetic Algorithms
  - **Monte Carlo Tree Search**
    - for discrete domains
  - **Cross Entropy Planning**
    - for continuous domains
3.2 Monte Carlo Tree Search for Discrete Domains

- **Strategy as tree**
  - Nodes represent states and action choices
  - Add a node per simulation
  - Aggregate simulation data in nodes
    - Reward and frequency
  - Sample actions w.r.t. aggregated data

Strategy Inside the Tree

- E.g. Upper Confidence Bounds for Trees
- Treat action selection as multiarmed bandit
- Select actions that maximize

\[ UCT_j = X_j + 2C \sqrt{\frac{2 \ln n}{n_j}} \]

Strategy Inside the Tree

- E.g. Upper Confidence Bounds for Trees
- Treat action selection as multiarmed bandit
- Select actions that maximize

\[ UCT_j = X_j + 2C \sqrt{\frac{2 \ln n}{n_j}} \]

Exploit observations

- \( X_j \): Average reward of child node \( j \)
- \( n \): Nr. of episodes from current node
- \( n_j \): Nr. of episodes from child node \( j \)
- \( C \): UCT exploration constant

Explore solution space

Expand the Tree

- Add a new node
  - When an episode leaves the tree

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Strategy Outside the Tree

- Simulate episode to depth $h_{\text{max}}$
- Observe result
  - E.g. reward observed
  - Here: 0 or 1

Initial $P_{\text{Action}}(A|S)$
Update Strategy

- Update the statistics
- This changes the strategy inside the tree
Trees Represent Strategies

- MCTS builds a skewed tree
- Tree can be interpreted as $P_{Action}(A|S)$
- Promising parts of the strategy space are preferred
Example Domain

- **Search and Rescue**
  - Victims, fires and ambulances
  - Unknown topology
  - Unknown initial situation

- **Agent actions**
  - Noop, Move
  - Load or drop a victim
  - Extinguish fire if adjacent

- **Noise**
  - Actions may fail
  - Fires ignite and cease

- **Experiment**
  - Monte Carlo Tree Search
  - Large state space (> $10^{12}$)
  - Large branching factor ($2^{18}$)
  - 0.2 seconds/decision
  - $P_{Sim}(S \mid S \times A)$ models domain perfectly
Experimental Results (I)

- Measured (in %)
  - Victims at ambulance (blue)
  - Victims in a fire (red)
  - Positions on fire (green)
- Provided reward
  - Victim at ambulance: +100
- System synthesized sensible behavior
- Results in 0.95 confidence interval
  - Checked with MultiVeStA


**Autonomy**
Experimental Results (II)

- Measured (in %)
  - Victims at ambulance (blue)
  - Victims in a fire (red)
  - Positions on fire (green)
- Expose system to unexpected events
  - At steps 20, 40, 60, 80
  - All carried victims are dropped
  - New fires break out
  - Events NOT simulated by planner
  - New situation incorporated by planner
- System showed sensible reactions
- Results in 0.95 confidence interval

Robustness
Experimental Results (III)

- Measured (in %)
  - Victims at ambulance (blue)
  - Victims in a fire (red)
  - Positions on fire (green)
- **Change system goals** while operating
  - Change of reward function
    - Steps 0-40: Reward for victims not in a fire
    - Steps 40-80: Reward for victims at ambulance
  - Change NOT simulated by planner
  - But planner incorporates new situation
- System adapted behavior wrt. goals
- Results in 0.95 confidence interval

**Flexibility**
From Discrete to Continuous Domains

- **Actions**
  - State and action space = $\mathbb{R}^n$
  - E.g. (speed, rotation, duration) for actions

- **Cross Entropy Planning**
  - Approximate (unknown) target distribution
    - Multivariate Gaussian distribution
    - Sample state space (locally) and choose „elite“ samples for updating the strategy („sharpen“ the Gaussian)

- **Here:** Gaussians over sequences of actions
  - Sequence length = planning depth
Cross Entropy Planning

- White circle represents agent
- Red boxes represent moving victims
- Black lines are simulation episodes
- Action parameters are speed, rotation and duration
- Images show iterations 1, 5 and 10
  - Simulation depth is adaptive here (reduced simulation cost)
  - Note the iterative “shaping” of a promising strategy
Video: Cross Entropy Planning
Video: Cross Entropy Planning

- The video showed **interleaving** planning and execution
- Illustrates iterative shaping of a probabilistic strategy
- When **parallelizing** planning and execution, this looks a little different...
Video: Continuous CE Planning
Cross Entropy Planning Experiments

- CE: Cross Entropy Planning
- TACE: Time Adaptive CE
- C3: Continuous CE Control

- h: Planning depth
- d: Action duration

![Diagram showing the comparison of CE, TACE, and C3 methods over time. The diagram highlights the effects of planning depth and action duration on time spent.]
Concluding Remarks

- **Motivation**
  - Complex dynamic domains
  - High degrees of non-determinism

- **Approach**
  - Model a space of solutions, instead of a single one
  - Online planning: Refine the solution space at runtime wrt. observations and knowledge to determine a currently viable action

- **This Talk**
  - Component framework for Online Planning
    - Parallelization of execution and planning
  - Instantiation: Simulation Based Planning
    - Two examples: MCTS, Cross Entropy Planning

- **Outlook**
  - Model learning of domain dynamics
  - Soft temporal logic for formal (statistical) verification
  - Learning and planning for ensembles
References


