Dimensionality Effects on the Markov Property in Shape Memory Alloy Hysteretic Environment

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Basic Overview

- Motivation
- Reinforcement Learning
- The Markov Property
- Simulation
- Conclusions
- Challenges and Open Problems
Motivation
Morphing Aircraft

Why should it have morphing capabilities?
- Improved efficiency at multiple flight conditions
- Wider range of possible maneuvers

How would it physically achieve morphing?
- SMA Actuators
Shape Memory Alloys (SMA)

- Metallic Alloys used as actuators
- Shape Memory Effect – SMA can fully recover from a plastically deformed shape change by the addition of heat
- Electricity can be used to induce a cycle of heating, cooling, and deformation in an SMA in order to execute a dynamic task

**PROBLEM:**
Efficiently characterizing and controlling SMA behavior
Why Is Characterizing SMAs Such A Challenge?

1. Uncertain Model Parameters
2. Temperature–Strain Relationship: **Hysteresis**
   - Behavior based on a 2-D FIELD, not a 2-D PATH
Reinforcement Learning
Reinforcement Learning

- Does not require any prior knowledge.
  - Knowledge is based on experience and interaction with the environment, not on input-output data supplied by an external supervisor.

- Achieves a specific **goal** by learning from interactions with the environment.
  - Considers **state** information (s)
  - Performs sequences of **actions**, (a), observing the consequences
  - Attempts to maximize **rewards** (r) over time
    - These specify what is to be achieved, *not how to achieve it*

  - Constructs an **action value function** (Q)
    - Learns an optimal control **policy**

- Memory is contained in the action value function
RL Algorithm: Sarsa

\[ Q(S, A, G) \leftarrow Q(S, A, G) + \alpha[R(S', A', G) + \gamma Q(S', A', G) - Q(S, A, G)] \]

3-D Control Policy Matrix

- **States (S)**: Temperature and Strain Dependent
- **Actions (A)**: Change Temperature (Voltage Application)
- **Goal (G)**: Desired Strain
- **\( \alpha \)**: Repetition Penalty
- **\( \gamma \)**: Future Policy Weight

Action Choice Method: \( \varepsilon \)-Greedy
- Explore or Exploit: Dependent upon \( \varepsilon \) (which varies with Episodes)

**Why Not Q-Learning?**
- On-policy v. Off-policy Learning
The Markov Property
The Markov Property

- In a general system, the probability of achieving a specific goal from a specific initial state is a function of both current and past information about states, actions, and rewards.

\[
\Pr\{s_{t+1} = s', r_{t+1} = r \mid s_t, a_t, r_t, s_{t-1}, a_{t-1}, \ldots, r_1, s_0, a_0\}
\]

- In a system with the Markov Property, the same probability distribution is obtained with only the current state and action information required.

\[
\Pr\{s_{t+1} = s', r_{t+1} = r \mid s_t, a_t\}
\]
The Markov Property

- Hysteresis is non-Markovian in nature because moving from one state to another in hysteresis space typically requires knowledge of state history.

- In the problem of learning to control the strain of an SMA wire during a thermally-induced transformation, this non-Markovian behavior is apparent.
The Markov Property

- For this research, we recognized that the past strain history is only needed so that we know the current point in temperature/strain space.

- By measuring temperature and including it in the current state information, the system becomes Markovian.
Simulation
**Simulation Model**

- **Temperature-Strain Relation:**
  - Hyperbolic Tangent Model
  
  \[ \varepsilon(i) = \frac{1}{2} h \tanh \left( (T(i) - \text{ctl})a \right) + s \left( T(i) - \frac{1}{2} \text{ctl} - \frac{1}{2} \text{ctr} \right) + \frac{1}{2} h + cs \]

- **Voltage-Temperature Relation:**

\[ \frac{dT}{dt} = \frac{V^2}{R} - h \pi D L (T - T_\infty) - \frac{m C_p}{R} \]

- Learns input-output data (how to apply voltage to achieve a particular position state), not the constitutive model of an SMA
Simulation Results

Strain Learning Only

Strain and Temperature Learning

- Goal States: Random Strain Goals
- Error range: ± 0.2% Strain
- Episodes: 50,000
Conclusions

- Measuring temperature and including it in the information composing the current state allows the Sarsa algorithm to converge for the SMA learning problem
  - The SMA hysteresis is a non-Markovian environment when only strain is considered in state information
  - Measuring temperature alters the system and provides the Markov Property

- With the improved description of the state-space, Sarsa is able to converge to a near-optimal control policy in finite time using the Sarsa algorithm.
Challenges and Open Problems

Open Problems
- Expanding scope from wire (one spatial dimension displacement) to surface (two and three-dimensional displacements) would expand these methods to greater generalities.
- Learning how to control arrays of 1-D wires needed to make 1-D SMA actuators usable for morphing.
- Design and construct SMA-based actuator for implementation on a Morphing UAV.

Challenges
- Extension to higher dimensions produces much longer learning times due to spatial complexity.
- The ability to heat 2-D and 3-D SMA objects is difficult to accomplish through electrical resistance.
- May need separate actuator designs for each degree of freedom being morphed.
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Kirkpatrick & Valasek - 19
Questions?
SMA Characterization Methodologies

**CURRENT METHOD**: Experimentation and Testing to approximate constitutive model

- Mainly based on material property parameters OR system identification
  - **Approximate Models**:
    - Neglect hysteresis
    - Arrange antagonist SMAs to “cancel” the hysteretic effect
    - Modified plasticity model composed of averaged thermal effects
    - Disregard coupling of hysteretic and structural response
    - Other averaging techniques
Experimental Forced Characterization: Water

SMA Major Hysteresis

![Graph showing SMA Major Hysteresis with axes labeled Temperature (C) on the x-axis and Strain on the y-axis. The graph includes data points indicating the relationship between temperature and strain.]
Experiment – Goals v. Time

Convergence Behavior for Goal of 2.7% Strain

mid learning
Experiment – Mid Learning Refinement

Episode 23 - 4 Actions to Goal Strain

Temperature (C)

Strain

Kirkpatrick & Valasek - 24