

Optimal Control for Remote Patient Monitoring with Multidimensional Health States

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Outline

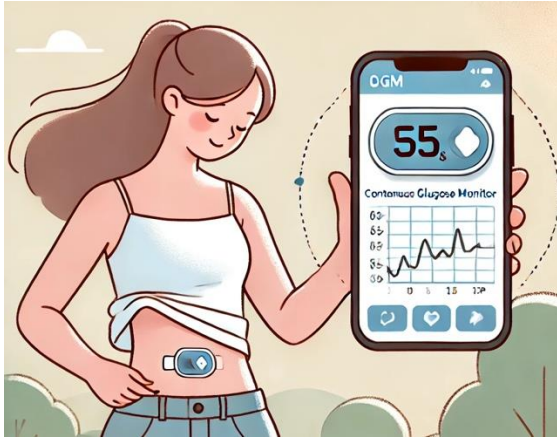
1 Background and Motivation

2 Service Architecture

3 Optimal Policy

Remote Patient Monitoring

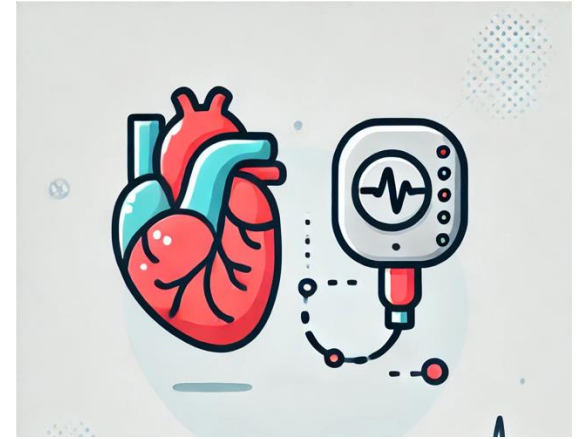
- Technology enabled healthcare



Continuous Glucose Monitors



Smartwatches



Implantable Devices

Images created using OpenAI's DALL-E 3 model. Prahalad et al. (2024). Nature Medicine, 1-9., Masoumian Hosseini et al. (2023). BMC Medical Informatics and Decision Making, 23(1), 248. , Zinzuwadia et al. (2023). In Emerging Practices in Telehealth (pp. 97-115). Academic Press.

Remote Patient Monitoring



Ordinary



Intensive

Remote Patient Monitoring

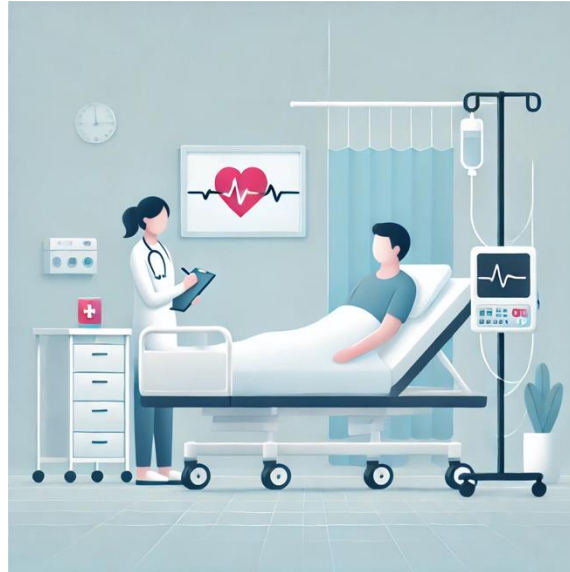


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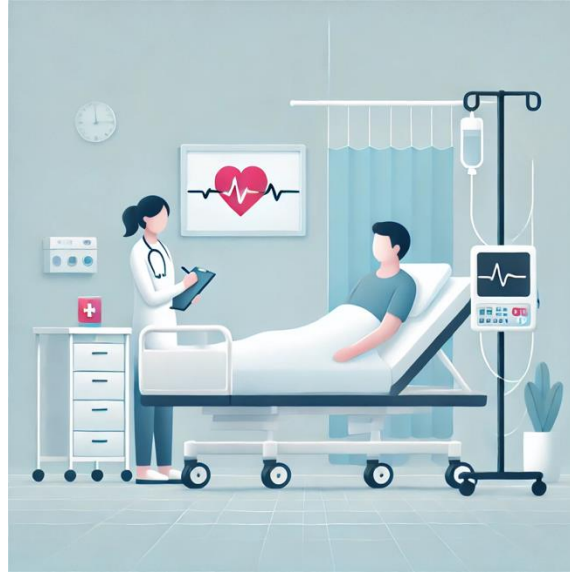
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Remote Patient Monitoring



Critical State

Remote Patient Monitoring

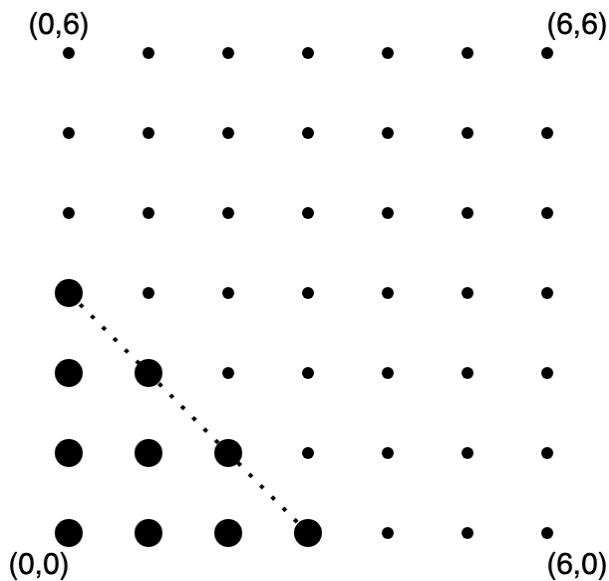


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Tiered Service Architecture

Multidimensional Health State

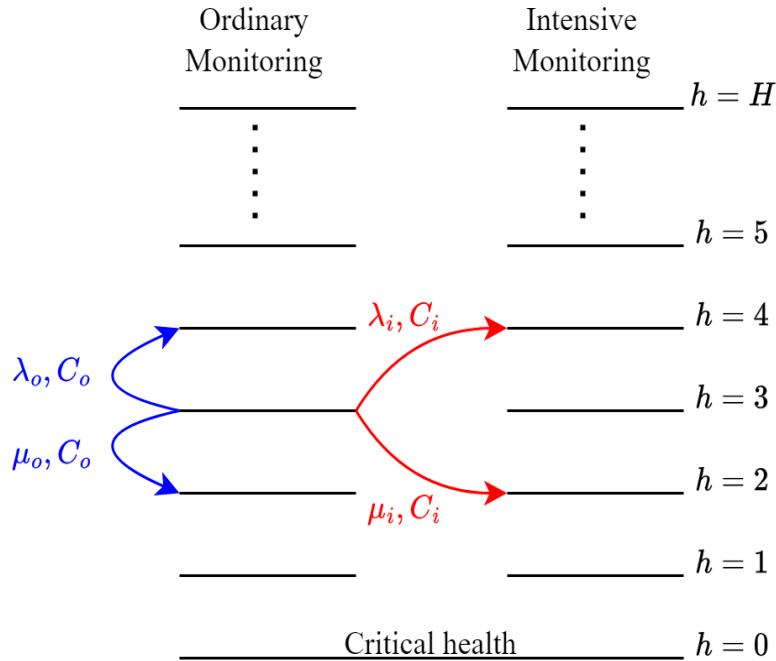
- Multidimensional health states: $\mathbf{h} = (h^{(1)}, h^{(2)}, \dots, h^{(n)})$
 - $h^{(i)} \in \{0, 1, \dots, H\}$
 - n different health measurements
 - “Higher” health state \Rightarrow Better health
- For better visualization, we work with 2 states
 - $\mathbf{h} = (h^{(x)}, h^{(y)})$
- Set of critical health states - $\mathcal{H}_c = \{\mathbf{h} \mid g(\mathbf{h}) \leq c\}$
 - Health falls below certain threshold
 - Examples:
 - Both measurements are zero
 - Either measurement is zero



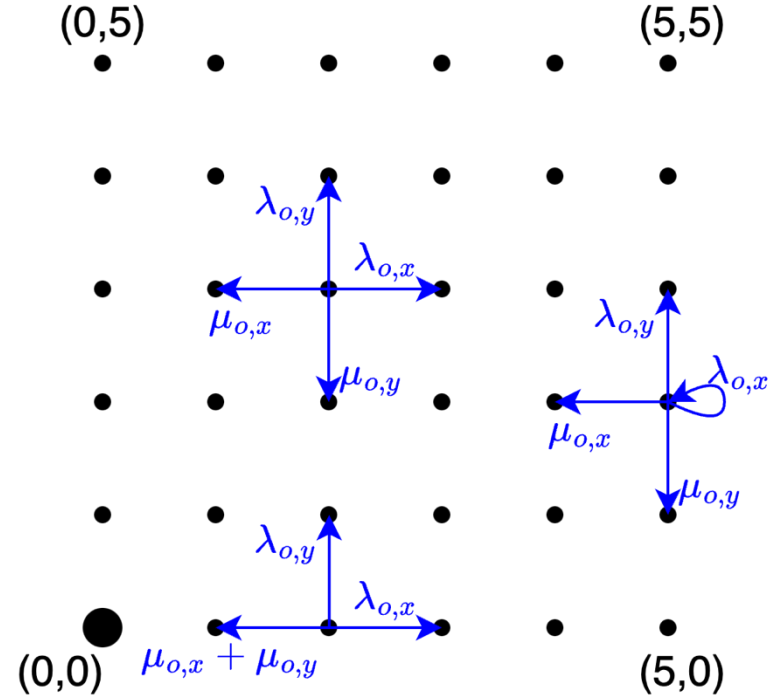
Markovian Model

- **Markov Decision Process**
- **Time period:** $t \in \{0, 1, 2 \dots\}$
- **Health states:** $h_t = (h_t^{(x)}, h_t^{(y)})$
- **Monitoring States:** $m_t \in \{o, i\}$
 - o : Ordinary Monitoring
 - i : Intensive Monitoring
- **Overall State:** $s_t = (h_t, m_t)$
- **Action/Control:** $a_t \in \{o, i\}$
- **Costs:** C_o, C_i, C_c
- Evolution stops when a critical health state is reached

One-Dimensional Model¹



Multidimensional Model



- ¹S. Chandak, I. Thapa, N. Bambos, D. Schienker, "Tiered Service Architecture for Remote Patient Monitoring", IEEE Healthcom 2024

Assumptions

- The transition probabilities satisfy:
 - $\lambda_{i,x} \geq \lambda_{o,x}$
 - $\lambda_{i,y} \geq \lambda_{o,y}$
- The costs satisfy:
 - $0 \leq C_o \leq C_i \ll C_c$

Optimal Policy

Optimal Control

- Value Function

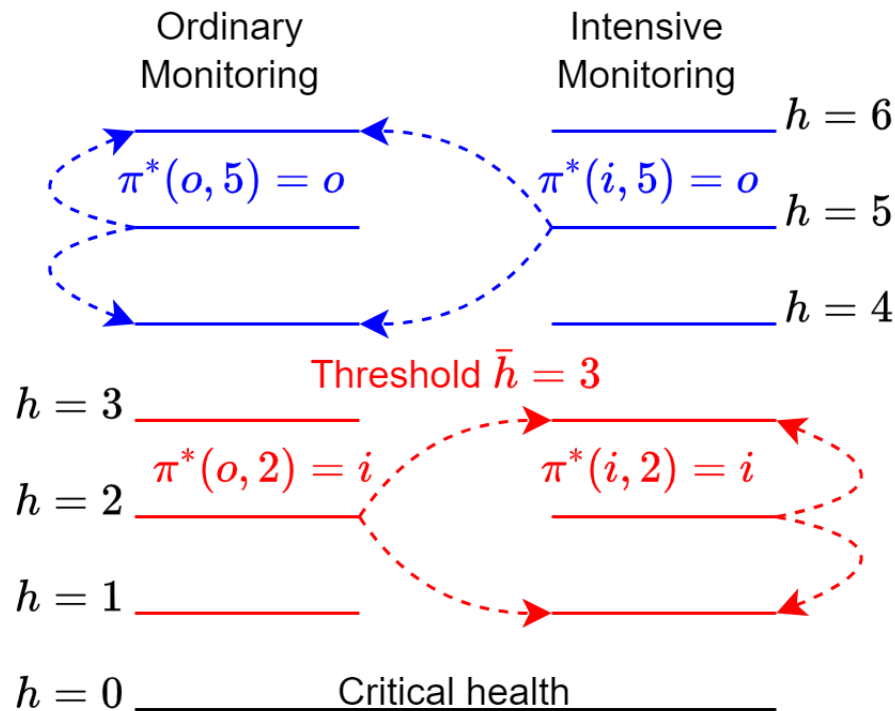
$$V^*(s) = \min_{a \in \{o,i\}} \left\{ c(s, a) + \gamma \sum_{s' \in S} P(s' | s, a) V^*(s') \right\}$$

- Optimal Policy

$$\pi^*(s) = \operatorname{argmin}_{a \in \{o,i\}} \left\{ c(s, a) + \gamma \sum_{s' \in S} P(s' | s, a) V^*(s') \right\}$$

Intuition from One-Dimensional Model¹

- Threshold-based policy
 - When $h > \bar{h}$:
 - Ordinary Monitoring
 - When $h \leq \bar{h}$:
 - Intensive Monitoring
- Proof Technique:
 - Moment Generating Function (MGF) of the hitting time of critical health state

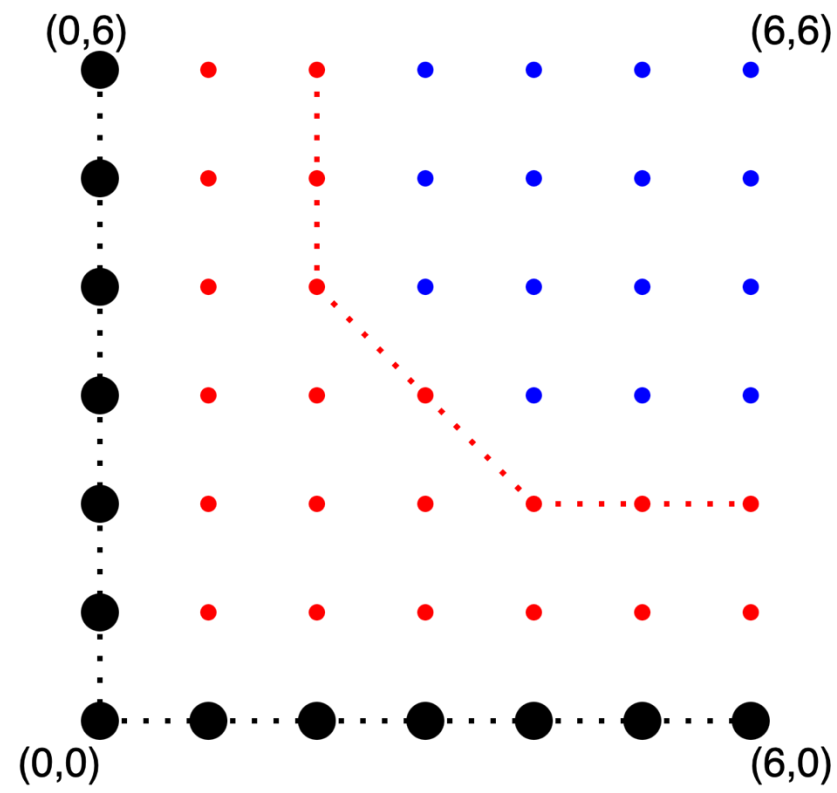


¹S. Chandak, I. Thapa, N. Bambos, D. Schienker, "Tiered Service Architecture for Remote Patient Monitoring", IEEE Healthcom 2024

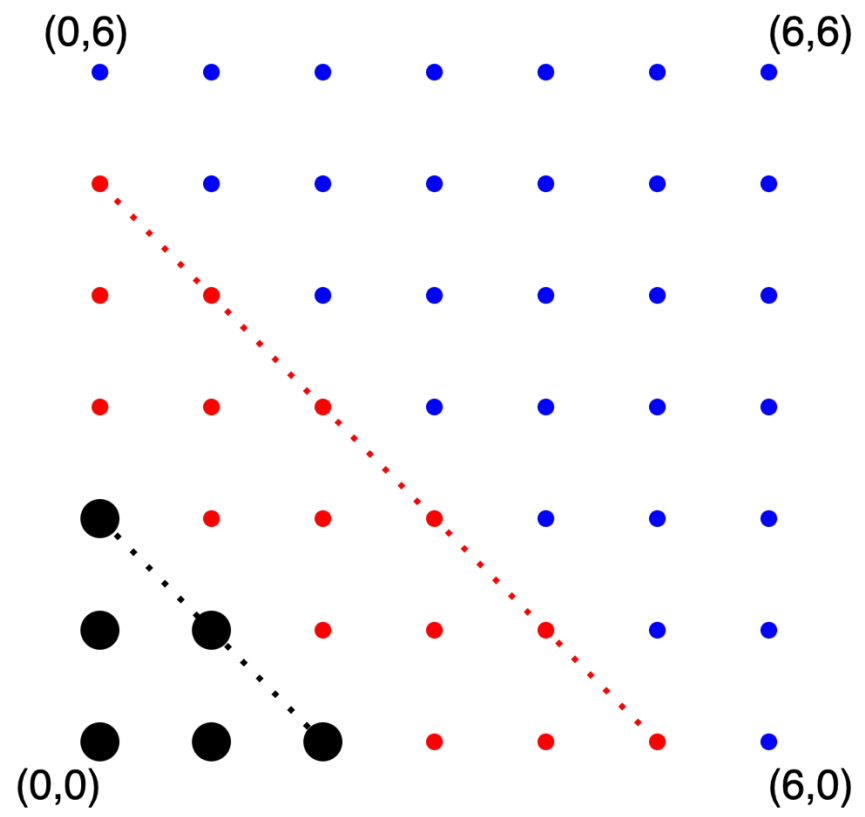
Switching Curve Policies

- Set of critical health states – $\mathcal{H}_c = \{\mathbf{h} \mid g(\mathbf{h}) \leq c\}$
- Optimal Policy characterized by some function $f(\cdot) : \mathcal{H} \mapsto \mathbb{R}$
 - If $f(\mathbf{h}) \leq 0$: Intensive Monitoring
 - If $f(\mathbf{h}) > 0$: Ordinary Monitoring
- $f(\mathbf{h}) = 0$ is the Switching Curve
- Same intuition as before:
 - Shape of switching curve dictated by the hitting time

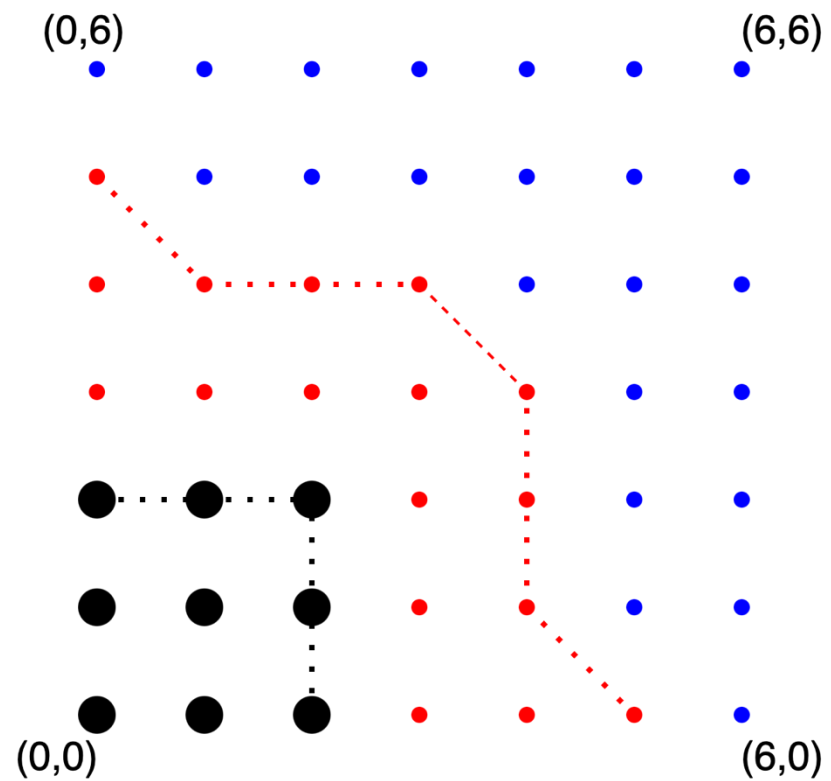
Critical Health State - 1



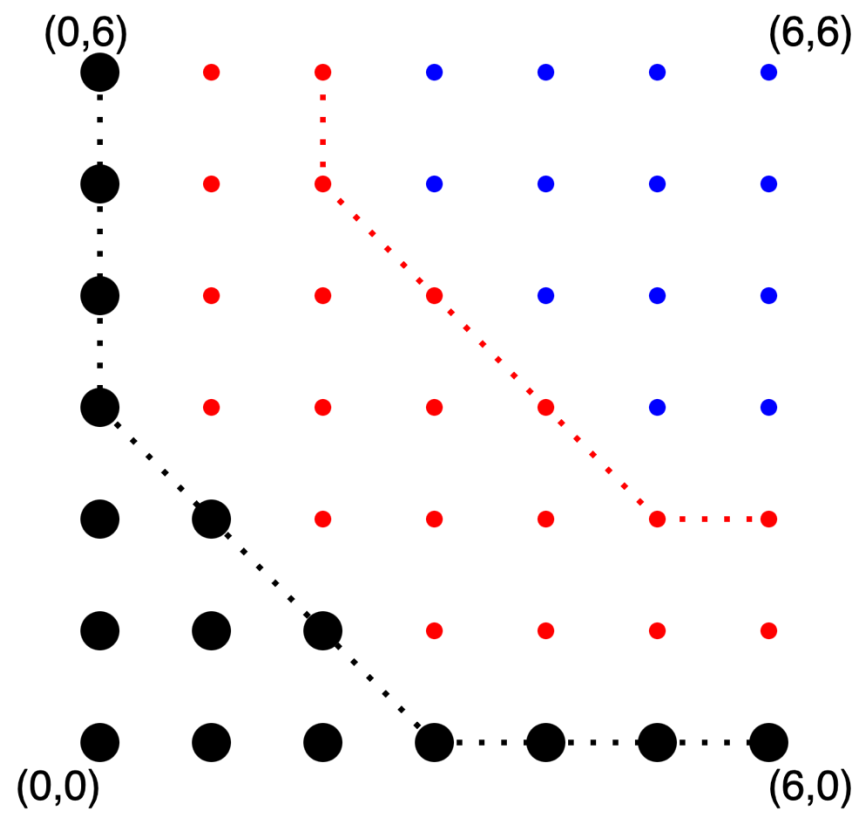
Critical Health State - 2



Critical Health State - 3



Critical Health State - 4



Conclusion

- Tiered monitoring system with multidimensional health states
- Policies based on Switching Curves
- Extensions
 - Learning
 - Non-Markovian model

Thank You

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