Robust and Adaptive Control Methods for Patient Response to Anesthesia

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Outline

- Introduction: the anesthesia control problem
- Modeling the Patient Response
- Robust and Adaptive Control Methods
- Control Simulation Results

Problem Statement



Anesthesiologist:

- Administers sedatives, analgesics, and neuromuscular blockades
- maintains ventilation parameters
- monitors cardiovascular and respiratory functions
- monitors blood chemistry:

blood-sugar levels, electrolyte concentrations, gas concentrations, coagulation parameters...

Goal: automate/optimize delivery and control of anesthesia



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Model-based feedback control requirements:

- means of sensing levels of sedation, analgesia, relaxation/neuromuscular blockade
- mathematical models of patient response

Goal: automate/optimize delivery and control of anesthesia

Sensing signals:

- **Neuromuscular block:** *Surface electrode or piezoelectric measurements of response to electrical stimuli; typically uncoupled from sedation effects*
- Analgesia: No standardized or widely accepted means of measuring extent of pain relief; appears to be correlated with sedation
- Sedation: Spectral entropies (GE), wavelet analysis methods, Bispectral Index (BIS)

Derived from EEG using combination of higher order spectra and other indicators such as spectral edge and median frequencies; reveals synchrony of cortical brain signals characterizing unconsciousness (Covidien)

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Model-based feedback control:

- Inputs: inhalational sedative
 Isoflurane and clinical stimuli
- Outputs: vital signs Heart Rate (HR) and Mean Arterial Pressure (MAP); BIS
- BIS values range from 0 to 100:
 - 100 completely alert
 - 60 moderately sedated
 - 40 deeply sedated



Control Goals:

- Track BIS reference trajectory signal while maintaining HR and MAP in healthy ranges
- *Must be adaptive and robust to patient variability*

Patient Response Models

Modeling Patient Response Compartment Models



- *Pharmacokinetic (PK) models:* Empirically derived linear ODEs
- *Pharmocodynamic (PD) models:* Static nonlinearity (e.g., sigmoidal function) fit to individual patient data
- Nonlinear SISO Grey-Box Models

Modeling Patient Response Clinical trial data

Input Data

Output Data





P. S. Glass, M. J. Bloom, et. al, Anesthesiology, 1997

Modeling Patient Response

Linear Parameter Varying (LPV) Models: Subspace Identification used to construct models for individual patients from clinical data

- Piecewise-linear models
 - Awake and Sedated patient states
 - Low-order (3rd to 5th order per patient state)

$$x_i(k+1) = A_i x_i(k) + B_i u(k) + w(k)$$

$$y(k) = C_i x_i(k) + D_i u(k) + v(k)$$

where $i = A$ (Alert), S (Sedated)

- LPV models
 - Gain-scheduled with respect to BIS value

$$A(\delta) = \frac{\delta(\delta-1)}{2}A_A + \frac{\delta+1}{2}A_S$$

$$B(\delta) = \frac{\delta(\delta-1)}{2}B_A + \frac{\delta+1}{2}B_S$$

$$C(\delta) = \frac{\delta(\delta-1)}{2}A_A + \frac{\delta+1}{2}A_S$$

$$With \ \delta(t) = 1 - \frac{2}{1 + \exp^{\eta * (70 - BIS(t))}}$$

Modeling Patient Response LPV model simulation results



H. H. Lin, C. L. Beck, and M. J. Bloom, IEEE Trans. on Biomed. Eng., 2004.

Modeling Patient Response

- \mathcal{L}_1 -Adaptive output feedback control design method based on standard transfer function models
 - Model structure

$$y(s) = G(s) \left(u(s) + d(s) \right)$$

- G(s) is LTI system transfer function; assumed strictly proper
- y(t) is measured BIS reading
- *u(t)* is input anesthesia flow *(percentage concentration of volume)*
- d(t) is time-varying disturbance (may be a function of y(t), assumed Lipshitz with constant L)
- State-Space Identification methods used to construct 4th order realizations {*A*, *B*, *C*}: $G(s) = C(sI A)^{-1}B$

LPV and \mathcal{L}_1 -Adaptive Control

LPV Controller Synthesis



A. Packard, System and Control Letters, 1994; Apkarian and Gahinet, IEEE Trans. on Auto. Control, 1995; S. Shahruz and S. Behtash, J. of Math. Analysis and Applications, 1992

\mathcal{L}_1 -Adaptive Control Methods Overview

- Goal: track a given reference input r(t) under modeling uncertainties
- Guarantee: asymptotic tracking with uniformly bounded system inputs and outputs
- *Prevents high frequency oscillations in control channel, and parameter drifts*

\mathcal{L}_1 -Adaptive Control Methods Overview

- Design controller such that output y(t) tracks reference input r(t) according to some desired model M(s): $y(s) \approx M(s)r(s)$
- Rewrite original input-output relationship using reference model:

$$y(s) = M(s) (u(s) + \sigma(s)), \text{ where}$$

$$\sigma(s) = \frac{(G(s) - M(s))u(s) + G(s)d(s)}{M(s)}$$

• Example:
$$M(s) = \frac{m}{s+m}$$

\mathcal{L}_1 -Adaptive Control Methods Design Architecture

Consider the closed-loop reference system:

$$y_{ref}(s) = M(s) \left(u_{ref}(s) + \sigma_{ref}(s) \right)$$

$$\sigma_{ref} = \frac{(G(s) - M(s))u_{ref} + G(s)d(s)}{M(s)}$$

$$u_{ref} = C(s)(r(s) - \sigma_{ref}(s)), \text{ with}$$

$$C(s) = \frac{w}{s+w}$$

- C(s) is low-pass filter used to attenuate high frequency uncertainty in control channel, and w is a design parameter
- r(s) is reference input

\mathcal{L}_1 -Adaptive Control Methods Design Architecture

Enforce the following stability condition:

Select C(s) and M(s) such that

$$H(s) = \frac{G(s)M(s)}{(C(s)G(s) + (1 - C(s))M(s))}$$

is BIBO stable, and

 $L \cdot \|H(s)(1 - C(s))\|_{\mathcal{L}_1} < 1$

Guarantees BIBO stability of closed-loop reference system

\mathcal{L}_1 -Adaptive Control Methods Design Architecture

The \mathcal{L}_1 -*Adaptive Controller consists of*

- Output Predictor:

$$\frac{d\tilde{y}(t)}{dt} = -m\tilde{y}(t) + m\left(u(t) + \tilde{\sigma}(t)\right), \quad \tilde{y}(0) = 0$$

- Parameter Adaptation Law: $\frac{d\tilde{\sigma}(t)}{dt} = \Gamma \cdot \Pi(\tilde{\sigma}(t), -mP(\tilde{y} - y)), \quad \tilde{\sigma}(0) = 0$

where $\Pi(\cdot, \cdot)$ is least-squares type projection operator, Γ is adaptation rate, P > 0 is arbitrary, and $|\tilde{\sigma}(t)| \leq \Delta$ is projection bound

- Feedback Control Law: $u(s) = C(s)(r(s) - \tilde{\sigma}(s))$

\mathcal{L}_1 -Adaptive Control Methods Performance Guarantees

It can be shown that for all $t \ge 0$, the \mathcal{L}_1 -Adaptive Output Feedback Controller guarantees uniform boundedness of the tracking error, i.e.,

$$\|\tilde{y}(t) - y(t)\|_{\mathcal{L}_{\infty}} \le \frac{k}{\sqrt{\Gamma P}}$$

where k is a (computable) constant

Design and Simulation Results

LPV Design and Simulation Results BIS reference tracking



- Reference signal r(t) constructed to emulate original BIS profiles in clinical data
- BIS signal should track *r*(*t*)
- MAP within 60-110mmHg

LPV Design and Simulation Results BIS reference tracking



H. H. Lin, C. L. Beck and M. J. Bloom, ACC, 2008

\mathcal{L}_1 -Adaptive Design and Simulation Results BIS Tracking – No Disturbances



- initial settings: P = 1, $\Delta = 100$, $\Gamma = 50,000$
- filters: $M(s) = \frac{1}{30s+1}$, $C(s) = \frac{0.001}{s+0.001}$

\mathcal{L}_1 -Adaptive Design and Simulation Results BIS Tracking – No Disturbances



- initial settings: P = 1, $\Delta = 100$, $\Gamma = 50,000$
- filters: $M(s) = \frac{1}{30s+1}$, $C(s) = \frac{0.002}{s+0.002}$

\mathcal{L}_1 -Adaptive Design and Simulation Results BIS Tracking – Robustness to Patient Variability



Time t [min]

\mathcal{L}_1 -Adaptive Design and Simulation Results BIS Tracking – Robustness to Patient Variability

Patient 1 controller on Patient 2, 3, 5, 6 and 7 models: *Performance Analysis*

Patient	1	2	3	5	6	7
Residual Tracking Error	0.0019	0.0062	0.0022	0.0016	0.0036	0.0064
Patient	1	2	3	5	6	7
Isoflurane Use (liters)	2.40	2.86	2.23	2.40	2.29	2.15
Previous control yielded residual tracking errors in the 5-10% range, and average total isoflurane consumption of approximately 3 liters						

\mathcal{L}_1 -Adaptive Design and Simulation Results MIMO Control – BIS Tracking and MAP Performance with Disturbances



MAP required to be maintained within 60-110 mmHg range

M. Ralph, C. L. Beck and M. J. Bloom, ACC 2011; E. Kharisov, C. L. Beck and M. J. Bloom, SIAM Conference, 2013

\mathcal{L}_1 - Adaptive Controller Designs



Conclusions

- First applications of LPV and \mathcal{L}_1 -Adaptive methods to anesthesia control
- Performance analysis includes intended patient and cross-patient evaluations

Implementation issues:

- Anesthesiologist controlled induction
- Enforce bounds on maximum drug concentrations "Hedging design"
- Predictor sampling
- \mathcal{L}_1 /LPV controllers with enable-disable control: "Human-Machine Interface"
- Multiple synergistic anesthetic agents

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