

Online parameter estimation for a bilinear control problem

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Summary

- 1 Motivation
- 2 Estimator construction & results
- 3 Conclusion & outlook

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Bloch-Torrey

Bloch-Torrey equation:

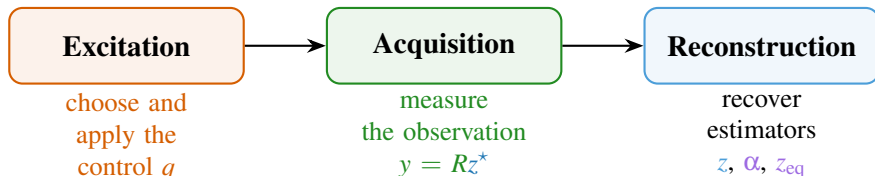
$$\partial_t z^\star + q \times z^\star + \alpha z^\star + \Delta z^\star = z_{\text{eq}}^\star.$$

- $z^\star$: magnetisation state.
- q : excitation / control.
- $\alpha, z_{\text{eq}}^\star$: unknown relaxation-type time-independent parameter.

From excitation to reconstruction

Bloch-Torrey equation:

$$\partial_t \mathbf{z}^* + \mathbf{q} \times \mathbf{z}^* + \alpha \mathbf{z}^* + \Delta \mathbf{z}^* = \mathbf{z}_{\text{eq}}^*.$$



Framework & objectives

System:

$$\begin{cases} \partial_t z^* + H_0(z^*)\theta^* + C(q)z^* = 0, \\ y = Rz^*. \end{cases} \quad (S)$$

Objectives:

- reconstruct the parameter θ^* ,
- do so quickly and precisely,
- design a control q to optimise the reconstruction.

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Online parameter estimation

$$\text{System: } \partial_t z^* + H_0(z^*)\theta^* + C(q)z^* = 0,$$

$$\text{Observation: } y = Rz^*,$$

$$\text{State estimator: } \partial_t z + H_0(z)\theta + C(q)z = \Psi^z(z, \theta, y),$$

$$\text{Parameter estimator: } \partial_t \theta = \Psi^\theta(z, \theta, y).$$

Advantages:

- starts reconstruction during acquisition
 $\implies \begin{cases} \text{quicker reconstruction} \\ \text{good initial condition for another reconstruction algorithm} \end{cases}$
- allows for observation-based excitation $q(t, x, y)$.

State of the art

Classical (control-less) approach¹: estimators θ and z such that

$$\begin{cases} \partial_t z + H_0(z)\theta = H_0(Re^z)\theta - \lambda R^* R e^z e^z, \\ \partial_t \theta = H_0(z)^* R e^z, \\ e^z = z - z^*, \\ e^\theta = \theta - \theta^*. \end{cases}$$

Energy estimates:

$$\Gamma = \frac{1}{2} \left(\|e^z\|^2 + \|e^\theta\|^2 \right).$$

$$\partial_t \Gamma = -\lambda(t) \|R e^z\|^2 + \langle H_0(R e^z) e^\theta - H_0(R^\perp e^z) \theta^*, e^z \rangle - \langle R^\perp e^z, H_0(z) e^\theta \rangle.$$

¹Baumeister et al. 1997; Kügler 2010; Boiger and Kaltenbacher 2016.

Estimator construction

$$\begin{cases} \partial_t z^\star + H_0(z^\star)\theta^\star + C(q)z^\star = 0, \\ y = Rz^\star. \end{cases} \quad (S)$$

Differentiate the observation: $\partial_t y = R\partial_t z^\star = -R[H_0(z^\star)\theta^\star + C(q)z^\star]$.

New information: $r = \partial_t(Rz^\star - y) = R([\tilde{H}_0(\theta^\star) + C(q)]e^z + H_0(\bar{z})e^\theta)$.

New estimators $z^\perp$ and θ of $R^\perp z^\star$ and $\theta^\star$:

$$\begin{cases} \bar{z} = y + z^\perp \\ \partial_t z^\perp + R^\perp (H_0(\bar{z})\theta + C(q)\bar{z}) = \Psi^\perp \\ \partial_t \theta = \Psi^\theta. \end{cases}$$

Literature: similar ideas in Lepsien et al. [2025](#).

Sketch of proof

For $\mu(t) > 0$ to be chosen, take

$$\begin{cases} \Psi^\perp = \mu [\tilde{H}_0(\theta) + C(q)]^* r, \\ \Psi^\theta = \mu [H_0(\bar{z})]^* r. \end{cases}$$

Then:

$$\begin{aligned} \partial_t \Gamma = & - \left\langle H_0(e^z) \theta^* + H_0(\bar{z}) e^\theta, e^z \right\rangle \\ & - \mu \langle [\tilde{H}_0(\theta^*) + C(q)] e^z + H_0(\bar{z}) e^\theta, R H_0(e^z) e^\theta \rangle \\ & - \mu \|r\|^2. \end{aligned}$$

Hypotheses:

- Continuity/coercivity of the operators involved.
- Smallness of initial parameter error: $\theta_0 \simeq \theta^*$.
- Persistence of excitation: $\exists \tau > 0, \exists \varepsilon > 0, \forall T > 0,$

$$\int_T^{T+\tau} \|r\|^2 \geq \varepsilon \|e^\theta\|^2.$$

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What about the control?

The persistence of excitation $\exists \tau > 0, \exists \varepsilon > 0, \forall T > 0$,

$$\int_T^{T+\tau} \left\| R([\tilde{H}_0(\theta^*) + C(q)]e^z + H_0(\bar{z})e^\theta) \right\|^2 \geq \varepsilon \|e^\theta\|^2.$$

boils down to a control-dependant observability inequality:

$$\int_0^T \left\| R([\tilde{H}_0(\theta^*) + C(q)]e_q^z + H_0(\bar{z}_q)e_q^\theta) \right\|^2 \geq \varepsilon_q \|e_q^\theta\|^2.$$

Control optimisation must be done:

- to maximise the observability constant ε_q ,
- with open-loop or observation-dependant controls.

Conclusion & outlook

We have:

- a nice general framework,
- an online method that should work.

On the way:

- convergence proof, including noise robustness,
- control design,
- numerical implementation.

Future works:

- what of differentiating the observation multiple times?
- Can we consider more general systems?

Thank you for listening!



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