



# The Observer Effect in Estimation with Physical Communication Constraints

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Joint work with

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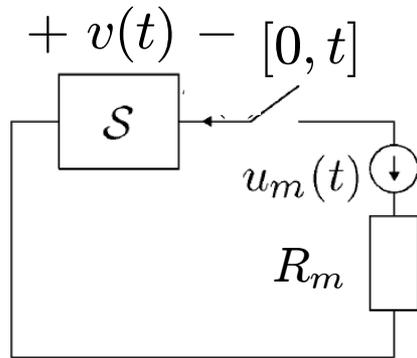
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# Observer Effect - Example

Voltage perturbation in passive circuit  $S$  —  $\Delta v(t)$

Uncertainty in optimal voltage estimate —  $\Delta \hat{v}(t)$



With or without active compensation, a trade-off exists:

$$|\Delta v(t)| |\Delta \hat{v}(t)| \geq 2k_B T_m / C \quad \text{small } t$$

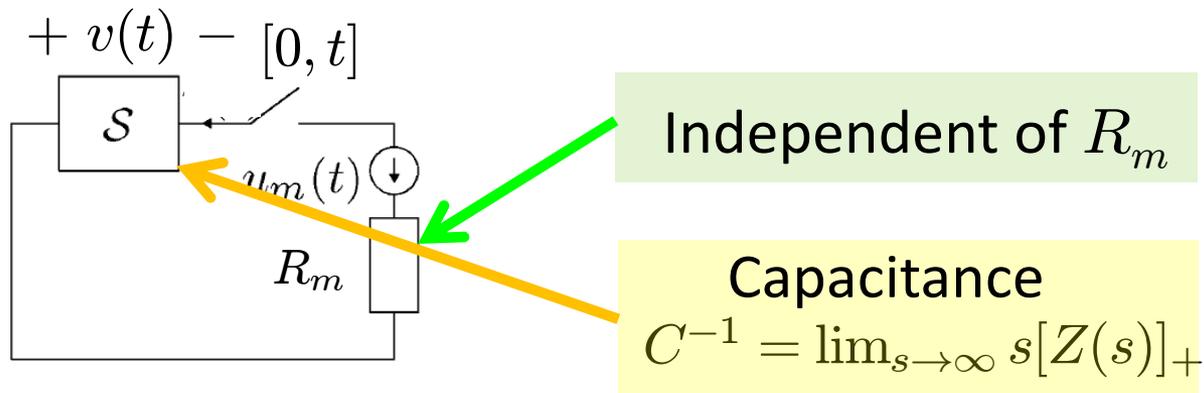
Sandberg, Delvenne, Doyle, IEEE TAC 2010

*How general is this trade-off?*

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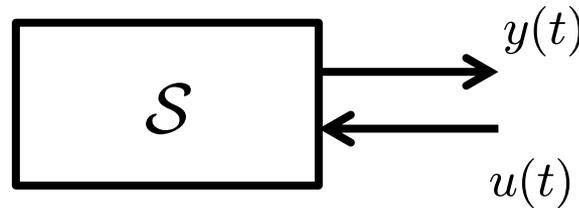
*How general is this trade-off?*

# Motivation

- The observer effect has been extensively studied in quantum mechanics, but seems overlooked in a classical mechanics setting
- We want to know the **performance limits** of devices when **resources**, such as DOFs, energy, temperature, and time, are **finite** or **limited**
- How well — and what — can we actually implement from a small collection of physical building blocks? Related to circuit synthesis (*M. Smith, B.D.O. Anderson, et al.*)
- Similar questions currently being asked in synthetic biology (*R. Murray, D. Del Vecchio, et al.*)

# Measurement Model

- A **physical system**  $S$  with a property  $y(t)$  we want to measure. Together with conjugate variable  $u(t)$  it forms a **port** [external work rate =  $u(t)^\top y(t)$ ]



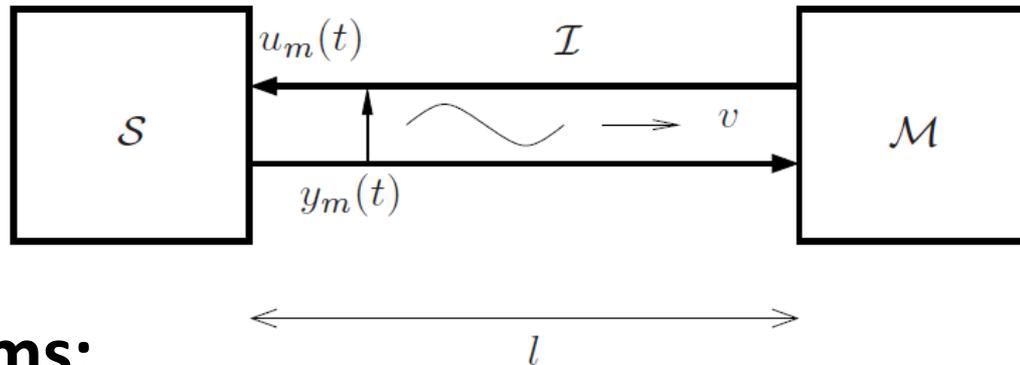
Example:  $y(t) = \text{velocity, voltage, ...}$   
 $u(t) = \text{force, current, ...}$

- Treat  $u$  as a *small perturbation*  $u_m$  from measurement

$$S \begin{cases} \dot{x}(t) = f(x(t), u_m(t)) \\ y_m(t) = g(x(t)) \\ x(0) = x_0 \end{cases} \approx \begin{cases} \dot{x}(t) = A(t)x(t) + B(t)u_m(t) \\ y_m(t) = C(t)x(t) \\ x(0) = x_0 \end{cases}$$

# Measurement Model

- Interconnect  $S$  to a measurement device  $M$  through a **communication medium  $I$** , during a short time  $[0, t]$



- **Problems:**
  - What is the best estimate of  $y(t)$  we can get?
  - How much must  $S$  simultaneously be perturbed? (=back action, retroactivity,...)
- **Assumption:** Medium  $I$  is well modeled by a *lossless wave equation*, in thermal equilibrium at time  $t=0$

# Why Lossless Wave Equation?

- Mechanics:



- Circuits:



- Electromagnetic fields: 
$$\left( \nabla^2 - \epsilon\mu \frac{\partial^2}{\partial t^2} \right) E(x, t) = 0$$

- At the terminals for times  $0 < t < l/v$ :

$$u_m(t) = -Zy_m(t) - \sqrt{2k_B T_Z Z} w_Z(t)$$

( $Z > 0$  [acoustic/characteristic] impedance,  $T_Z$  temperature,  $v$  wave velocity,  $l$  medium length, and white noise  $w_Z(t)$  due to FD-theorem.)

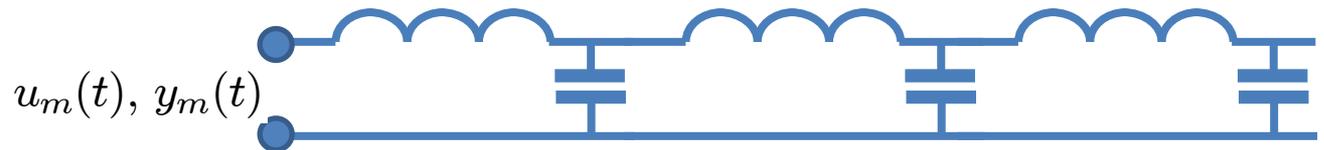
Transmission line  $Z = \sqrt{\frac{R+i\omega L}{G+i\omega C}} \rightarrow \sqrt{\frac{L}{C}}, \quad \omega \sim 1/t \rightarrow \infty.$

# Where Does the Noise Come From?

- Mechanics:



- Circuits:

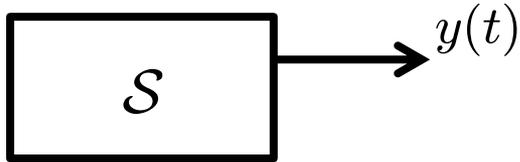


- Electromagnetic fields: 
$$\left( \nabla^2 - \epsilon\mu \frac{\partial^2}{\partial t^2} \right) E(x, t) = 0$$

- 
- Assume exact initial state of wave equation unknown
  - **In thermal equilibrium:** Assign the expected energy  $\frac{1}{2}k_B T_Z$  to each mode
  - Total effect at the terminal sums up to white noise, see *Nyquist, 1928* (or *Sandberg, Delvenne, Doyle, 2010*)

# Unmeasured vs. Measured System

- Unmeasured system

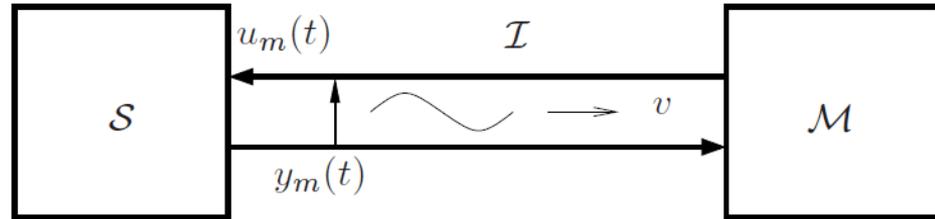


$$\begin{aligned} \dot{x}(t) &= Ax(t) & x(0) &= x_0, \\ y(t) &= Cx(t) & y_0 &:= Cx_0 \end{aligned}$$

- For small  $t$ :

$$\begin{aligned} y(t) &= Ce^{At}x_0 \\ &= y_0 + CAx_0t + O(t^2) \end{aligned}$$

- Measured system



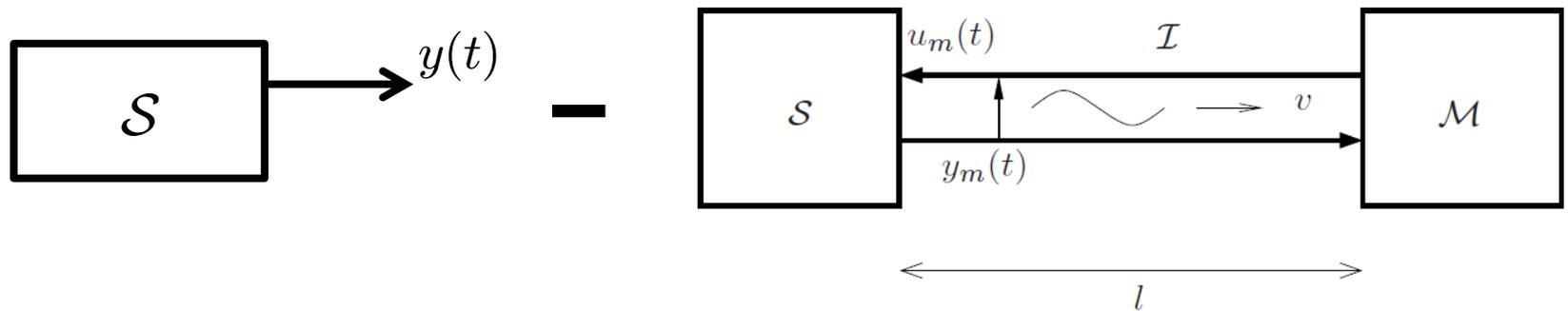
$$\begin{aligned} \dot{x}_m(t) &= (A - BZC)x_m(t) - B\sqrt{2k_B T_Z Z}w_Z(t), \\ y_m(t) &= Cx_m(t), & x_m(0) &= x_0, \\ u_m(t) &= -Zy_m(t) - \sqrt{2k_B T_Z Z}w_Z(t), \end{aligned}$$

- For small  $t$ :

$$\begin{aligned} y_m(t) &= Ce^{(A-BZC)t}x_0 \\ &\quad - \int_0^t Ce^{(A-BZC)(t-\tau)} B\sqrt{2k_B T_Z Z}w_Z(\tau)d\tau \\ &= y_0 + C(A - BZC)x_0t \\ &\quad - CB\sqrt{2k_B T_Z Z} \int_0^t w_Z(\tau)d\tau + O(t\sqrt{t}), \end{aligned}$$

# Measurement Back Action

- Difference between un-measured and measured output  
=: **back action of measurement**



- **Deterministic back action:**

$$y(t) - \mathbf{E}y_m(t) = M^{-1}Zy_0t + O(t^2)$$

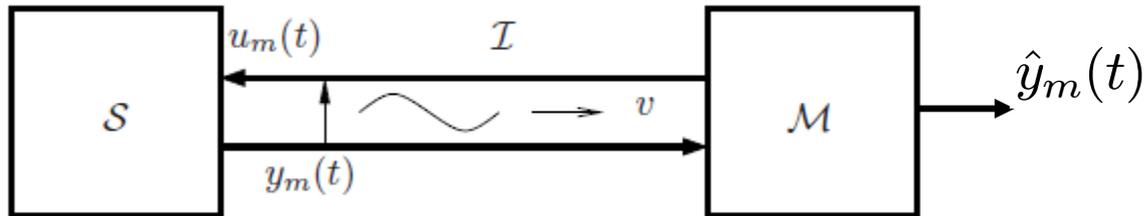
(Present even when  $T_Z = 0$ .  $M^{-1} := CB$  is the “inverse inertia” of  $S$ )

- **Stochastic back action:**

$$\text{Var}[y_m(t)] = 2k_B T_Z M^{-1} Z M^{-T} t + O(t^2)$$

# Idealized Measurement Device $M^*$

- The measurement device  $M$  produces an estimate  $\hat{y}_m$  of  $y_m$



- In best case,  $M$  has exact models of  $S$  and  $I$ , and knows the temperature  $T_z$  (but not exact state of  $I$ )  $\Rightarrow$  Kalman filter  $M^*$  optimal:

$$\dot{\hat{x}}_m(t) = (A - BZC)\hat{x}_m(t) + K(t)(u_m(t) - \hat{u}_m(t))$$

$$\hat{u}_m(t) = -ZC\hat{x}_m(t),$$

$$\hat{y}_m^*(t) = C\hat{x}_m(t),$$

- Any  $M$  with less or equal knowledge is no better than  $M^*$*

# Lower Bounds on Accuracy

- Accuracy of  $M^*$  determined from differential filter Riccati equation:

$$\begin{aligned} \dot{P} = & (A - BZC)P + P(A - BZC)^T \\ & - (PC^T Z - 2k_B T_Z BZ)(2k_B T_Z Z)^{-1}(PC^T Z - 2k_B T_Z BZ)^T \\ & + 2k_B T_Z BZB^T \end{aligned}$$

- Assume zero knowledge at  $t = 0$ :  $P(0) = \mathbf{E}[\hat{x}_m(0) - x_0]^2 = +\infty$

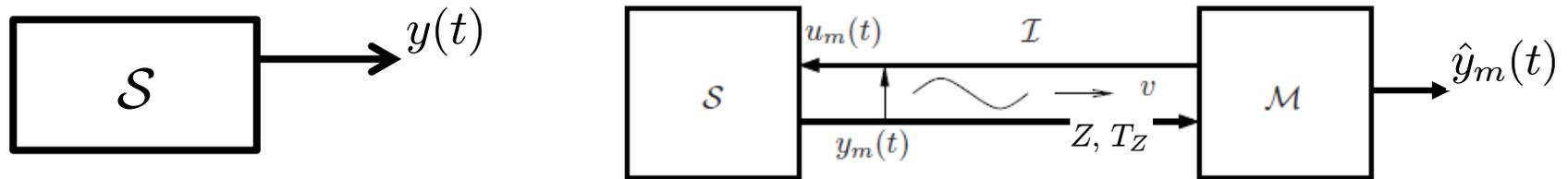
- Series expansion of  $P(t)$  gives

$$P(t) = P_{-1}t^{-1} + P_0 + P_1t + O(t^2) \quad P_{-1} = P_{-1}C^T ZCP_{-1}/2k_B T_Z$$

- Optimal measurement accuracy:

$$\text{Var}[\hat{y}_m^*(t) - y_m(t)] = 2k_B T_Z Z^{-1}t^{-1} + O(1)$$

# Back Action and Accuracy Trade-Off



- Back action:**

$$y(t) - \mathbf{E}y_m(t) = M^{-1}Zy_0t + O(t^2),$$

$$\text{Var}[y_m(t)] = 2k_B T_Z M^{-1}ZM^{-T}t + O(t^2)$$
- Measurement accuracy:**

$$\text{Var}[\hat{y}_m(t) - y_m(t)] \geq \text{Var}[\hat{y}_m^*(t) - y_m(t)]$$

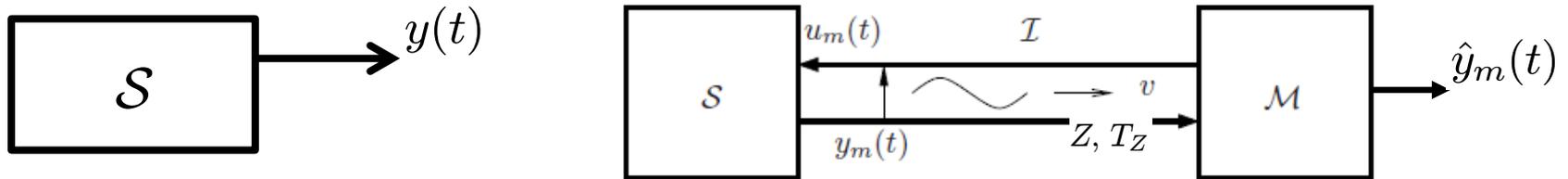
$$= 2k_B T_Z Z^{-1}t^{-1} + O(1)$$
- Trade-off:**

$$\sqrt{\text{Tr Var}[y_m(t)]} \sqrt{\text{Tr Var}[\hat{y}_m(t) - y_m(t)]}$$

$$\geq 2k_B T_Z \text{Tr } M^{-1} + O(t)$$

*Trade-off independent on small  $t$  and medium impedance  $Z$ !*

# Back Action and Accuracy Trade-Off



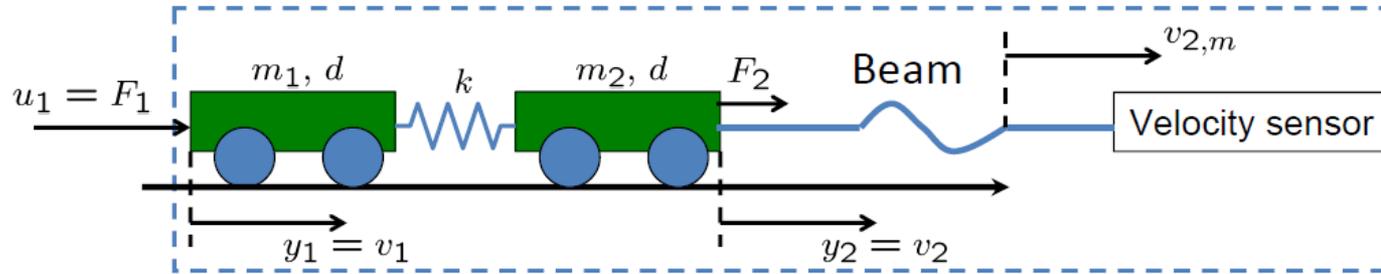
- **Back action:**  $y(t) - \mathbf{E}y_m(t) = M^{-1}Zy_0t + O(t^2)$ ,  
 $\text{Var}[y_m(t)] = 2k_B T_Z M^{-1}ZM^{-T}t + O(t^2)$
- **Measurement accuracy:**  $\text{Var}[\hat{y}_m(t) - y_m(t)] \geq \text{Var}[\hat{y}_m^*(t) - y_m(t)]$   
 $= 2k_B T_Z Z^{-1}t^{-1} + O(1)$

back action  $\times$  accuracy

- **Trade-off:**  $\sqrt{\text{Tr Var}[y_m(t)]} \sqrt{\text{Tr Var}[\hat{y}_m(t) - y_m(t)]}$   
 $\geq 2k_B T_Z \text{Tr } M^{-1} + O(t)$

*Trade-off independent on small  $t$  and medium impedance  $Z$ !*

# Mechanical Example

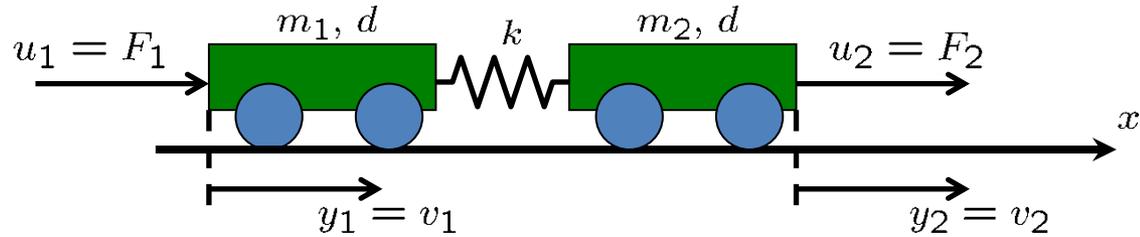


$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ -k/m_1 & -d_1/m_1 & k/m_1 & 0 \\ 0 & 0 & 0 & 1 \\ k/m_2 & 0 & -k/m_2 & -d_2/m_2 \end{pmatrix}, \quad B = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1/m_2 \end{pmatrix}$$

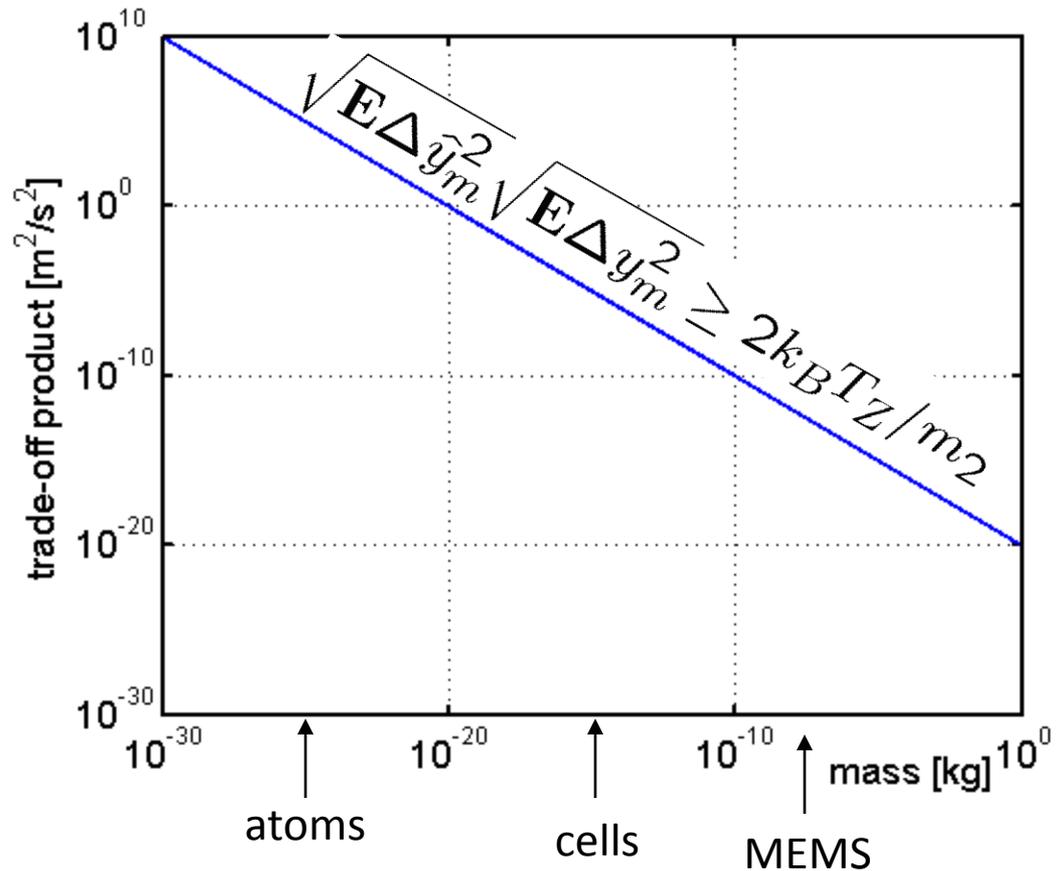
$$C = (0 \ 0 \ 0 \ 1),$$

- Inverse inertia  $M^{-1} := CB = 1/m_2$
- Det. back action  $Zv_{2,0}t/m_2$ , stoch. back action  $2k_B T_Z Zt/m_2^2$
- Measurement accuracy  $2k_B T_Z / Zt$
- Trade-off: back action  $\times$  accuracy  $\geq 2k_B T_Z / m_2$

# Mechanical Example



- $k_B = 1.4 \cdot 10^{-23}$  J/K
- $T_Z = 300$  K
- Not visible at macroscopic level
- Significant at microscopic level



# Outline

- Measurement model
- Measuring deterministic systems
- Measuring port-Hamiltonian systems in thermal equilibrium (details in paper)

# System $S$ in Thermal Equilibrium

$$\text{back action} \geq \frac{2T_Z}{T_S} \times \Delta\text{accuracy}$$

- Only ratio  $T_Z/T_S$  determines trade-off. Is this result essentially different from before?

$$\text{back action} \times \text{accuracy} \geq 2k_B T_Z / m$$

- Not really, as system temperature  $T_S \rightarrow \infty$  we obtain earlier result since rate of learning also goes to infinity
- System inertia disappeared and was replaced by system temperature  $T_S$
- When  $T_S$  is really small, only small improvement in accuracy since we already know a lot about the system

# Summary

- There are general **trade-offs** between **measurement accuracy** and **back action** for classical measurements
- Holds not only for passive system  $S$  and particular  $M$  (compare *Sandberg, Delvenne, Doyle, IEEE TAC 2010*)
- Lossless measurement medium of temperature  $T_Z$
- System with “inverse inertia”  $M^{-1} = CB$  (first Markov parameter) and completely unknown initial state

$$\text{back action} \times \text{accuracy} \geq 2k_B T_Z \text{Tr} M^{-1}$$

- System of temperature  $T_S$

$$\text{back action} \geq \frac{2T_Z}{T_S} \times \Delta \text{accuracy}$$