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The Internet-Based Teleoperation: Motion and Force Predictions Using Particle Filters

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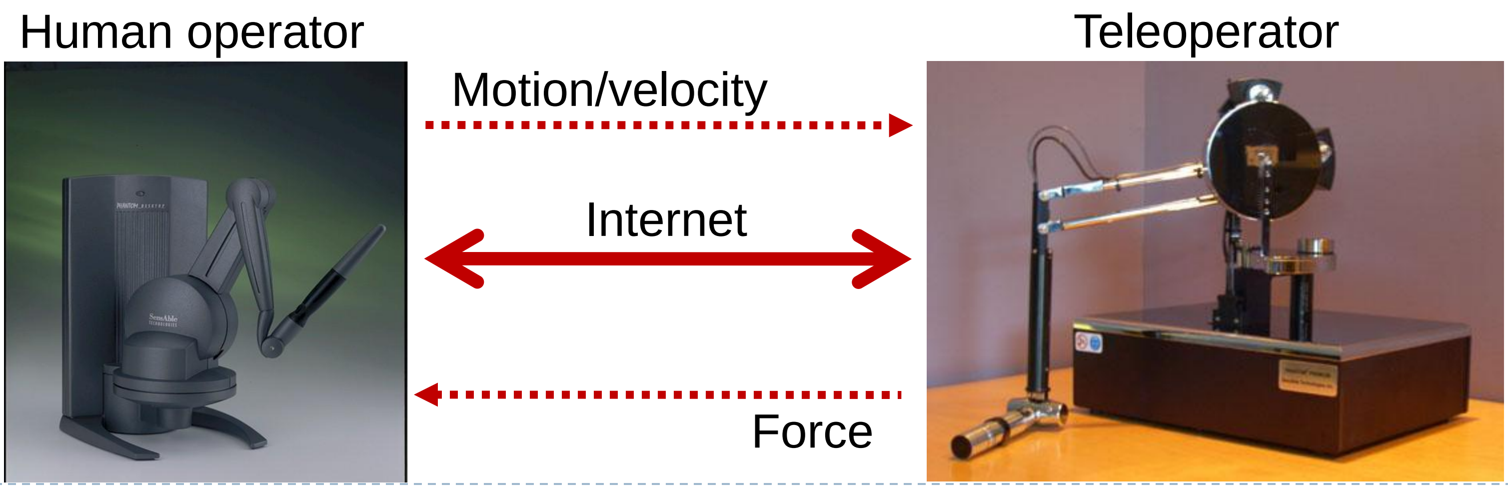
Introduction

- Internet-based teleoperations:
  - human operator sends motion/velocity data and receives reflecting force data from a teleoperator through the Internet
- Time delay:
  - unknown and varying Internet delay may impair motion, velocity, and force data
  - data loss due to network congestion
  - instability of the overall teleoperation system



Related work

- Related work on the time delay issue:
  - Control system approach:
    - based on controller designs for a stable operation between a human operator and a teleoperator in the case of constant delay
    - scattering transform and its combination with other methods
  - Transport protocol approaches:
    - modifications to existing TCP and UDP protocols
    - interactive real-time protocol (IRTP), real-time network protocol (RTNP), efficient transport protocol (ETP)

- R. J. Anderson and M. W. Spong, “Bilateral control of teleoperators with time delay,” *IEEE Trans. on Automatic Control*, vol. 34, no. 5, pp. 494–501, May. 1989.
- Y. Uchimura, T. Yakoh, and K. Ohnishi, “Bilateral robot system on the real-time network structure,” *IEEE Trans. on Industrial Electronics*, vol. 51, no. 5, pp. 940–946, Oct. 2004.
- R. Wirz, M. Ferre, R. Marín, J. Barrio, J. Claver, and J. Ortego, “Efficient transport protocol for networked haptics applications,” in *Proc. Int. Conf. on Haptics: Perception, Devices, and Scenarios*, Madrid, Spain, June 2008, vol. 5024, pp. 3–12.

Related work

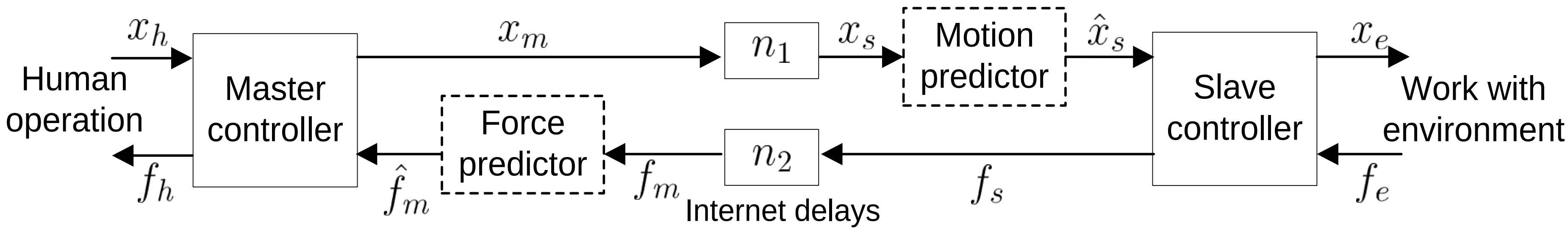
- Related work on the time delay issue:
  - Prediction-based approaches:
    - motion and force data prediction/estimation methods to compensate for varying time delay
    - Bayesian filters:
      - ✓ Kalman filters used for linear predictions
      - ✓ Particle filters used for nonlinear/non-Gaussian predictions due to the unpredictable nature of the Internet

- S. Clarke, G. Schillhuber, M. Zach, and H. Ulbrich, “Prediction-based methods for teleoperation across delayed networks,” *Springer-Verlag, Multimedia Systems*, vol. 13, no. 4, Oct. 2007.
- S. Munir and W. Book, “Internet-based teleoperation using wave variables with prediction,” *IEEE Transactions on Mechatronics*, vol. 7, no. 2, pp. 124-133, June 2002.
- J. Lee, S. Payandeh, and Lj. Trajković, “Application of prediction-based particle filters for teleoperations over the Internet,” in *Proc. IASTED Int. Conf. on Robotics and Applications*, Cambridge, MA, USA, Nov. 2009, pp. 22–27.

Prediction-based approach

- Motion and force data flows are formulated using state-space models to be predicted by Bayesian (Kalman and particle) filters

	Motion flow	Force flow
True state	$x_m[k]$	$f_s[k]$
Delayed observation	$x_s[k]$	$f_m[k]$
Predicted state	$\hat{x}_s[k] = \hat{x}_m[k - n_1]$	$\hat{f}_m[k] = \hat{f}_s[k - n_2]$



Motion and force data flows in a teleoperation system.

Particle filter basics

- Sub-optimal solution of Bayesian approaches:
  - Find estimates of nonlinear state (motion) $x_m[k]$ based on available observations $x_s[1:k]$ by constructing the *posterior* density $p(x_m[k-n_1]|x_s[1:k])$
  - The posterior density is approximated by a simulation-based approach (sequential Monte Carlo method):

$$p(x_m[k-n_1]|x_s[1:k]) \approx \frac{1}{N}\sum_{i=1}^{N} w^i[k]\delta(\cdot)$$

$w^i[k]$: importance weight

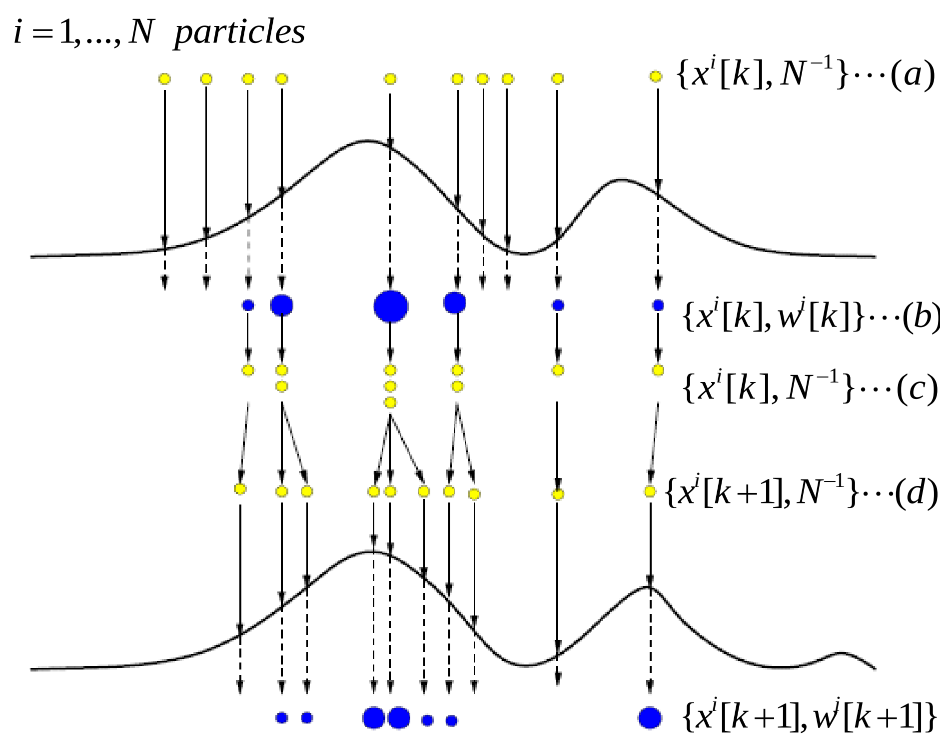
$\delta(\cdot)$: Dirac delta function

N: number of particles

  - Approximations converge to true estimates as the number of particles tends to infinity

Particle filter basics

- Re-sampling:
  - multiply/suppress samples with high/low weights given number of particles
  - samples with high weights are used for predictions and low weights are eliminated
- Graphical representation:
  - (a) define an initial state
  - (b) weighted measure
  - (c) re-sampling
  - (d) prediction of next state



Visualization of a particle filter

Particle filters for motion/force models

- Motion prediction:
  - Bayesian formulation: the estimate of motion data is represented by an integral form:

$$\hat{x}_s[k] = \int x_m[k-n_1]\, p(x_m[k-n_1] | x_s[1{:}k])\, dx_m[k-n_1]$$

  - Particle filter approach: the posterior density is approximated:

$$p(x_m[k-n_1] | x_s[1{:}k]) \approx \frac{1}{N} \sum_{i=1}^{N} w^i[k]\, \delta(x_m[k-n_1] - x_m^i[k-n_1])$$

  - A simple way to solve the importance weight:

$$w^i[k] = p(x_s[k] | x_m^i[k-n_1])$$

Particle filters for motion/force models

- Motion prediction:
  - Gamma density function is used for a non-Gaussian process:

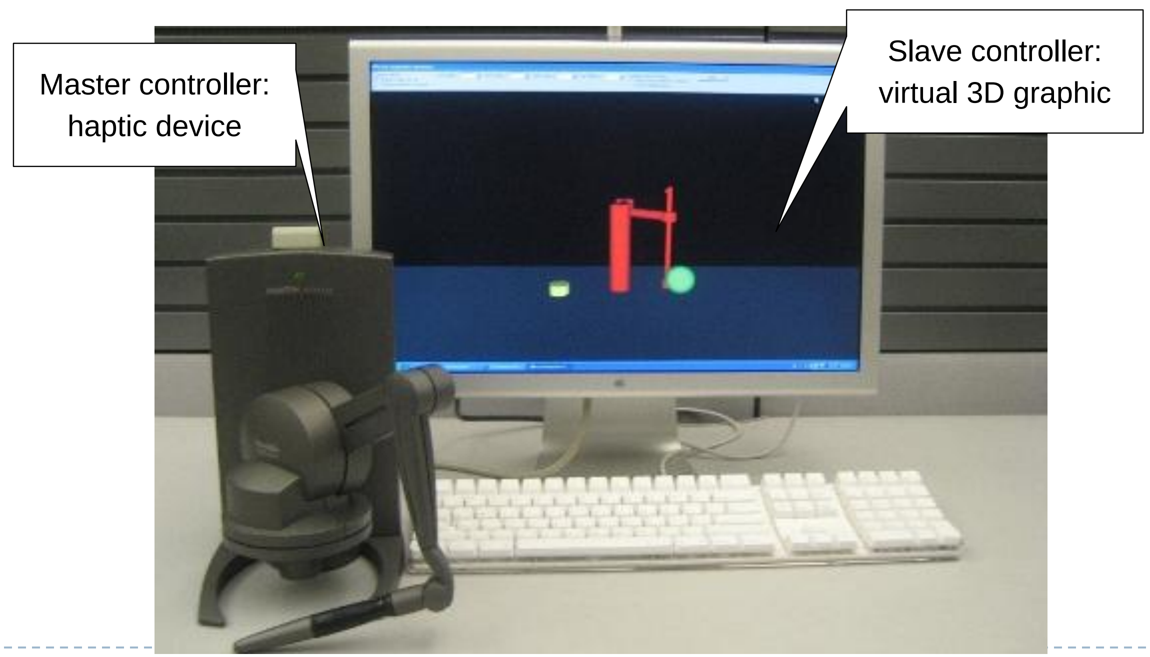
$$p(x_s[k]) = \frac{\beta^\alpha}{(\alpha-1)!} x_s^{\alpha-1}[k] e^{\beta x_s[k]} \quad \text{for} \quad x_s[k] > 0$$

α/β: mean, α/β^2: variance

    - more robust model than a Gaussian distribution
  - Re-sampling:
    - high weights are used for prediction within a given number of particles
- Force prediction:
  - achieved by a similar approach

Experimental setup

- Master controller: Phantom desktop haptic device
- Slave controller: virtual 3D model (4-DoF SCARA model)
  - programmed in Visual C++ and OpenGL libraries
  - sampling haptic data:
    - motion data: 50 Hz, force data: 1 kHz



Master and slave controllers using Phantom desktop haptic device

Experimental setup

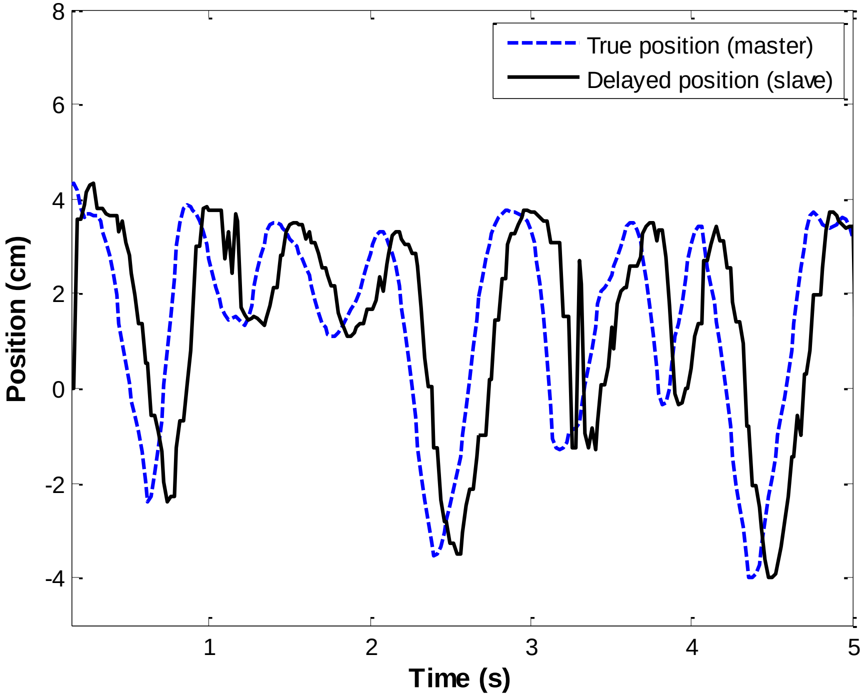
- Internet delay model:
  - time-varying delay is modeled using a random number generator
    - motion and force flows experience the identical delay
    - typically observed in UDP transmission

Delay	Time (ms)
Average delay	63 ms
Maximum delay	132 ms
Minimum delay	51 ms
Standard deviation	21 ms

Delay profile for experiments

Experimental results

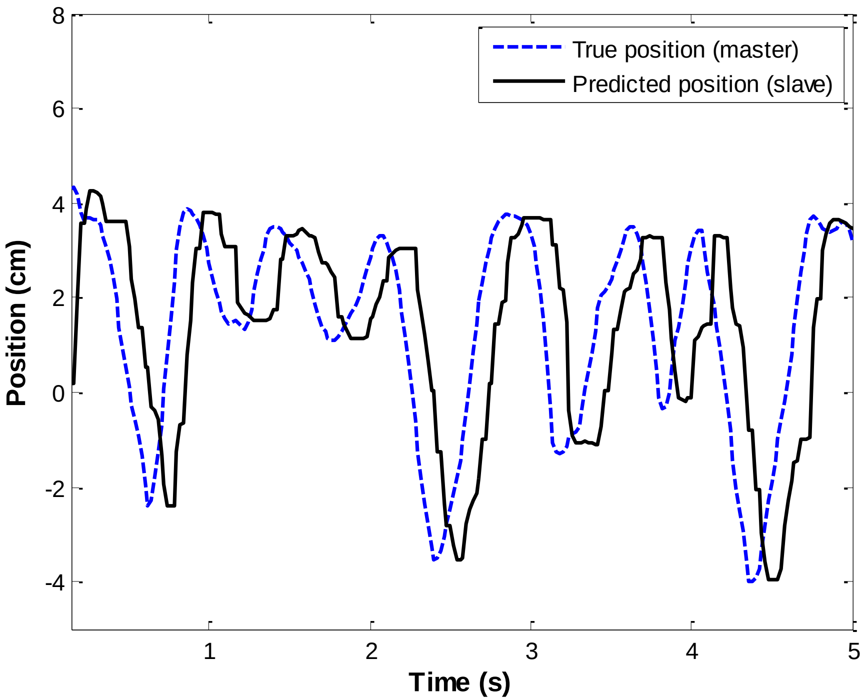
- Motion data:
  - 1-DoF motion data are collected over a five-second interval
  - motion data are delayed by the time-varying delay model
  - true motion (master) and delayed motion (slave) are shown



True and delayed motion data

Experimental results

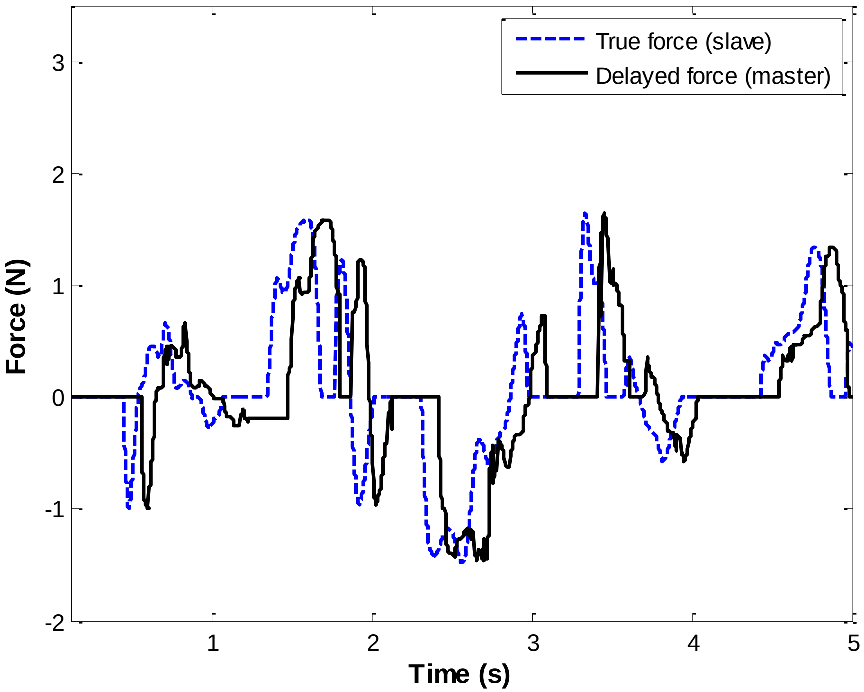
- Motion prediction:
  - motion data are predicted by a particle filter
  - initial state (position) is assumed to be known to a slave controller
  - number of particles: 200
  - mean square error: 0.59 cm



Motion data prediction

Experimental results

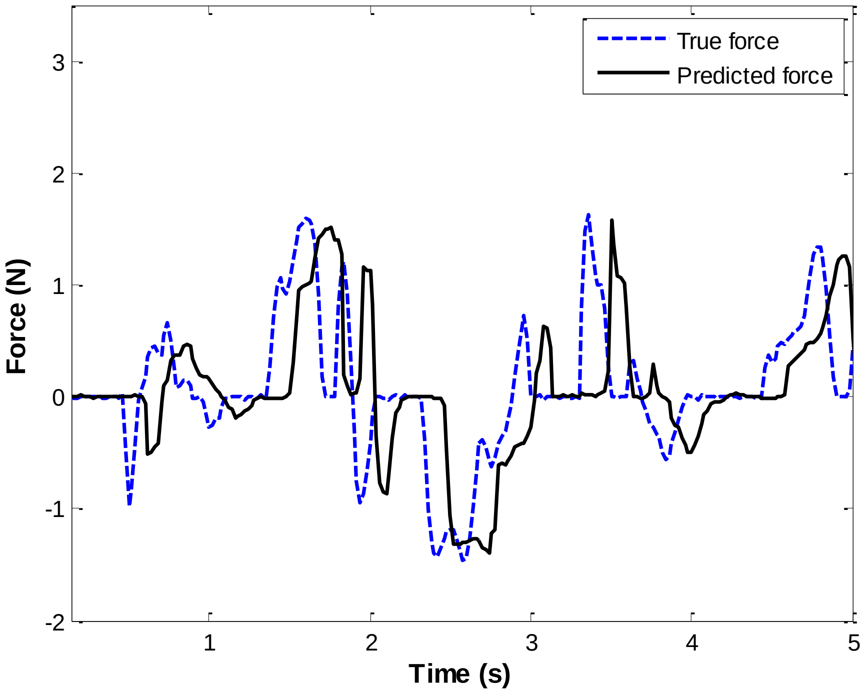
- Force data:
  - 1-DoF force data are collected over a five-second interval
  - motion data are delayed by the time-varying delay model
  - true force (slave) and delayed force (master) are shown



True and delayed force data

Experimental results

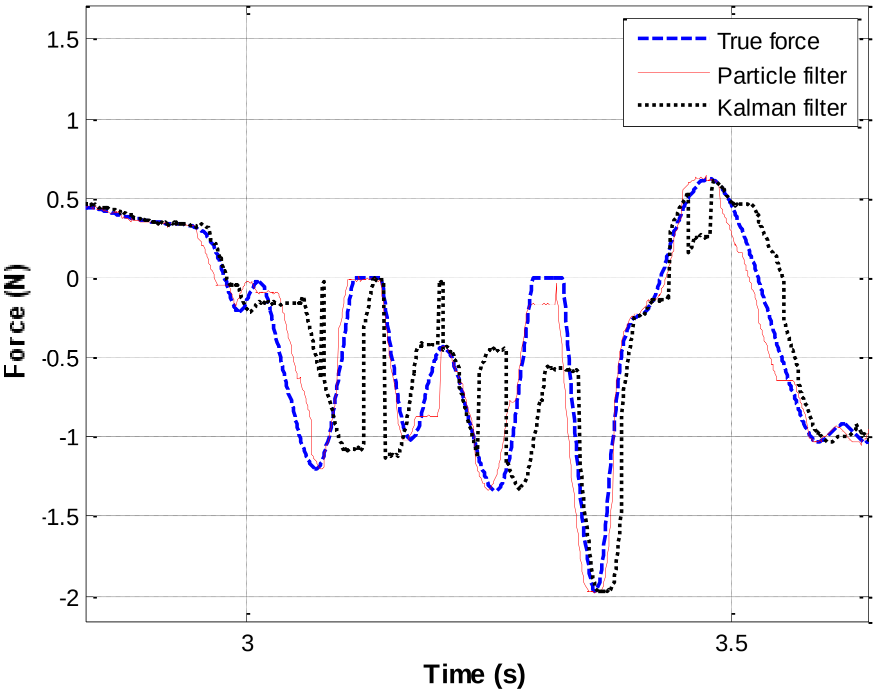
- Force prediction:
  - force data are predicted by a particle filter
  - initial state (force) is assumed to be known to a slave controller
  - number of particles: 200
  - mean square error: 0.14 N



Force data prediction

Experimental results

- Comparison with the Kalman filter:
  - force data are predicted by both Kalman and particle filters
  - number of particles: 200
  - mean square errors:
    - Kalman filter: 1.74 N
    - Particle filter: 0.2 N



Kalman vs. particle filters

Conclusions

- Motion and force data flows were formulated in state-space models to be predicted by Bayesian (Kalman and particle) filters
- Stability of an overall teleoperation system was improved by using Bayesian predictions
- In nonlinear and non-Gaussian cases (Gamma density), the particle filter outperforms the Kalman filter in terms of mean square errors
- An efficient number of particles should be chosen to reduce the complexity of the proposed method

Thank you

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