Center for Automation Technologies and Systems

Active Thermal Management for Precision Positioning

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April 17, 2007

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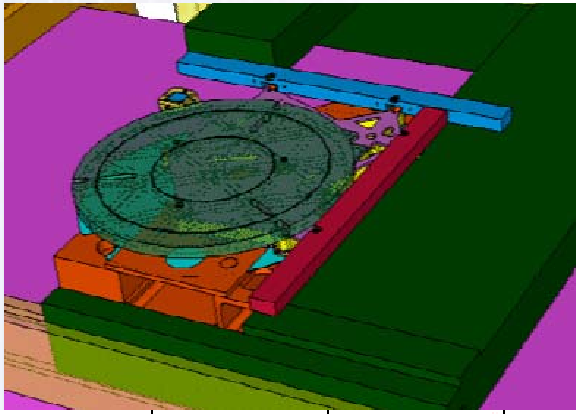
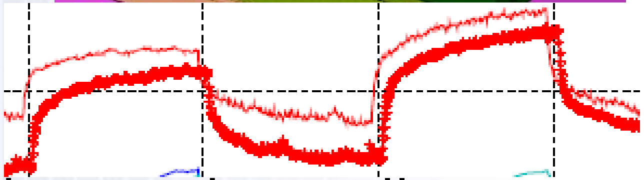
Outline

- Motivation
- Problem statement and overall approach
- Simplified 2D problem
- State-space model identification
- Sensor placement and Kalman estimator design
- Actuator placement and active heating controller design
- Conclusions and future work

Motivation





- Laser processing of semiconductor wafers requires high precision (<100nm) and speed.
- Large acceleration/deceleration results in thermal cycling from motor heating.
- Expansion and contraction from motor thermal cycle lead to positioning error.
- As the error budget of positioning system tightens, thermally induced positioning error consumes an increasing portion of the limited budget, and thus need to be actively managed. Current solution: frequent re-calibration.
- Challenge: Components in the positioning system are made of materials of different thermal properties – Thermal conductivity, specific heat, thermal expansion coefficient

Problem Statement

- Estimation:

  Predict positioning error based on system model, temperature measurements, and *known* motor heating output

- Control:

  Correct for positioning error based on system model, temperature measurements, active heaters, and possibly complete motor heat output trajectory.

Approach: Estimation

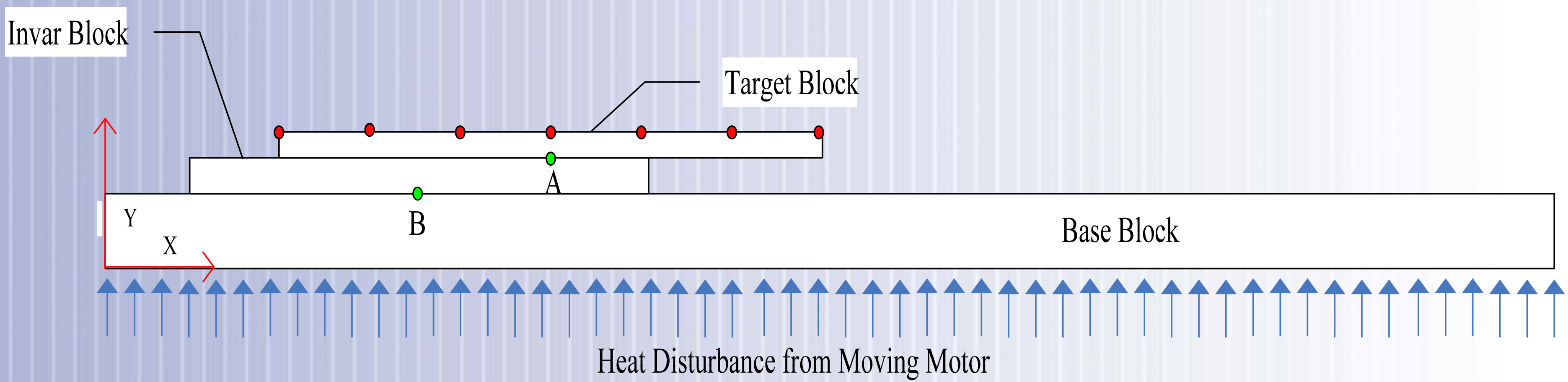
- **Model identification:** Identify a linear time invariant (LTI) multi-input/multi-output (MIMO) model based on temperature and position measurements.
- **Model order reduction:** Reduce dimension of model based on preservation of input/output property.
- **Sensor placement:** Use the reduced order model to evaluate candidate sensor locations.
- **State estimator design:** Use a smaller set of sensors and reduced order model to estimate positions of 7 locations of interest.

Approach: Control

- **Model identification and order reduction:** Develop control design model based on candidate actuator locations.
- **Actuator placement:** Use the reduced order model to evaluate actuator (heater) locations.
- **Controller design:** Use a smaller set of actuators and reduced order model to design active heating controller to reduce fluctuation from position.

Challenge: Heating is one-way, only heating and no cooling!

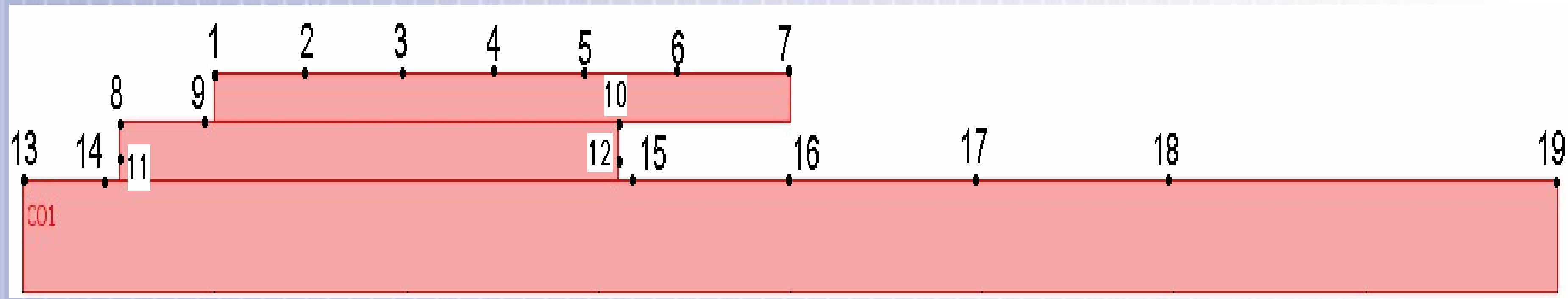
Case Study: A Simplified 2D System



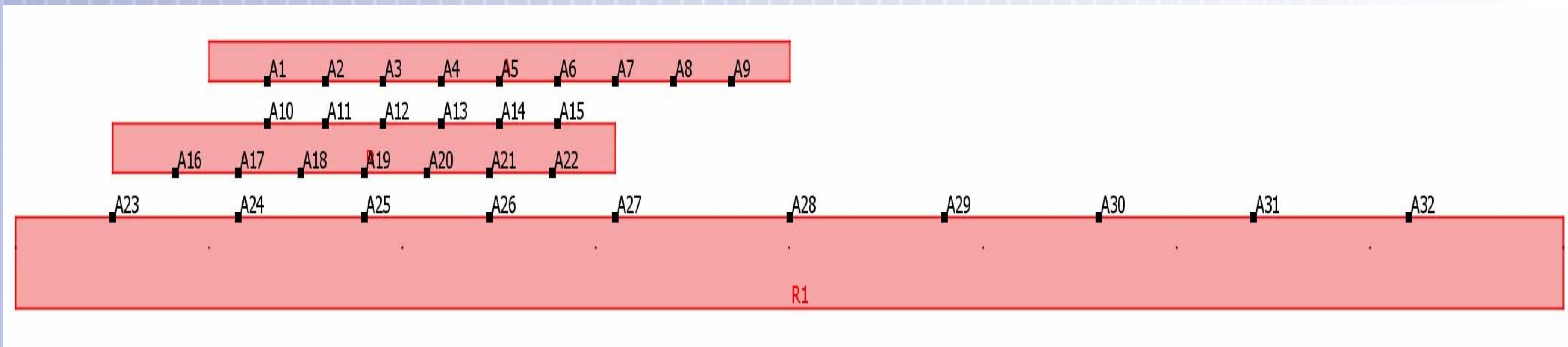
- Middle block made of Invar, target and base blocks made of aluminum .
- Bottom boundary of the base block fixed.
- Target block fixed to Invar block at A, invar block fixed to base block at B.
- Motor heating from bottom boundary of base block as thermal disturbance (17W in average, time-varying in both amplitude and location).
- Ambient temperature maintained at 20 degrees Celsius.
- 7 locations of interest on target block, desired accuracy: 100nm.
- Finite element model (FEM) simulation considered as the truth model.

Candidate Sensor and Active Heater Locations

19 candidate temperature sensor locations



32 candidate active heater locations



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Modeling

- Inputs:
  - 8 disturbance heat sources
  - 32 candidate active heater sources
- Outputs:
  - 14 displacements (x-y for 7 locations on target block)
  - 19 candidate temperature sensors
- 40 single-input/multi-output (SIMO) models are identified based on on/off heat input with varying period, using time domain subspace identification method.
- The SIMO models are combined into a single MIMO model, and with order reduced down to 30.

Sensor Placement

- Represent the system in state space form:

$$x(k+1) = Ax(k) + B_m u_m(k) + w(k)$$
$$y_T(k) = C_T x(k) + v(k)$$
$$y_D(k) = C_D x(k)$$

  with zero mean white Gaussian sensor and state noises: v, w.

- Consider minimum error covariance estimator (Kalman filter): estimate y_D based on measurement of y_T, known u_m and model, and given covariance of v and w (sensor covariance based on manufacturer spec, state covariance chosen small – representing modeling error.

Sensor Placement (Cont.)

- Compute steady state error covariance by solving Riccati Eq.

$$\Sigma_\infty = A\Sigma_\infty A^T + Q_{noise} - A\Sigma_\infty C^T (C\Sigma_\infty C^T + R_{noise})^{-1} C\Sigma_\infty A^T$$

- Steady state displacement output error covariance (14 x 14 matrix):

$$\Sigma_D = C_D \Sigma_\infty C_D^T$$

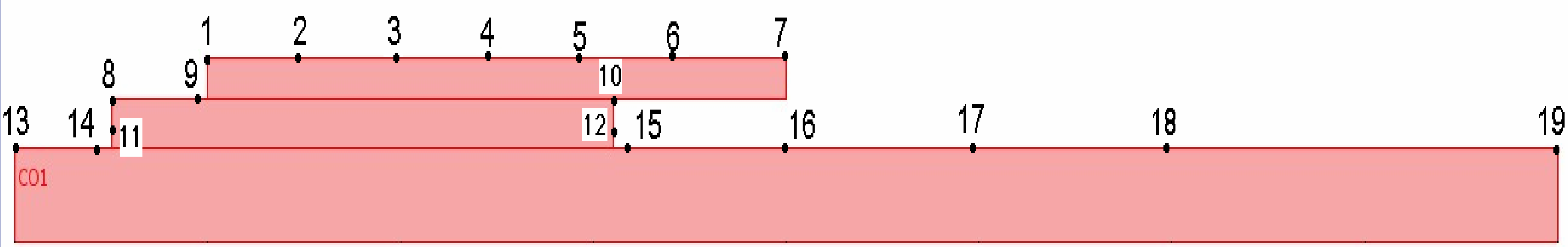
- Choose sensor location to minimize

$$J_x = \max_{i=1..7}(\sigma_i^2), \quad J_y = \max_{i=8..14}(\sigma^2{}_i)$$

$$[\sigma_1^2\, \sigma_2^2 \cdots \sigma_{14}^2] = diag(\Sigma_D)$$

Sensor Placement Result

Criteria / # of sensors	Minimize J_x	Minimize J_y
1	9	15
2	9, 12	14, 17
3	3, 9 ,12	14, 16, 17
4	1, 3, 9, 10	14, 15, 16, 17
5	1, 2, 9, 10, 12	14, 15, 16, 17, 18
6	1, 2 ,3, 9, 10, 12	12, 14, 15, 16, 17, 18
7	1, 2 ,3, 4, 9, 10, 12	10, 12, 14, 15, 16, 17, 18
8	1, 2 ,3, 4, 5, 9, 10, 12	9, 10, 12, 14, 15, 16, 17, 18
9	1, 2 ,3, 4, 5, 6, 9, 10, 12	9, 10, 12, 14, 15, 16, 17, 18, 19
10	1, 2 ,3, 4, 5, 6, 7, 9, 10, 12	4, 9, 10, 12, 14, 15, 16, 17, 18, 19



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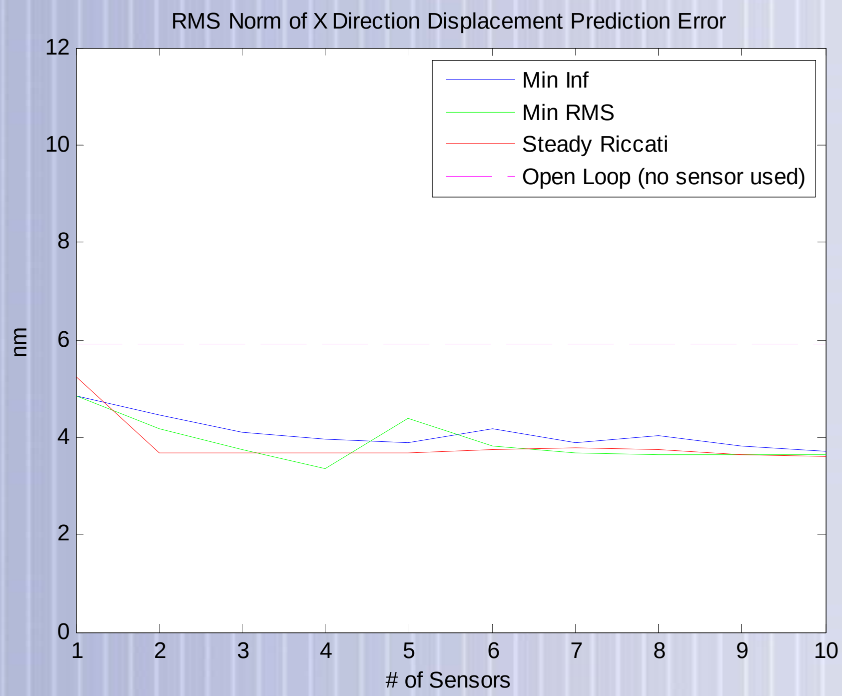
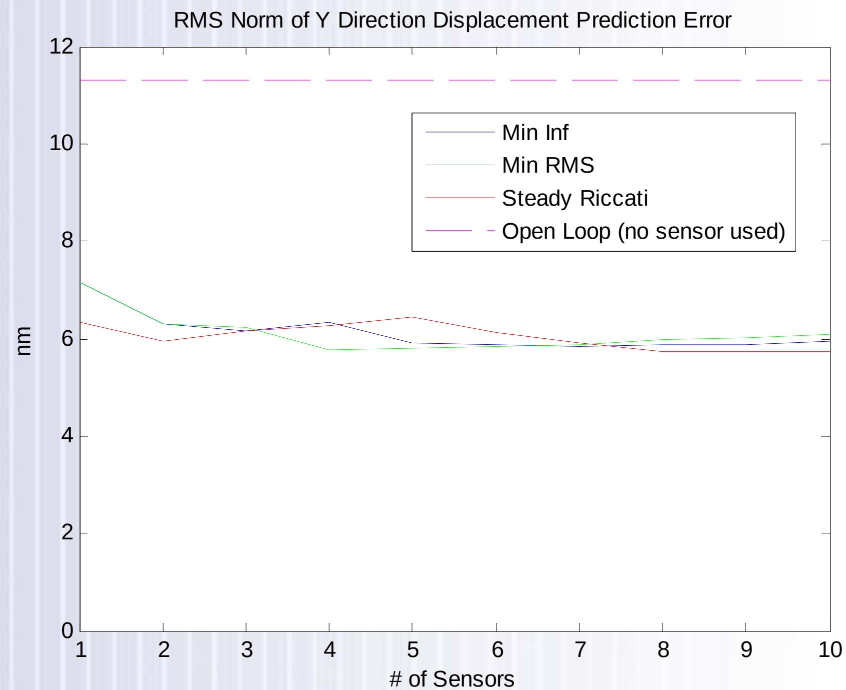
RMS Displacement Prediction Error





Comparison of RMS prediction error between open loop (with *v* and *w* set to zero), sensor selection based on steady state position output error covariance (proposed method), sensor selection based on random search of sensor combinations with worst case and RMS criteria.

Actuator Placement

- Model used for heater placement (32 candidate locations)

$$x(k+1) = Ax(k) + B_h u_h(k)$$
$$y_D(k) = C_D x(k)$$

- Evaluate heater selection based on controllability grammian projected to the displacement outputs:

$$\min_{n=1,2,\cdots 14} \left| \lambda_n (C_D W C_D^T) \right|$$

W = controllability grammian of selected inputs

$A\,W + W\,A^T + B_{select}B_{select}^T = 0$

- Result: Not surprisingly, heaters at bottom of target block and top of Invar block have strongest effect.

Controller Design

- Control design model:

$$x(k+1) = Ax(k) + B_h u_h(k) + B_m u_m(k)$$
$$y_D(k) = C_D x(k)$$
$$y_T(k) = C_T x(k)$$

- Control objective: Choose u_h to maintain target displacement output y_{target}. Assume u_m is known *a priori*.
- To address one-way actuation of active heaters, shift control input by u_{shift}, so effective control input $u-u_{shift}$ may be of either signs.

Controller Design (Cont.)

- Apply Linear Quadratic Gaussian (LQG) design. Objective function for the LQR portion:

$$J(u(i)) = 1/2\,(y_d(n) - y_{target})^T G (y_d(n) - y_{target}) +$$

$$1/2 \sum_{0}^{n-1} \left\{ (y_d(i) - y_{target})^T Q (y_d(i) - y_{target}) + (u_h(i) - u_{shift})^T R (u_h(i) - u_{shift}) \right\}$$

- Optimal control:

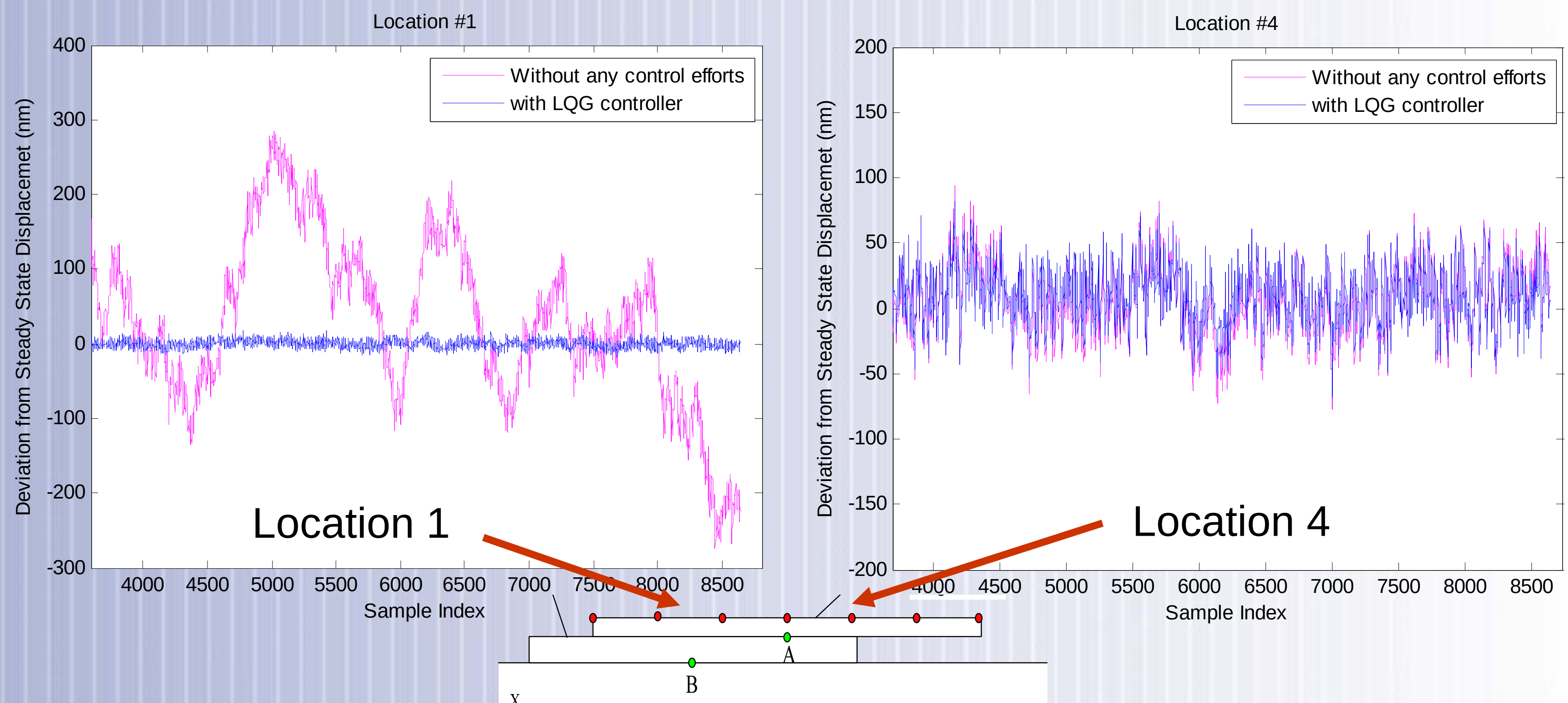
$$u_h(k) - u_{shift} = -R^{-1} B_h^T [Kz(k+1) + \gamma(k+1)]$$

$$z(k) = x(k) - x_{target}$$

z is the estimated state, K is the steady state feedback gain, γ is the bias heat due to motor heating and y_{target} (computed based on the known trajectory of u_m).

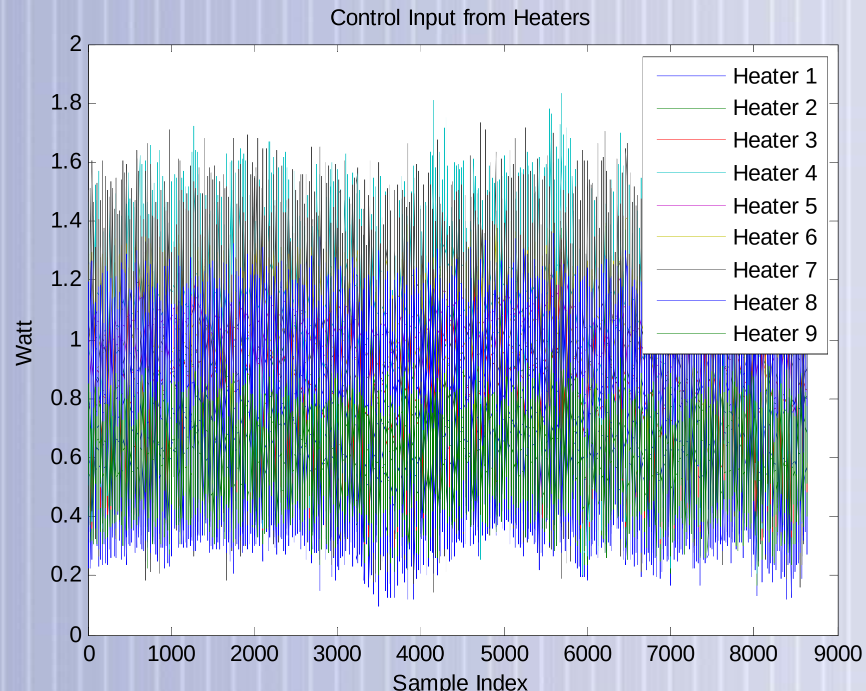
- Tuning parameters: u_{shift}, y_{target}, Q, R, Q_{noise}

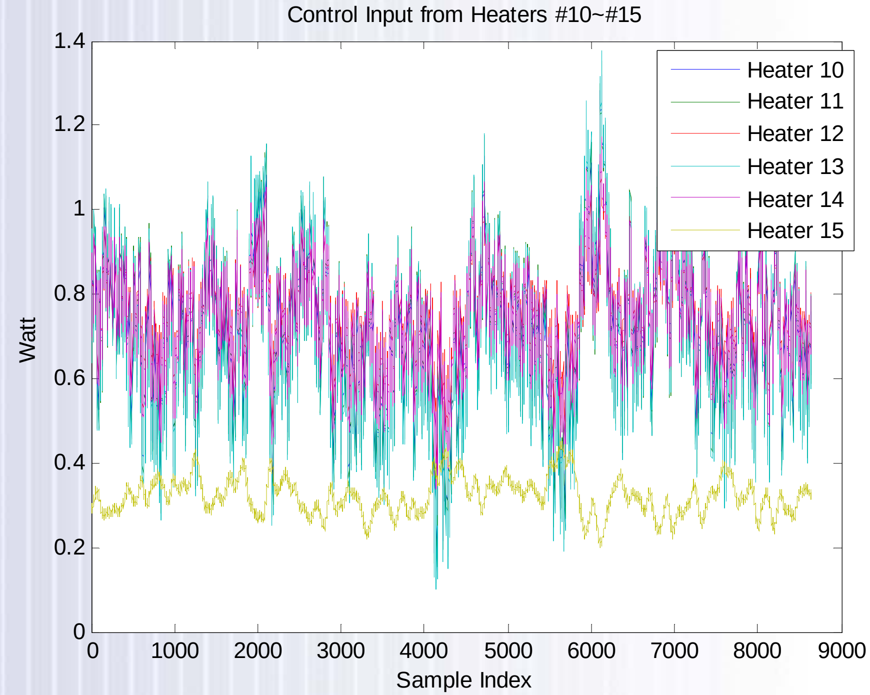
Controller Performance



- Controller works best at locations 1, 2, 6, 7, and has little effect at 3, 4, 5 (due to fixed position constraint at point *A*).

Heater Control Effort





With u_{shift} and control weighting R chosen appropriately, all heater inputs are constrained between 0 to 2 Watt

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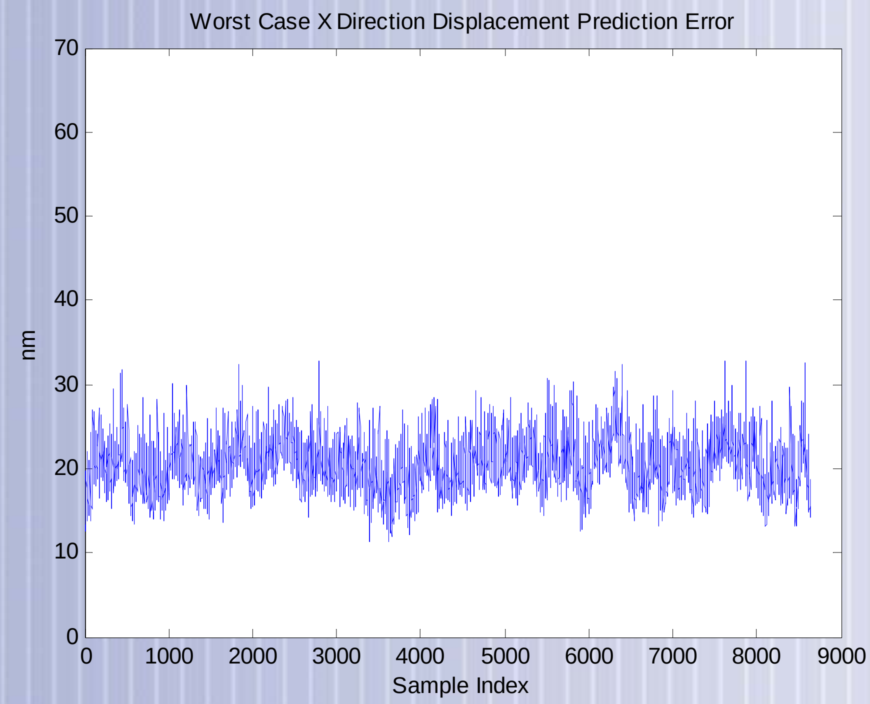
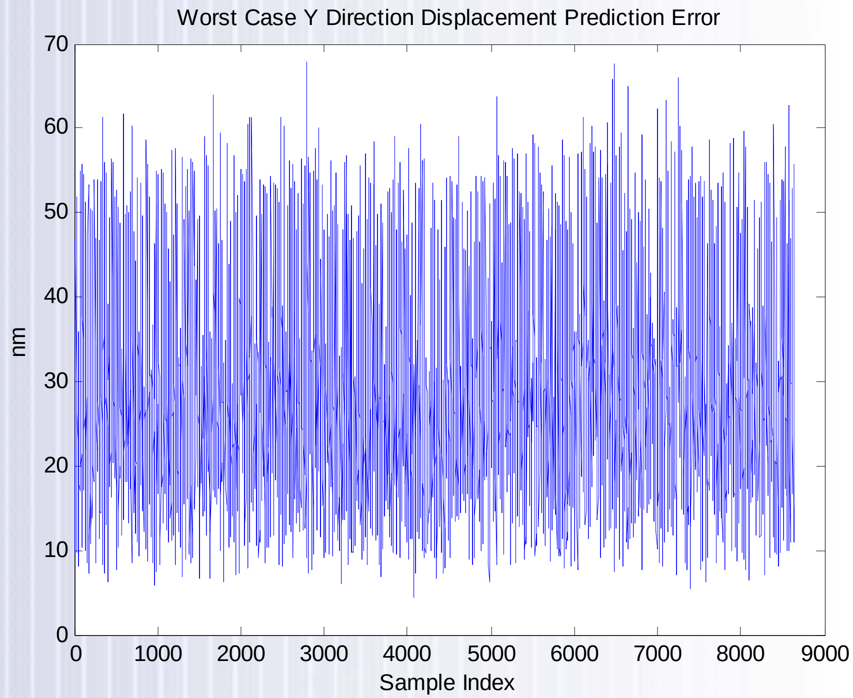
Performance of Kalman Filter in Closed Loop





- *X* direction displacement prediction error is within 40nm
- *Y* direction displacement prediction error is within 70nm
- Improvement over open loop prediction error (>100nm in *x* direction, >100nm in *y* direction).

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Conclusions

- The methodology of position estimation and control in the presence of thermal disturbances is presented and demonstrated on a simplified 2D problem.
- Sensors and actuators are selected based on model based position estimation error and position controllability.
- LQG controller is effective in controlling target position of interest.
- Future work:
  - No knowledge of disturbance heat input u_m
  - More realistic simulation model
  - Experimental validation

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