SOME THOUGHTS ON MACHINE LEARNING FOR GW DETECTOR CONTROL SYSTEMS

CONTROLS WORKSHOP

GWADW

26 MAY 2016

LIGO-G1601212

PLAN OF ATTACK … perhaps obvious

- Formulate suitable target problems including metrics or requirements
  - *Rana et. al. have identified some suitable problems*
  - *Hope to discuss & expand target problem list in this workshop*
- Create or identify a 'test bed'
  - A model or simulation that represents the plant and its disturbances, including the variations which warrant adaptation, and/or
  - A physical emulator (e.g. LASTI or 40m Lab systems)
- Identify a suitable ML technique(s)
  - Discuss experience from the GW community in application of ML techniques in this workshop, e.g. DetChar has applied ML techniques – are they applicable to our control problems?
- Pair up problems & ML techniques with volunteers
- Continue pursuit through the Control Systems Working Group (CSWG) monthly meetings
  - All GW community members are encouraged to participate

SOME THOUGHTS REGARDING MACHINE LEARNING (ML)

- ML is most often not applied to control problems
  - Classification / Clustering
  - Image recognition / Pattern recognition
  - Data mining / Deep Learning
  - Optimization / Minimization
- When applied to control, it is generally for the purpose of
  - Adaptation of control parameters
  - System Identification
  - Few examples of application to complex MIMO systems

Towards Automated Control

Jenne Driggers, Vivien Raymond, Rory Smith, Brett Shapiro, Dirk Schuette, Bas Swinkels, Rana Adhikari
California Institute of Technoloy

LIGO-G1400567

INTRODUCTION:

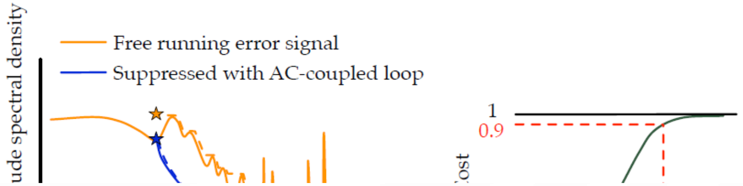
The manual tuning of hundred control loops can become a delay in interferometer commissioning. We present here an effort towards a technique to address this delay.

Ultimately, we would like to formulate an optimal control problem that allows us to incorporate arbitrary information about the controller requirements and constraints (inspired by [1]). Our current approach can be divided into three steps:

- Write a cost function that incorporates the goals and requirements for the particular control task.

Reduce In-Band Error Signal

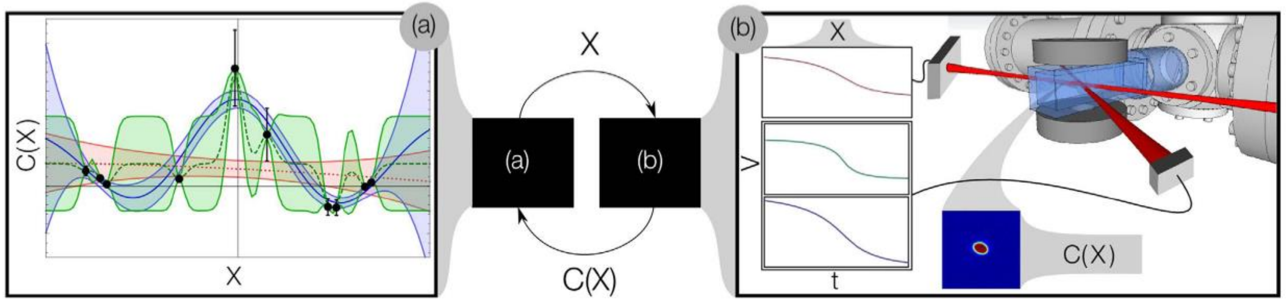
Suppress error signal in the control band. Use RMS in in the control band. Minimize ratio of suppressed error signal's RMS to free running RMS.



EXAMPLE: BOSE-EINSTEIN CONDENSATE (BEC) MACHINE

- Reference: “Fast machine-learning online optimization of ultra-cold-atom experiments”, P. B. Wigley, et. al., Nature, Scientific Reports, 2016; 6: 25890 DOI: 10.1038/srep25890
- Machine-learning online optimization (MLOO)
  - Real time optimization
  - Creates an internal statistical model (fits to previous observations)
  - Models the experiment using a Gaussian process (GP)
  - Chooses to do future experiments that will best refine its model, making it an automation of scientific method (Oh No! We’ll all be out of jobs!)

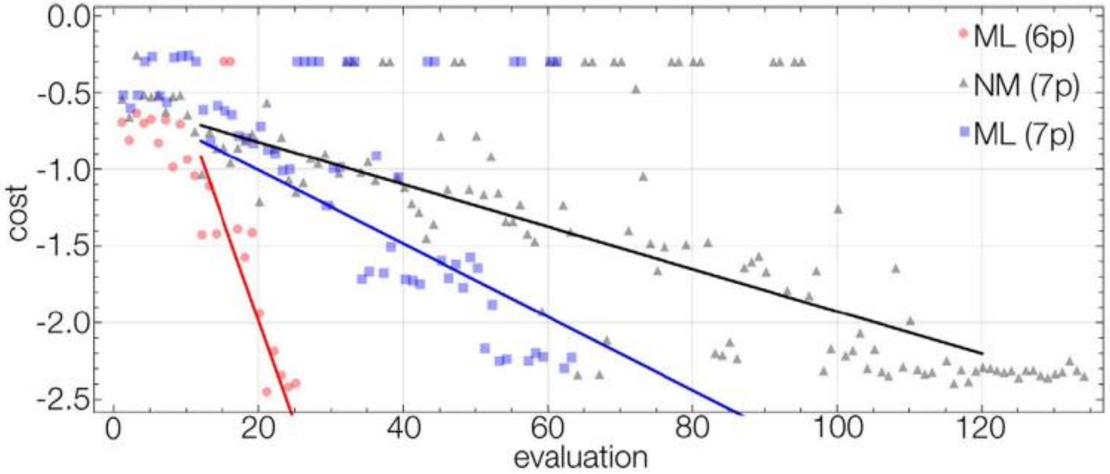
ML (red and blue) optimizes faster than Nelder-Mead (black).
Eliminated a parameter based on ML model & convergence improves (red).



Cost C for parameters X

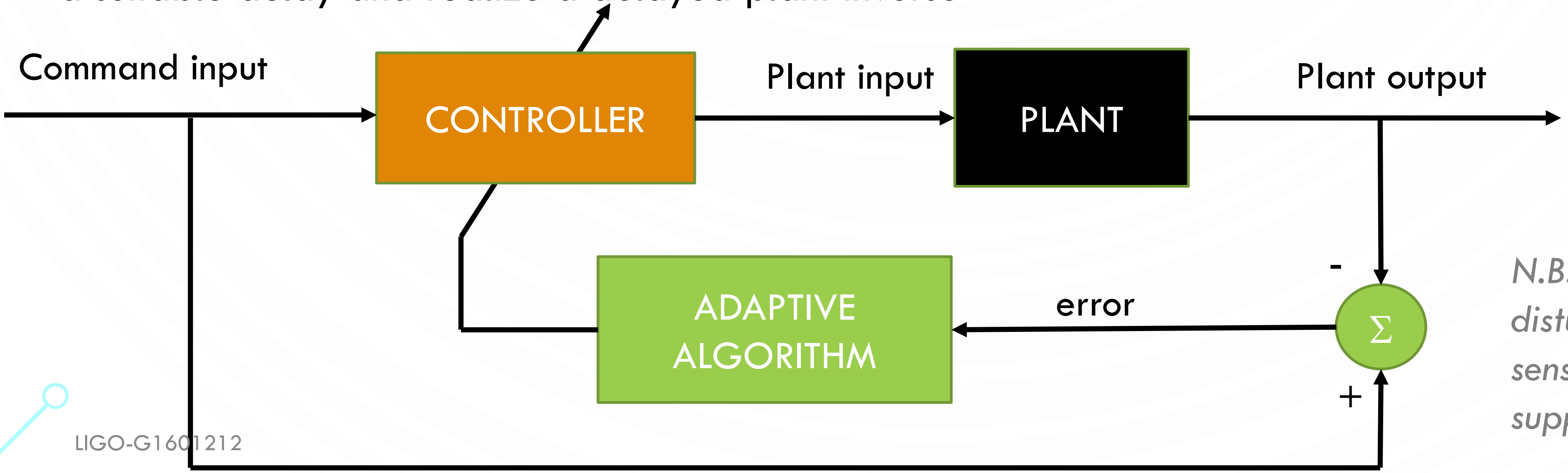
Experiment on Machine

LIGO-G1601212



ADAPTIVE INVERSE CONTROL CONCEPT

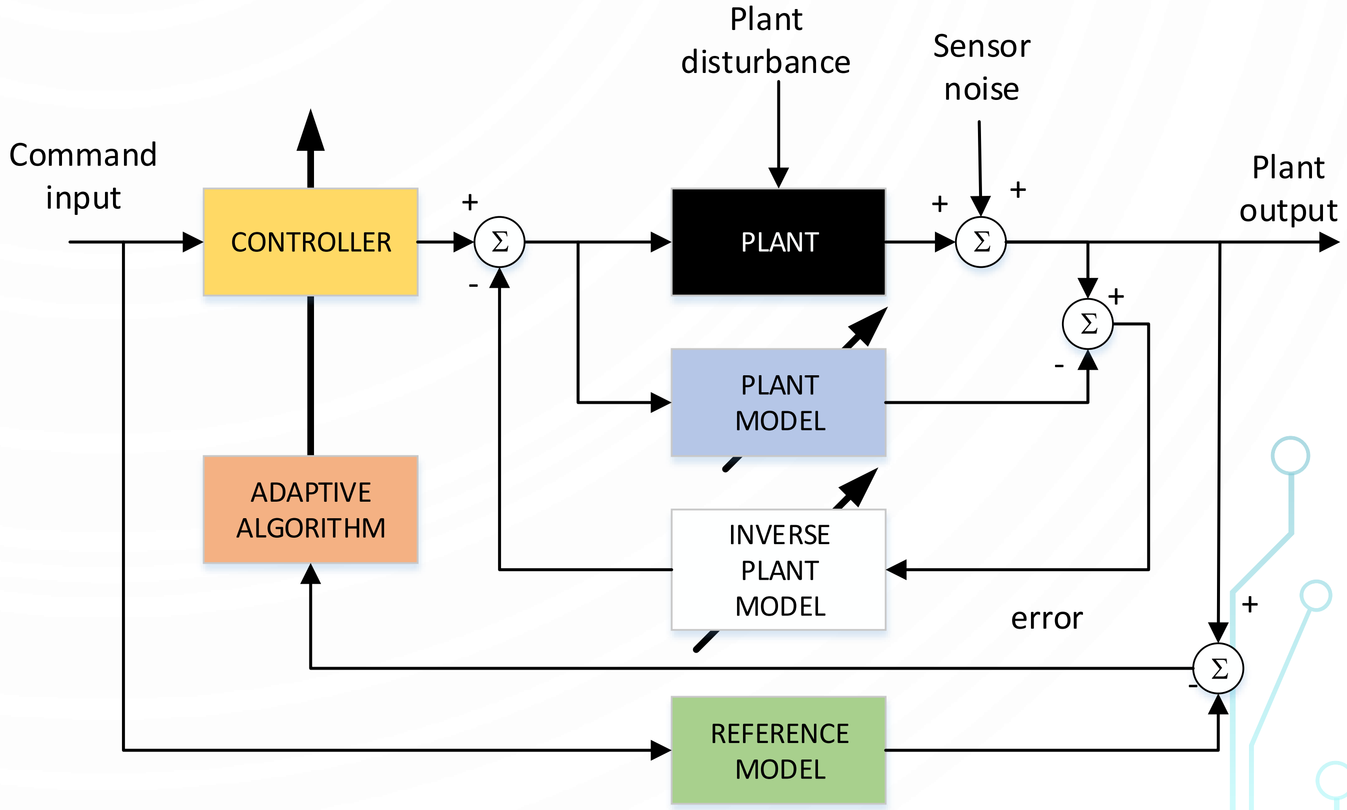
- Concept developed by Widrow & Walach (~1971 - 1986) and then married to neural networks (late 80s, early 90s)
- Adapt the controller (adjust its parameters) until the error is small, i.e. until the controller is the inverse of the plant
- The adaptation algorithm uses an objective such as minimizing the mean square error
- The adaptation is a form of feedforward control
- If the plant has delays, then the controller must be a predictor
- If the plant is non-minimum phase, then the inverse controller would be unstable. However one can introduce a suitable delay and realize a delayed plant inverse



N.B.: as shown plant disturbances and sensor noise are not suppressed

MODEL-REFERENCE ADAPTIVE INVERSE CONTROL WITH PLANT NOISE AND DISTURBANCE CANCELING

- A reference model is chosen to have the desired system response
- Plant noise and disturbances are cancelled by feedback through an inverse plant model
- Requires 3 adaptation processes
- objective function must be chosen carefully to whiten and/or filter the error
- Inverted plants are notoriously non-robust due to plant variation → the adaptation rate must be fast

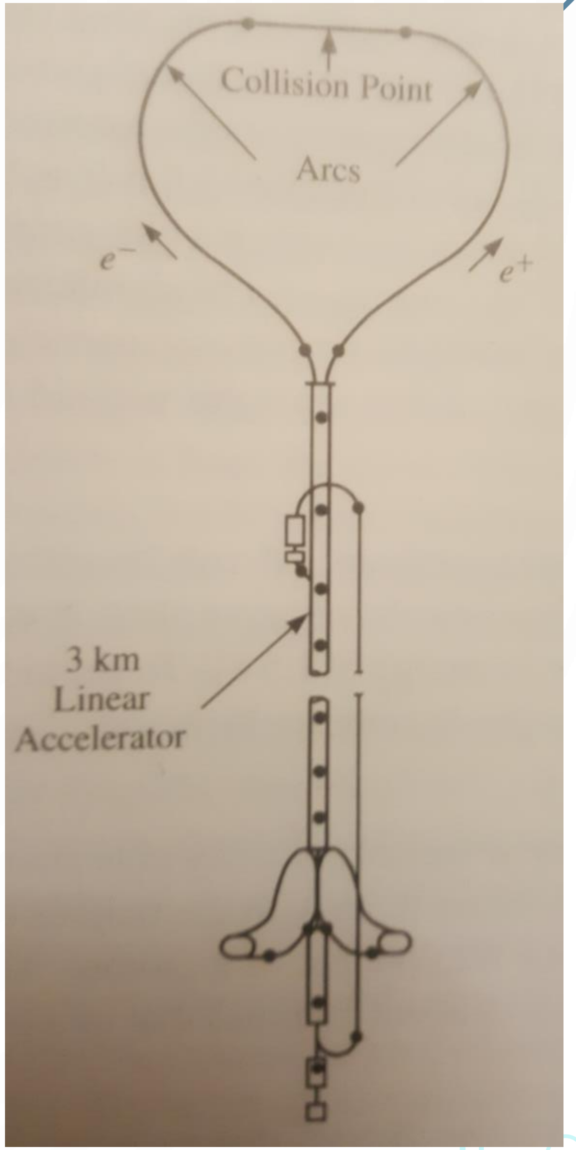


EXAMPLE: MIMO APPLICATION OF ADAPTIVE-NOISE CANCELATION

- Beam Trajectory control for the SLC (SLAC Linear Collider)

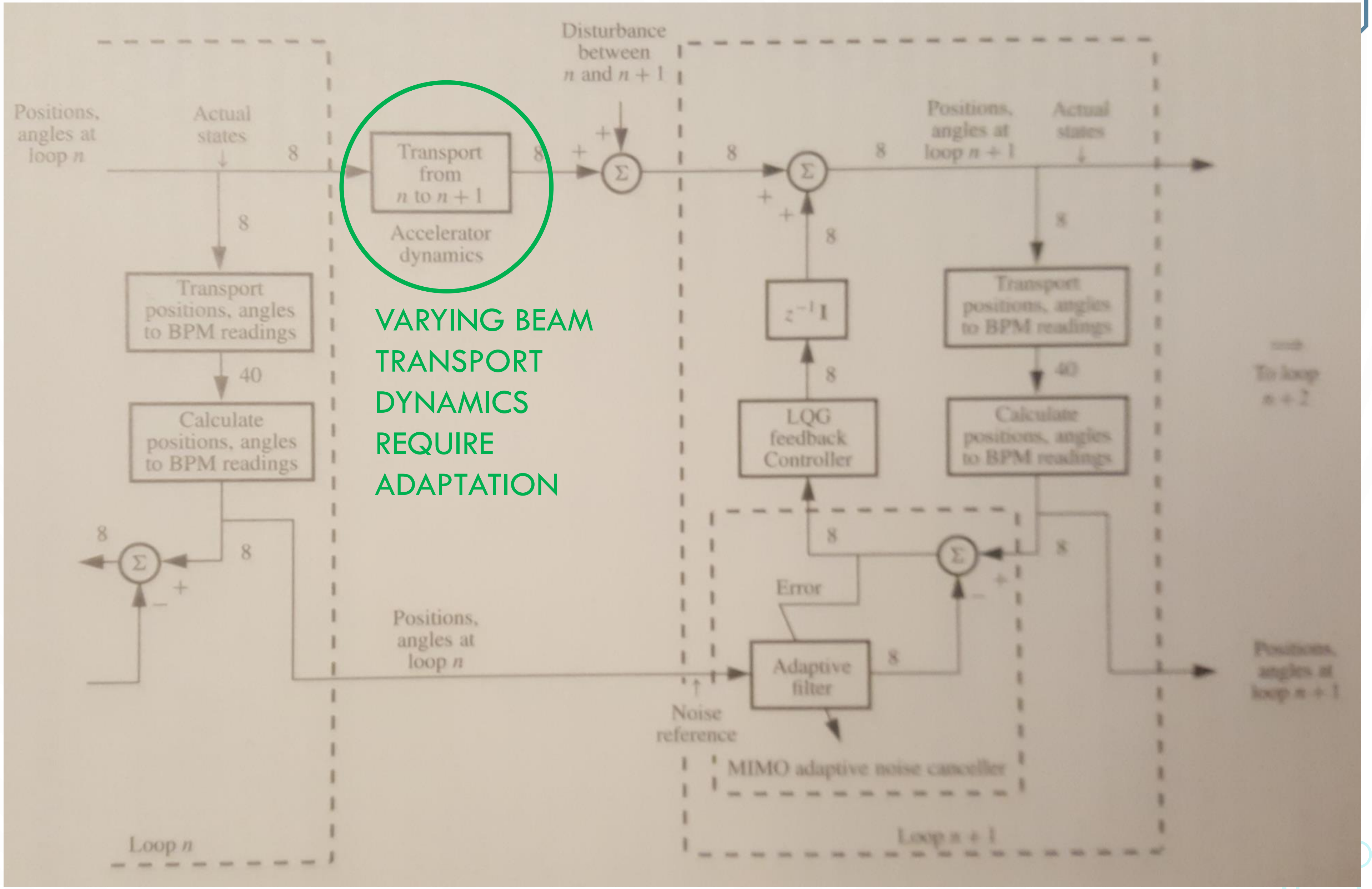
  Ref: B. Widrow, E. Walach, Adaptive Inverse Control, 1996.

- Beam centering
  - Passive: set of 300 Quadrupole electromagnets focus the beam
  - Quasi-DC dipole electromagnets (V & H sets near each quadrupole) steer the beam
  - Capacitive Beam Position Monitors (set of 300) used to calculate drive amplitudes for the quasi-DC dipole magnets
  - 20 Steering feedback loops, in sequence
    - Each controls measures & controls 8 states: position & angle, in V & H, for e^- and e^+
    - 20 Hz sample & update rate (120 Hz beam pulse rate)



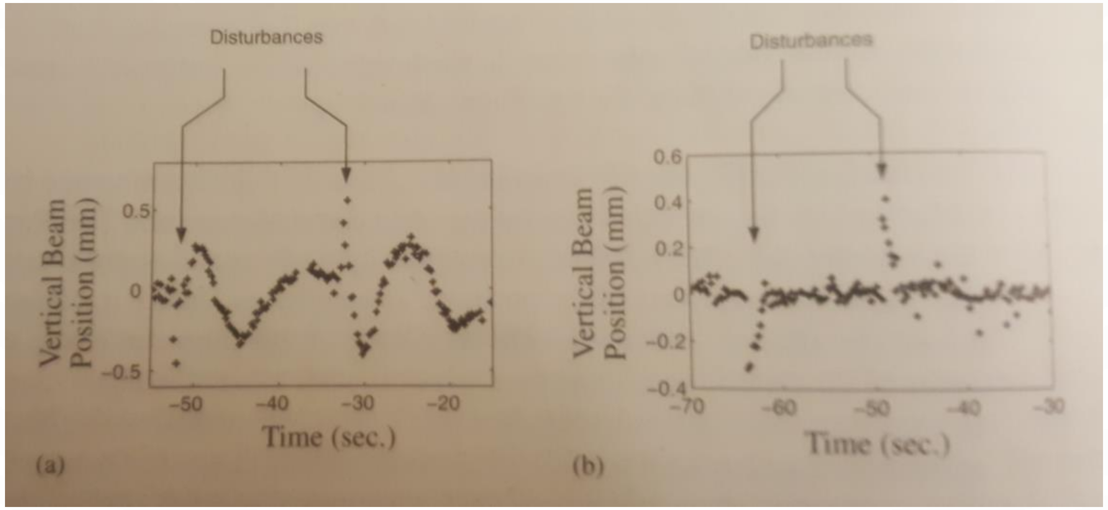
EXAMPLE: MIMO APPLICATION OF ADAPTIVE-NOISE CANCELATION

- LQG optimal filters to minimize beam position RMS
- 7 sequential loops
- Consider "upstream" {positions, angles} as noise – Loop n corrects for these errors, Loop n+1 corrects for errors due to transport (or residuals after Loop n)



EXAMPLE: MIMO APPLICATION OF ADAPTIVE-NOISE CANCELATION

- Least Mean Square (LMS) Algorithm for updating the weights (matrix elements)
  - Only stable if the learning rate is less than the inverse of the largest eigenvalue on the input correlation matrix
  - Magnet supply & klystron fluctuations can cause jitter amplitude to increase 10x in short time, hence eigenvalues change proportionally → leads to a low learning rate and slow convergence
  - LMS has different convergence rates for each eigenmode
- Sequential Regression Algorithm (SER)
  - Adaptively estimates the inverse of the correlation matrix
  - Scales the inputs so that all the eigenvalues of the correlation matrix of the scaled inputs are unity (solves both problems of the LMS algorithm)
  - However calculated weights are unstable initially when large updates occur; Delay updating weights until converged



GW DETECTOR PROBLEMS 'RIPE' FOR ML?

- Angular controls
  - Angular loops introduce noise to DARM by the beam off-centering
  - DC coupling is removed by the coil balancing (angle to length feedforward)
  - AC coupling due to unsuppressed angular motion, and imperfect balancing
  - Bandwidth limited to keep angular control noise injection low
  - Let ML adaptively adjust feedforward gains for the unsuppressed angular motion (ASC error point)? (Essentially a time-varying coil balancing)
- Interferometer Global control parameters
  - Let ML tune up the global controls, just as an operator does …
  - Blends, Michelson feedforward, ASC bandwidth, bounce/roll servos, …
  - Based on the seismic noise in a particular band, wind speed, …
- TCS control
  - Compensate for TM radius of curvature when IFO is locked or transitioning in and out of lock
  - Let ML discover the model, or predictor, for TM thermal lens
- Others?