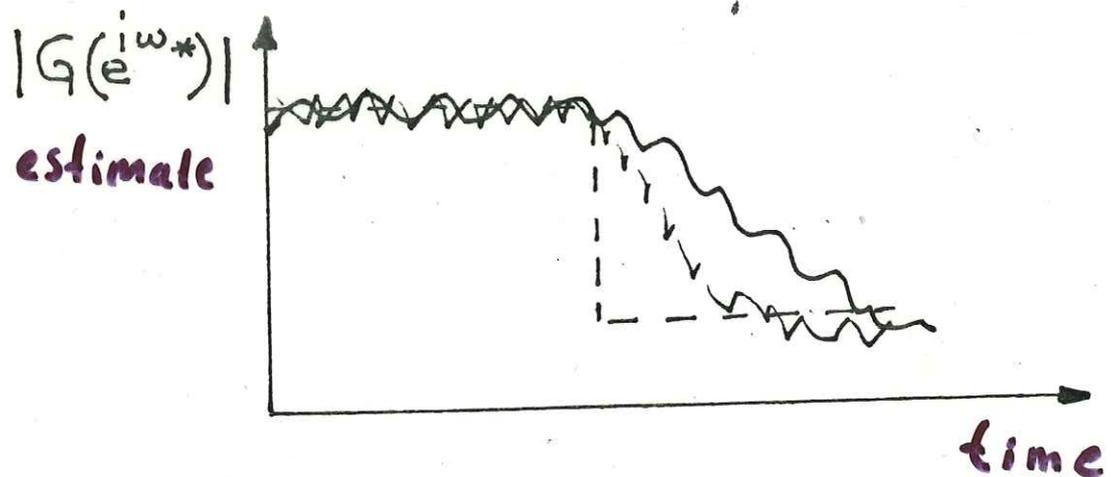


**SYSTEM IDENTIFICATION**  
**IN A**  
**NOISE-FREE**  
**ENVIRONMENT**

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# THE PROBLEM

THE WORLD CHANGES -  
ADAPT TO IT QUICKLY



- - - - True system

\_\_\_\_\_ Estimate

**THINGS TAKE TIME!**

## ● WHY DO THINGS TAKE TIME?

- measurements are not reliable
- noise effects must be averaged out over time
- trade-off between noise sensitivity and tracking ability

## ● WHAT IF (VIRTUALLY) NO NOISE?

## THE QUESTIONS

- Noise free system:  $y(t) = G_0(q) u(t)$
- Apply standard (recursive) prediction error method
- Design variables
  - Forgetting factor
  - Data prefilter
- What are the properties of the estimates?
- How do they depend on forgetting factor and prefilter?
- What are the trade-offs for quick adaptation?

# THE MACHINERY I

○ SYSTEM:  $y(t) = G_0(q) u(t)$

$$G_0(q)u(t) = \left( \sum_{k=1}^{\infty} g_k q^{-k} \right) u(t) = \sum_{k=1}^{\infty} g_k u(t - k)$$

○ FREQUENCY FUNCTION:  $G_0(e^{i\omega})$

○ MODEL:

$$y(t) = G(q, \theta) u(t) + H(q, \theta) e(t)$$

## THE MACHINERY II

### ○ FORM PREDICTION ERRORS

$$\varepsilon(t, \theta) = H^{-1}(q, \theta)[y(t) - G(q, \theta)u(t)]$$

### ○ FILTER DATA:

$$\varepsilon_F(t, \theta) = L(q) \varepsilon(t, \theta)$$

### ○ CHOOSE FORGETTING FACTOR $\lambda$

### ○ MINIMIZE

$$\sum_{t=1}^N \lambda^{N-t} \varepsilon_F^2(t, \theta)$$

GIVES  $\hat{\theta}_N$

# OUTLINE

- THE PROBLEM
- THE QUESTIONS
- THE MACHINERY
- THE ANSWERS
  - Asymptotic properties for  $\lambda \rightarrow 1$
  - How to explain variability
  - Prefilter and variability
  - Transient behaviour
  - Quick adaptation
- THE CONCLUSIONS

# ASYMPTOTIC PROPERTIES AS $\lambda \rightarrow 1$

$$\hat{\Theta}_N \rightarrow \Theta^*$$

$$\Theta^* = \arg \min_{\theta} \int_{-\pi}^{\pi} |G_0(e^{i\omega}) - G(e^{i\omega}, \theta)|^2 \frac{\Phi_u(\omega) \cdot \underbrace{|L(e^{i\omega})|}_{d\omega}}{|H(e^{i\omega}, \theta)|^2} d\omega$$

$\Phi_u(\omega)$  input spectrum

$$R_u(\tau) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{t=1}^N u(t+\tau)u(t)$$

$$\Phi_u(\omega) = \sum_{\tau=-\infty}^{\infty} R_u(\tau) e^{-i\tau\omega}$$

# ASYMPTOTIC PROPERTIES AS $\lambda \rightarrow 1$

If  $\{u(t)\}$  stochastic process

$$(\hat{\theta}_N - \theta^*) \in As N(0, P)$$

$$* P = \frac{(1 - \lambda)}{2} \cdot Q \quad (\text{If } \lambda = 1, \frac{1}{N} Q)$$

$$Q = R^{-1} S R^{-1}$$

$$R = E \psi(t) \psi^T(t); \quad \psi(t) = -\frac{d}{d\theta} \epsilon_F(t, \theta) \Big|_{\theta = \theta^*}$$

$$S = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{t=1}^N \sum_{s=1}^N E \psi(t) \psi^T(s) \epsilon(t) \epsilon(s)$$

$$\epsilon(t) = \epsilon_F(t, \theta^*)$$

## ASYMPTOTIC PROPERTIES cont.

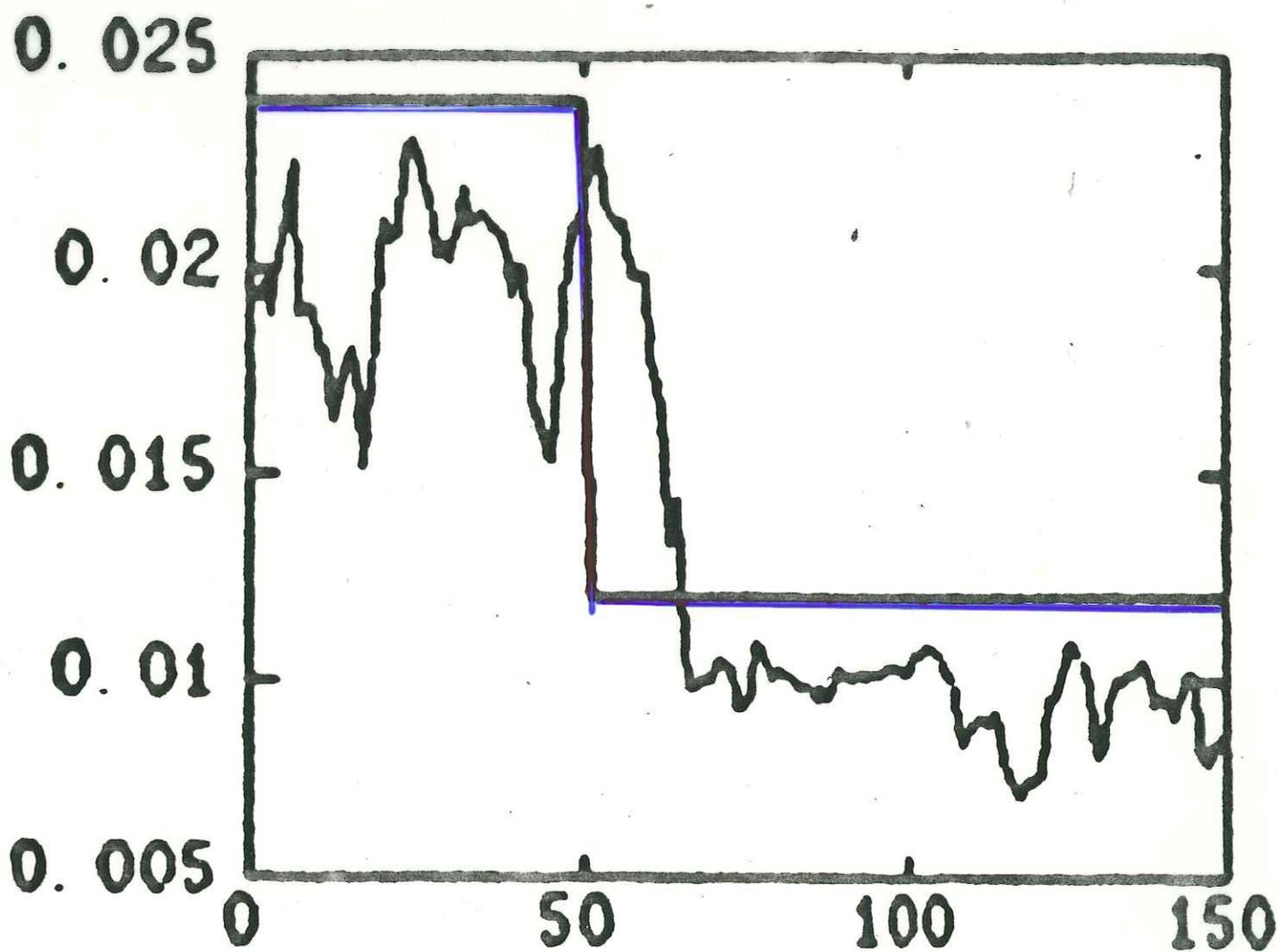
CONCEPTUALLY:

$$\text{Variance } P \sim (1 - \lambda) \cdot \frac{\text{Energy in } \varepsilon}{\text{Energy in } \Psi}$$

NOTE:

- Decays as if noise were present
- Model error plays the role of noise
- Variance - Variability

$|G(e^{+i\omega}, \hat{\theta}_t)|$  as a function of  $t$



**Figure 13: As Figure 11, but  $\lambda = 0.8$ .**

## HOW TO EXPLAIN VARIABILITY?

- True system  $G_0(e^{i\omega})$

Consider model

$$y(t) + a y(t-1) = bu(t-1)$$

a & b can be fitted using

$$y(t_1) + a y(t_1-1) = b u(t_1-1)$$

$$y(t_1 + 1) + a y(t_1) = b u(t_1)$$

What is the resulting model?

$$\frac{be^{-i\omega_* t}}{1 + ae^{-i\omega_* t}} = G_0(e^{i\omega_*}) \quad !$$

for  $\omega_*$  being the unique frequency that fits

$$y(t_1-1), y(t_1), y(t_1+1)$$

- \* Exact fit at "instantaneous frequency"
- \* Normally  $\hat{G}_t(e^{i\omega_0})$  will vary.

When no variability?

- Instantaneous frequency time-  
independent

or

- True system first order

## ❧ CONCEPTUALLY:

The model varies since it tries to adjust to the true system in the frequency range reflected by the recent inputs. This range fluctuates, though, even for a "stationary" input.

## VARIABILITY OF TRANSFER FUNCTION

Translated to the transfer function estimate, for high order models

$$E \left| \hat{G}_N(e^{i\omega}) - G^*(e^{i\omega}) \right|^2 \sim \frac{n}{2} (1 - \lambda) \left| G_0(e^{i\omega}) - G^*(e^{i\omega}) \right|^2$$

*estimate* (under  $\hat{G}_N$ )      *limit model* (under  $G^*$ )      *model order* (under  $n$ )      *forgetting factor* (under  $\lambda$ )      *true system* (under  $G_0$ )

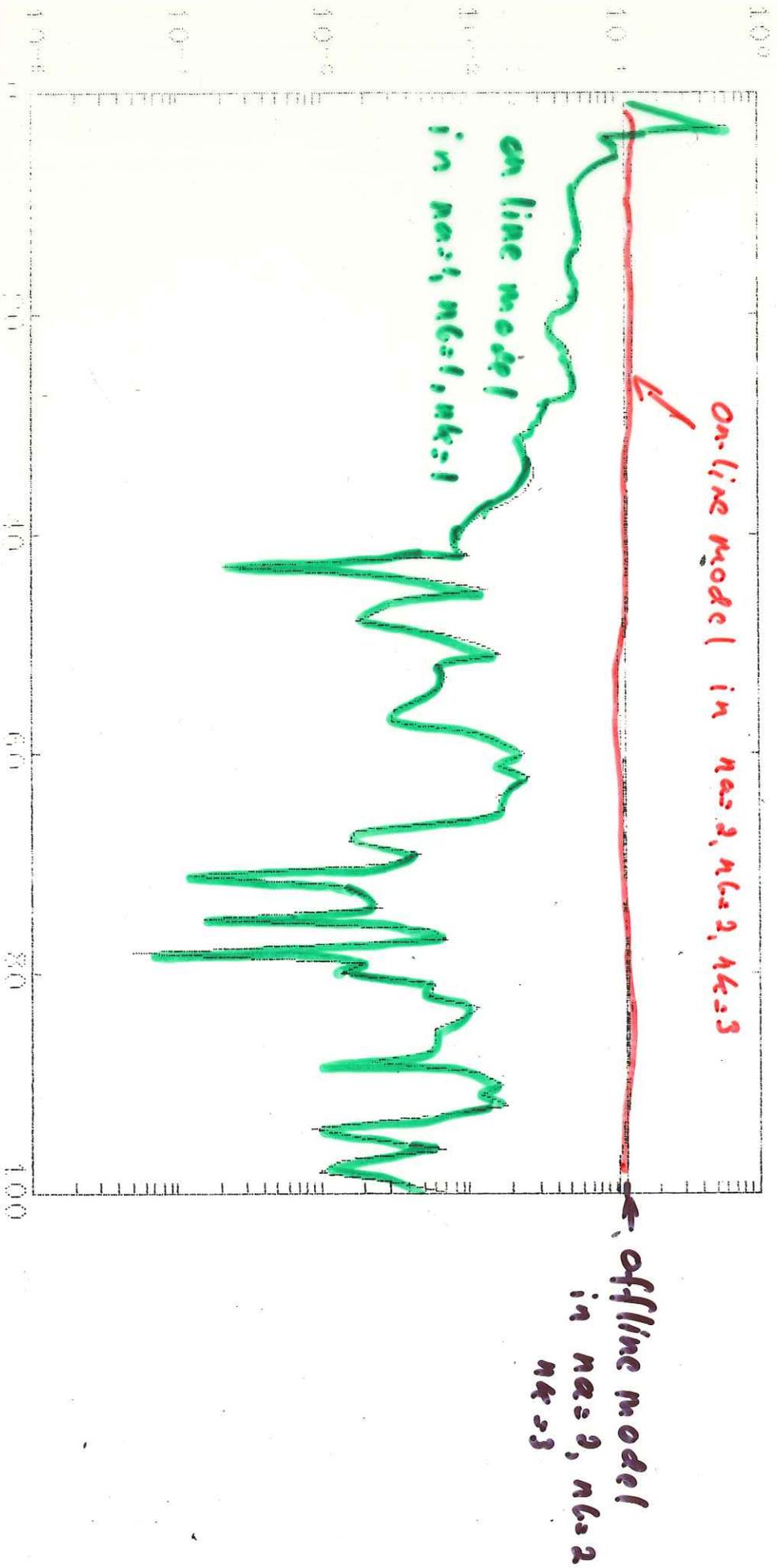
(Formally correct for FIR model with white noise input)

### • IMPLICATIONS!

# "HAIR DRYER DATA"

$$\lambda = 0.95$$

$$|G(e^{i\omega})| \quad 12.5 \text{ rad/s}$$



## PREFILTER AND VARIABILITY

- \* Prefilter will affect limit model.

Recall

- \* 
$$Q \sim \frac{\text{energy in } \epsilon_F}{\text{energy in } \Psi_F}$$

- \* Can  $Q$  be reduced by prefilter?

Well ...

- Let  $L(q)$  be a narrow band ideal BP-filter with BW  $W$ .

Then

- energy in  $\Psi_F \sim C_1 \cdot W$

$$\epsilon_F = L(q) H^{-1}(q, \theta^*) [G_0(e^{i\omega}) - G_*(e^{i\omega})] u(t)$$

energy in  $\epsilon_F =$

$$\sim \int_{\omega_0 - W}^{\omega_0 + W} |G_*(e^{i\omega}) - G_0(e^{i\omega})|^2 d\omega \sim$$

$$\sim \int_{\omega_0 - W}^{\omega_0 + W} |G_*(e^{i\omega_0}) - G_0(e^{i\omega_0}) + G'_0(e^{i\omega_0}) \cdot (\omega - \omega_0)|^2 d\omega \sim$$
$$\sim D_2 \cdot W^3$$

implies

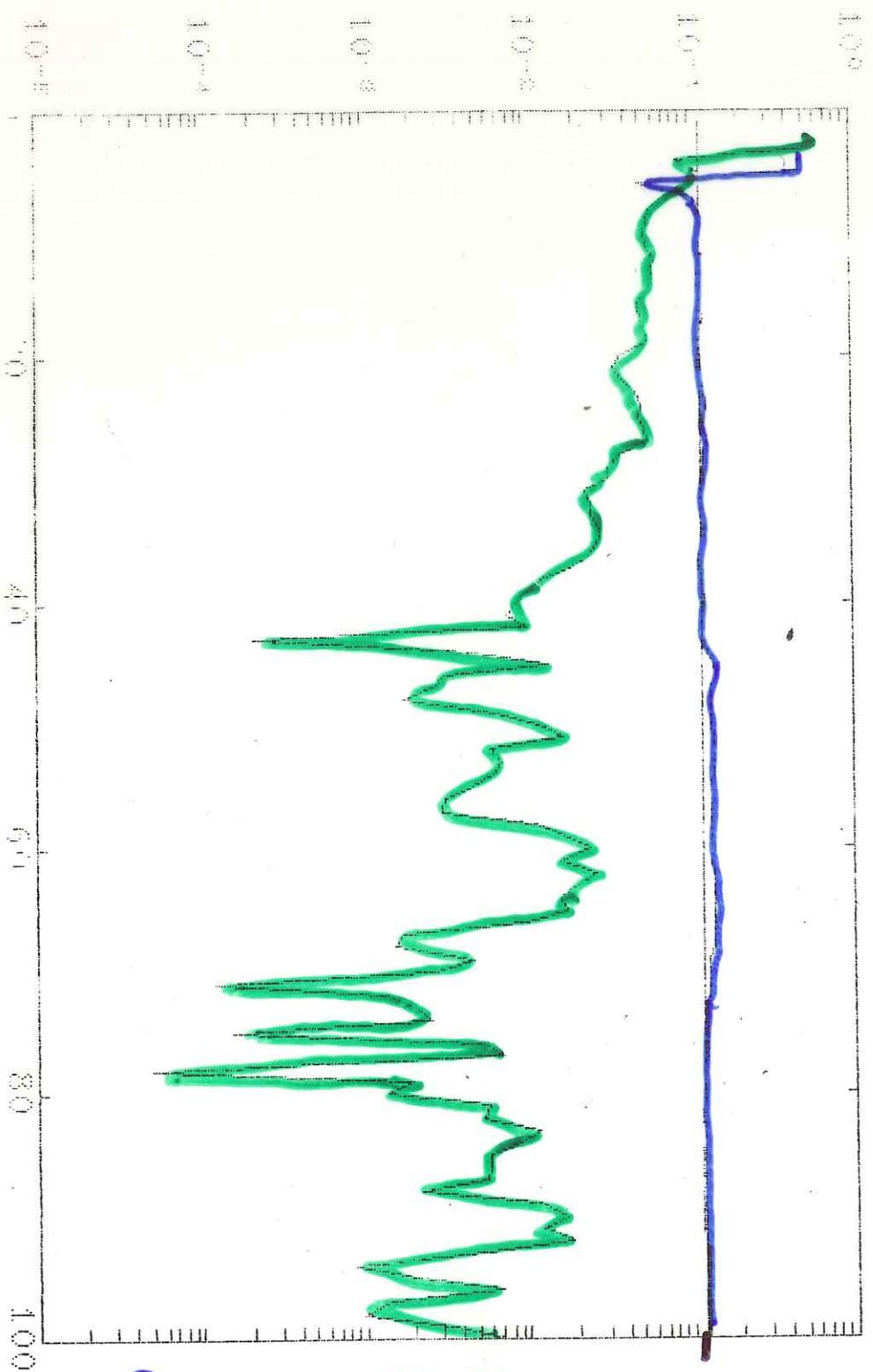
$$Q \sim C \cdot W^2$$

Variability will be reduced by prefiltering!

# HAIR DRYER DATA

ON-LINE MODELS IN  
 $n_{a-1}, n_{b-1}, n_{k-1}, \lambda = 0.95$

(Gce'j)



OFFLINE MODEL  
in best structure

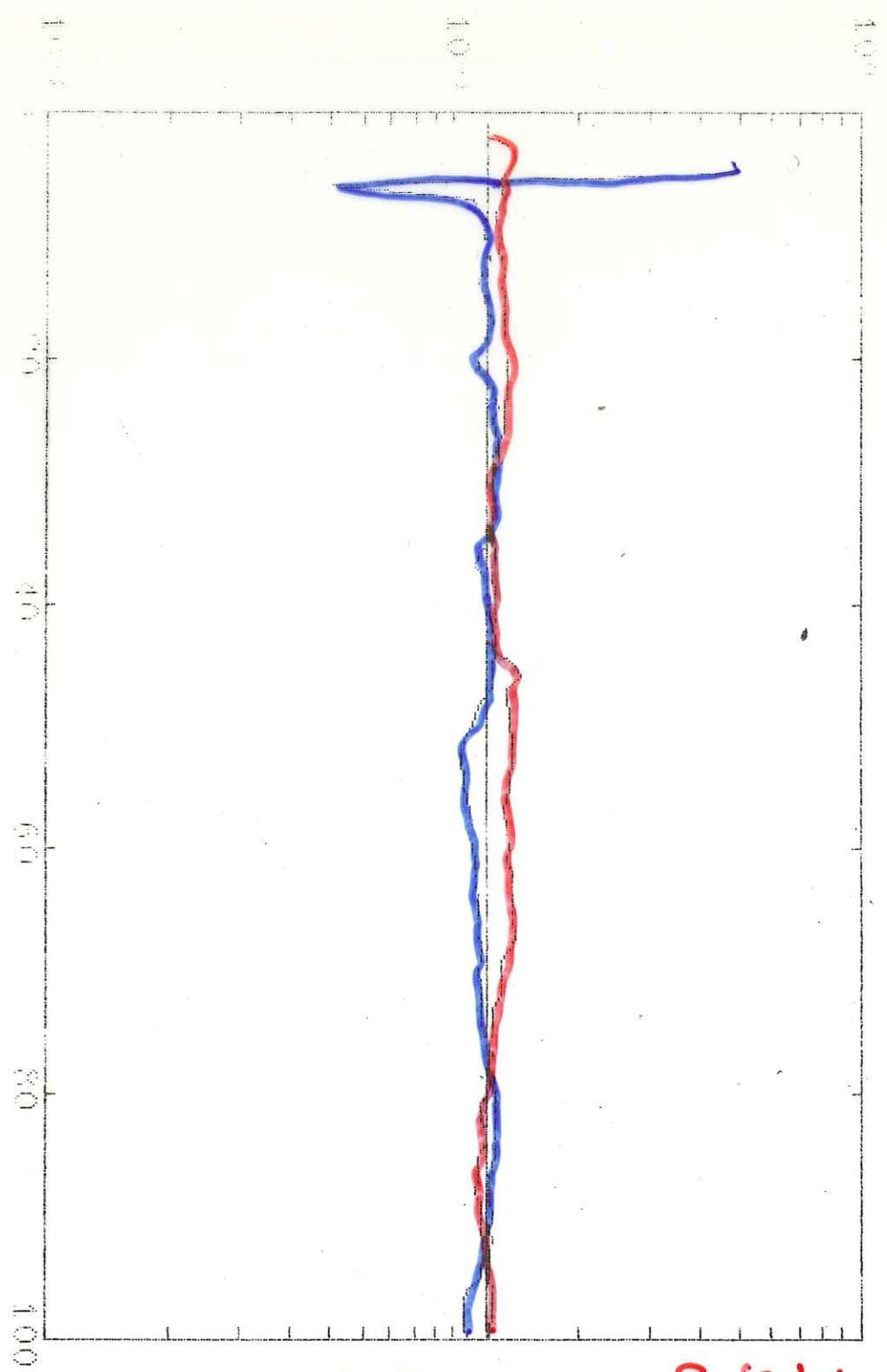
UNFILTERED  
DATA

FILTERED  
DATA  
(5th order Butter-  
worth BP)

# HARDDRYER DATA

1 GeV

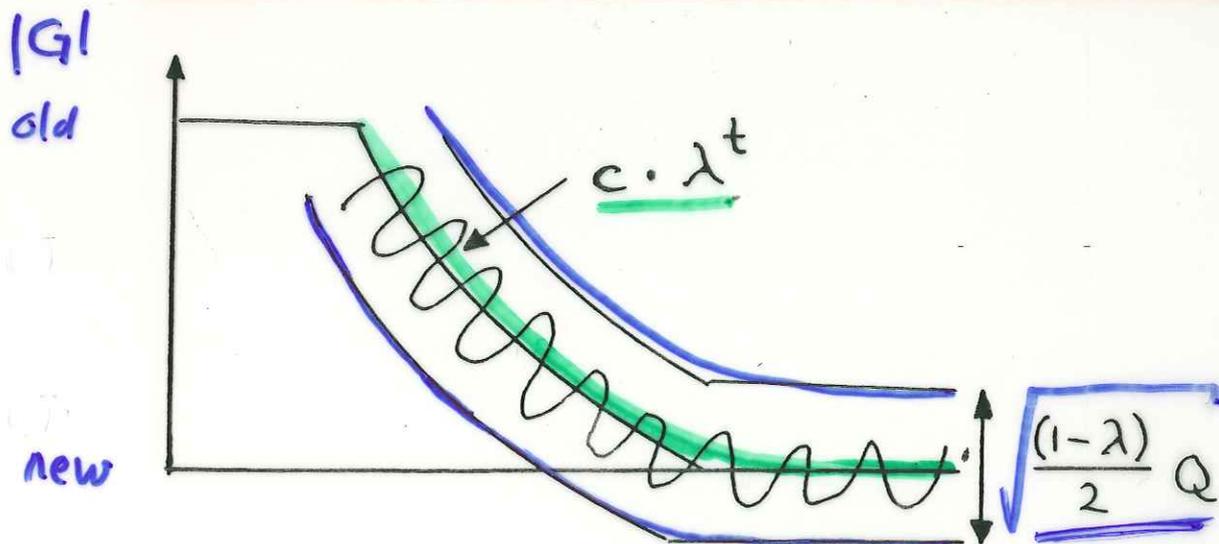
ON-LINE MODELS  $\lambda=0.95$



IN BEST  
STRUCTURE -  
UNFILTERED DATA

IN SIMPLEST  
STRUCTURE -  
FILTERED DATA

# TRANSIENT BEHAVIOUR



\*  $Q \sim C \cdot W^2$

\* Quick adaptation?

\* What about prefilter?

## FILTER BEHAVIOUR

n:th order BP Butterworth filter with bandwidth  $W$  has a transient

$$C \cdot \mu^t$$

$$\mu = e^{-W \cdot \sin \frac{\pi}{2n}} \approx \left(1 - W \cdot \frac{\pi}{2n}\right)$$

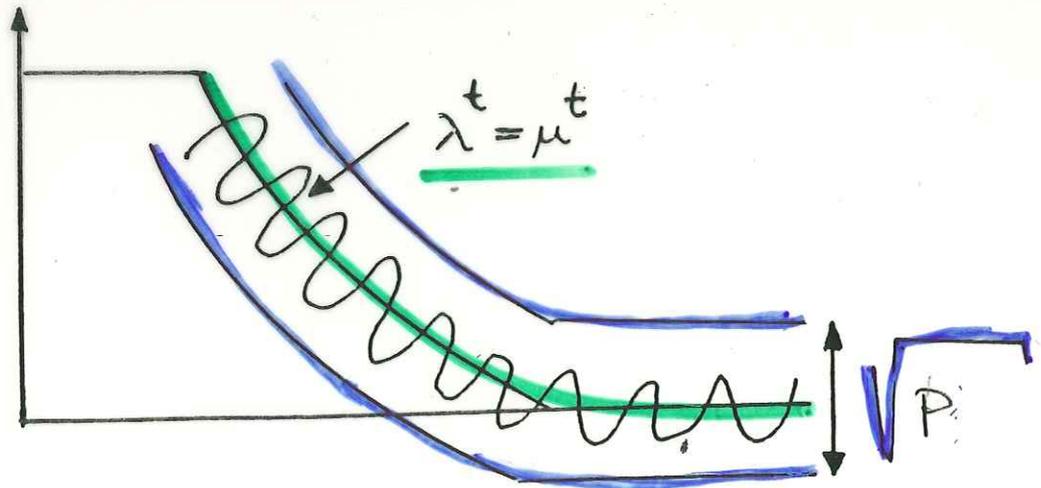
\*Narrow band/high order will delay information.\*

\* LINK  $\lambda$  and filter so that

$$\lambda \approx \mu$$

$$\Rightarrow (1 - \lambda) \approx W \cdot \frac{\pi}{2n}$$

# QUICK ADAPTATION



$$P \sim (1 - \lambda)Q = W \cdot \frac{\pi}{n} \cdot C \cdot W^2$$

$$\mu = \left(1 - \frac{W \cdot \pi}{n}\right)$$

$$\min_t \left| \left(1 - \frac{W \cdot \pi}{n}\right)^t + \sqrt{\frac{W^3}{n}} \right| < \delta$$

## **CHOICE OF FORGETTING FACTOR**

- Still a trade-off between estimate variability and tracking alertness
- Prefilter opens up important new dimensions

## CONCLUSIONS

- ★ NO NOISE - STILL PROBLEM
- ★ MODEL ERROR TAKES UP THE PART OF THE NOISE
- ★ "SIGNAL-TO-NOISE RATIO" CAN BE IMPROVED BY PRE-FILTERING
- ★ MODEL VARIABILITY INDICATION OF MODEL ERROR
- ★ QUICK ADAPTATION: A JOINT VENTURE FOR FORGETTING FACTOR AND PREFILTER (AND MODEL COMPLEXITY!)