

Recent HBT-EP Kink Mode Control Results

David A. Maurer

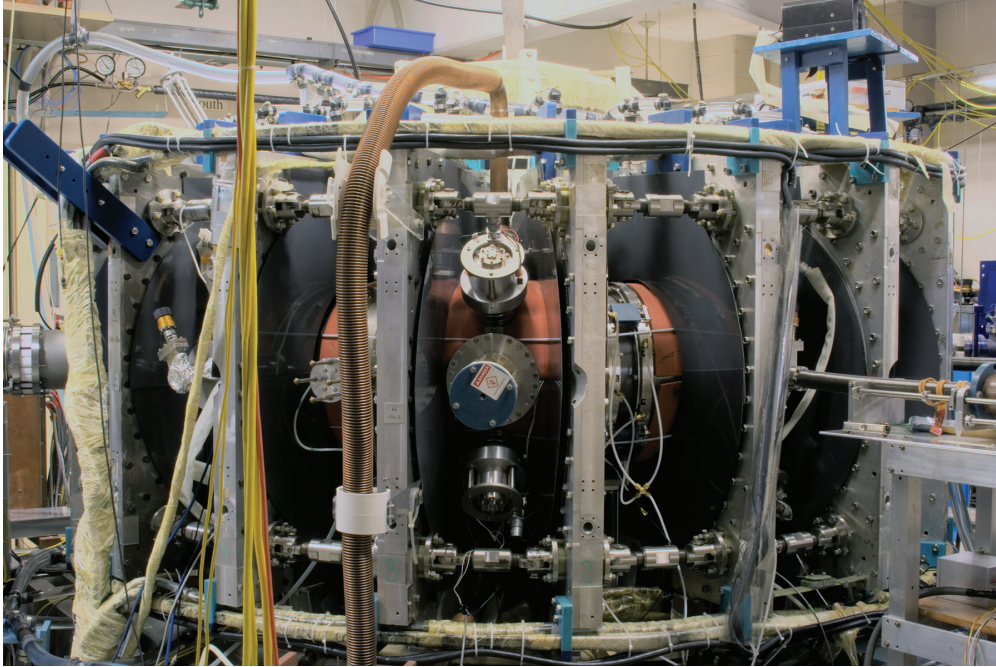
for

J. M. Hanson, J. Bialek, B. DeBono, R. James, J. P. Levesque,
M. E. Mauel, G. A. Navratil, T. S. Pedersen, D. Shiraki
Columbia University

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Austin Texas

Previous results from HBT-EP

HBT-EP has been used to study external kink and resistive wall modes for over a decade.



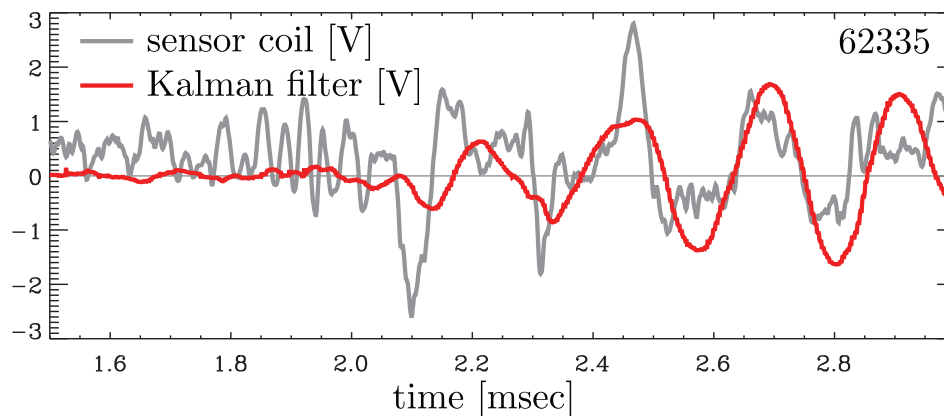
- The effect of a close-fitting conducting wall on external kink stability was investigated as early as 1996 [Ivers, *et. al.*, 1996].
- Next, feedback suppression of the external kink mode was demonstrated using radial sensors and radial control coils [Cates, *et. al.*, 2000].
- This coil set was also used to apply resonant perturbations to plasmas near the marginal stability limit. Agreement with the Fitzpatrick-Aydemir model in the high-dissipation limit was found [Shilov, *et. al.*, 2004].
- Feedback suppression of the external kink *near the ideal wall limit* was achieved using the present network of poloidal sensor coils and radial control coils. [Klein, *et. al.*, 2005].

New results

- A **Kalman filter** algorithm has been implemented on a set of low-latency digital feedback controllers, and used to **excite** and **suppress** the $(m, n) = (3, 1)$ external kink instability on HBT-EP.
- The Kalman filter uses a simple, internal model for a growing, rotating mode.
- **Excellent performance** was achieved with initial guesses for filter model parameters; performance was a bit better when the parameters were optimized.
- Kalman filter feedback **works** under **noisy conditions** that disrupt feedback with conventional algorithms.

Motivation: tokamaks are noisy

- We are interested in using **magnetic feedback** to suppress the tokamak **external kink instability**.
- The external kink is a **rotating, helical perturbation** to the plasma's surface and magnetic field. As it rotates by a magnetic pickup coil, oscillations are observed.
- However, there's a lot of noise in measurements due to other magnetic activity: **tokamaks are noisy!**
- **Noise can impair feedback**, but an advanced filtering algorithm called the Kalman filter can come to the rescue.



- Future burning plasma experiments will likely need advanced filtering to optimize feedback in the presence of edge-localized modes and other MHD noise.

Outline

Simulating external kink mode feedback

The Kalman filter

HBT-EP diagnostics and control hardware

Experimental results

Conclusions and future work

Simulating external kink mode feedback

The reduced Fitzpatrick-Aydemir model is used to simulate feedback

- The reduced Fitzpatrick-Aydemir equations^{a,b} are used to simulate the $(m, n) = (3, 1)$ external kink mode.^c
- The Fitzpatrick-Aydemir model has been shown to accurately characterize experimental observations on HBT-EP.^d
- Growing, rotating, $n = 1$ plasma and wall modes are produced.
- The stabilizing effects of viscous damping and plasma rotation are accounted for.
- Coupling physics for the wall and feedback coils is included from a VALEN^e model for HBT-EP.
- Noise can be added to measurements of the mode, in the form of a random amplitude and phase.
- It's interesting to see how noise affects feedback!

^aR. Fitzpatrick and A. Y. Aydemir, *Nucl. Fusion* **36**, 11 (1996).

^bR. Fitzpatrick, *Phys. Plasmas* **9**, 3459 (2002).

^cM. E. Mauel, *et. al.*, *Nucl. Fusion* **45**, 285 (2005).

^dM. Shilov, *et. al.*, *Phys. Plasmas* **11**, 2573 (2004).

^eJ. Bialek, *et. al.*, *Phys. Plasmas* **8**, 2170 (2001).

The reduced Fitzpatrick-Aydemir model is used to simulate feedback

- The reduced Fitzpatrick-Aydemir equations^{a,b} are used to simulate the $(m, n) = (3, 1)$ external kink mode.^c
- The Fitzpatrick-Aydemir model has been shown to accurately characterize experimental observations of the RWM on HBT-EP.^d
- Growing, rotating, $n = 1$ plasma and wall modes are produced.
- The fluxes at the plasma and the wall are given as a function of plasma parameters, coupling parameters and a control flux.

$$\frac{d\vec{y}}{dt} = A\vec{y} + \vec{R}\psi_c,$$

where

$$\vec{y} = \begin{pmatrix} \psi_a \\ \psi_w \end{pmatrix}, \quad A = \begin{pmatrix} (1 - \bar{s} - i\bar{\alpha})\frac{\gamma_{mhd}^2}{\nu_d} & -\frac{\gamma_{mhd}^2}{\nu_d\sqrt{c}} \\ \frac{\gamma_w\sqrt{c}}{1-c} & -\frac{\gamma_w}{1-c} \end{pmatrix}, \quad \text{and} \quad \vec{R} = \begin{pmatrix} \frac{-c_f\gamma_{mhd}^2}{\nu_d} \\ \frac{\gamma_w(1-c c_f)}{1-c} \end{pmatrix}$$

With the normalized stability parameter $\bar{s} = 1.0$ and the rotation-dissipation parameter $\bar{\alpha} = -\nu_d\Omega/\gamma_{mhd}^2 = -1.41$ (corresponding to a rotation rate of 5 kHz).

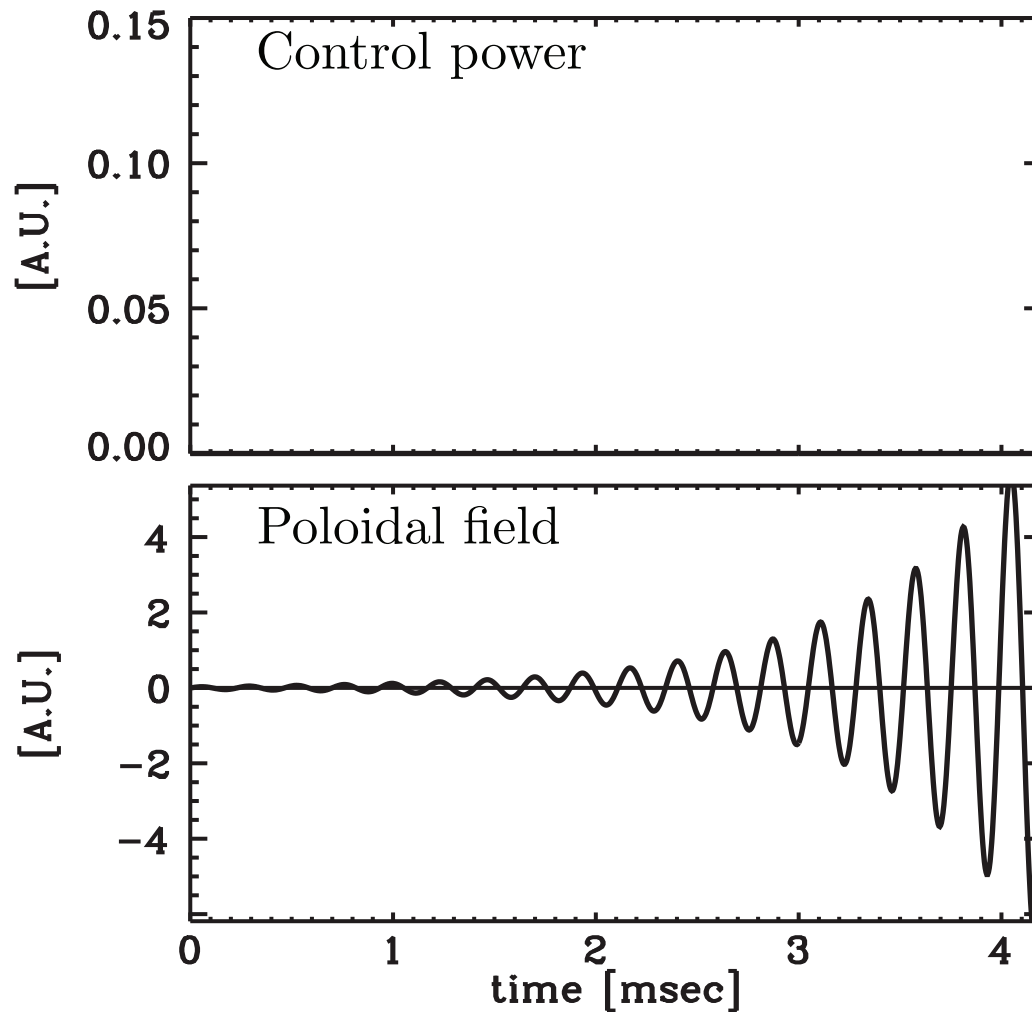
^aR. Fitzpatrick and A. Y. Aydemir, *Nucl. Fusion* **36**, 11 (1996).

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^cM. E. Mauel, *et. al.*, *Nucl. Fusion* **45**, 285 (2005).

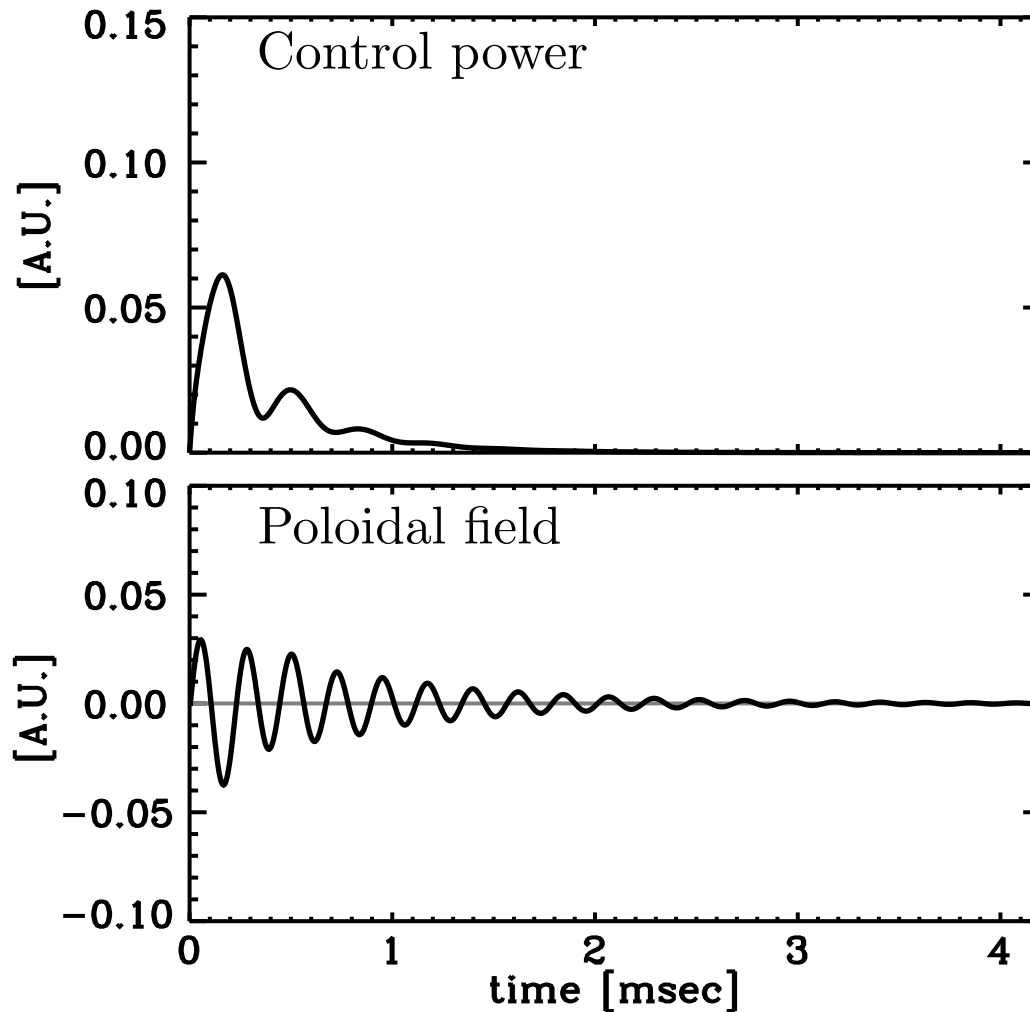
^dM. Shilov, *et. al.*, *Phys. Plasmas* **11**, 2573 (2004).

Instability grows exponentially without feedback



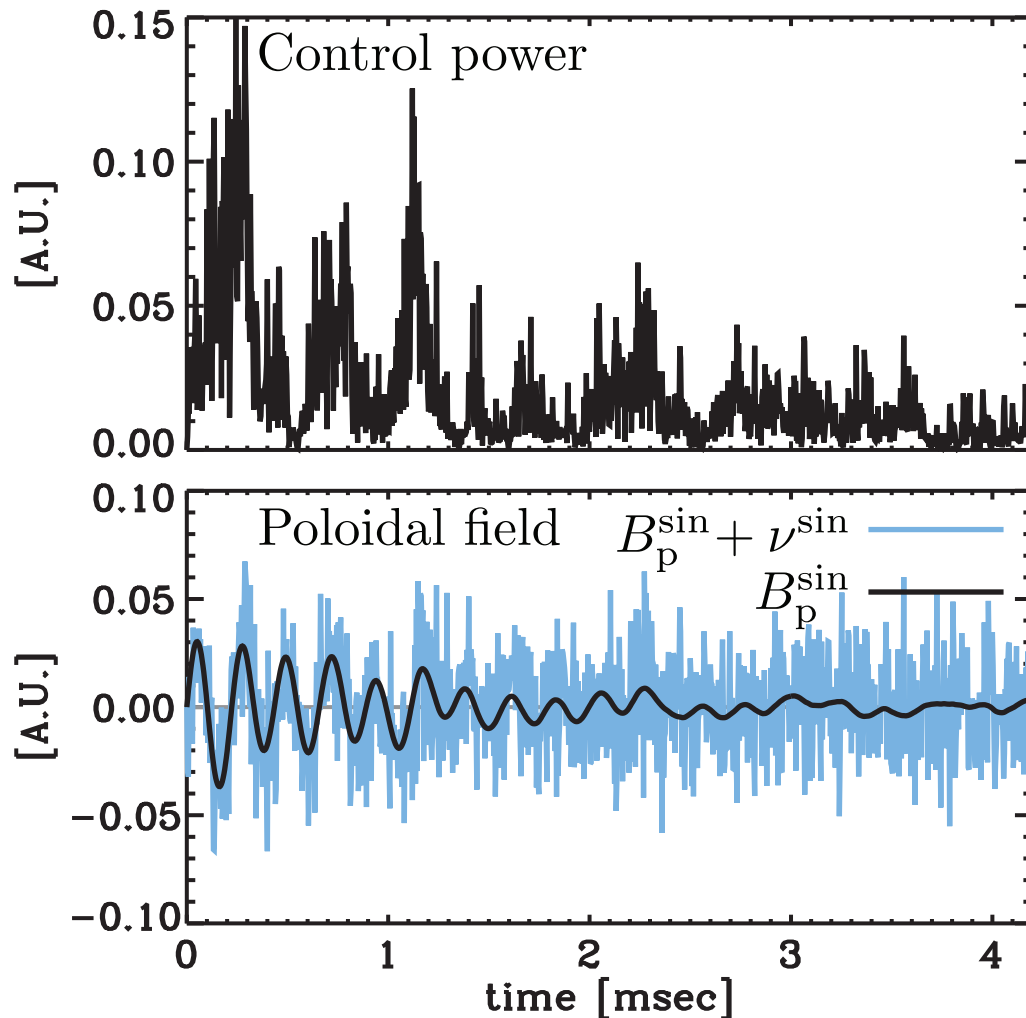
With feedback turned off, we see a growing, rotating mode.

Proportional gain feedback can stabilize the mode



- Proportional gain feedback efficiently stabilizes the mode.
- What about when we add noise?

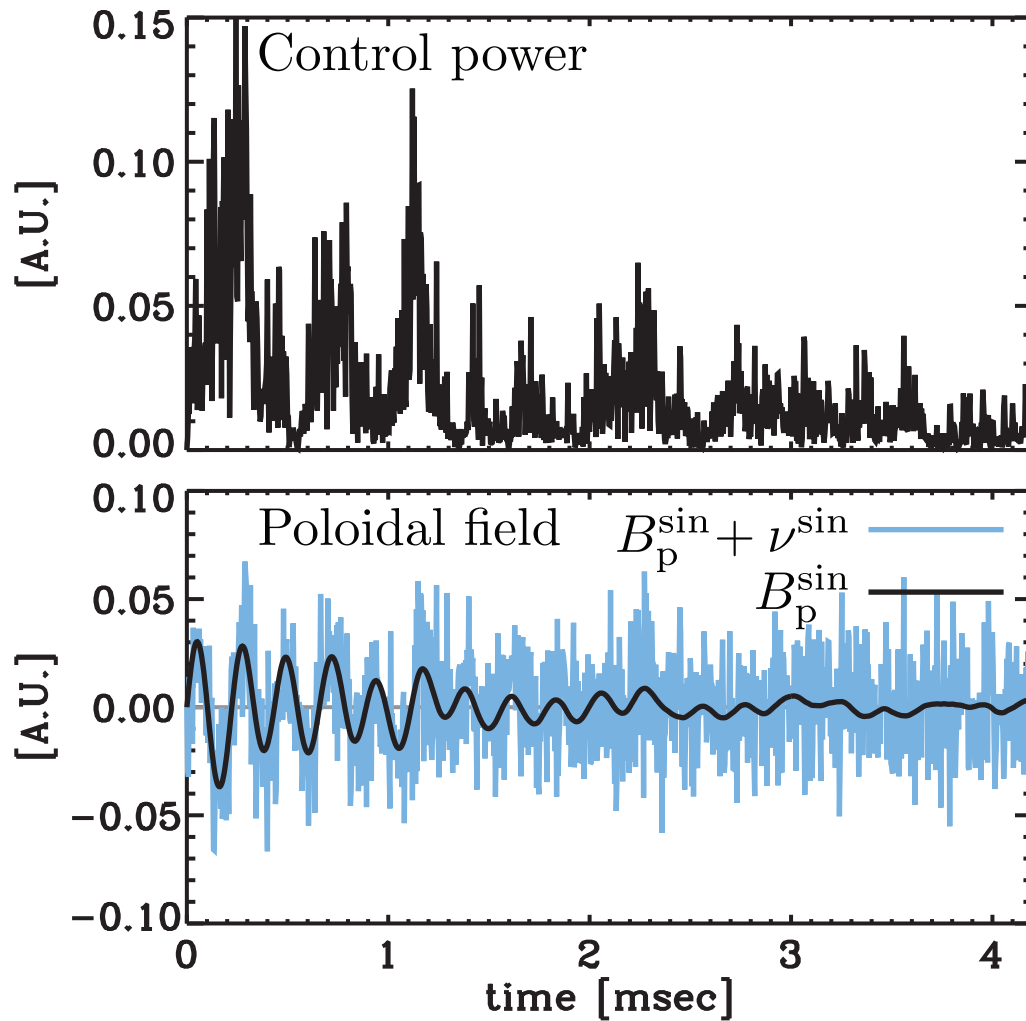
Stabilization is possible with noise, but power requirement is high



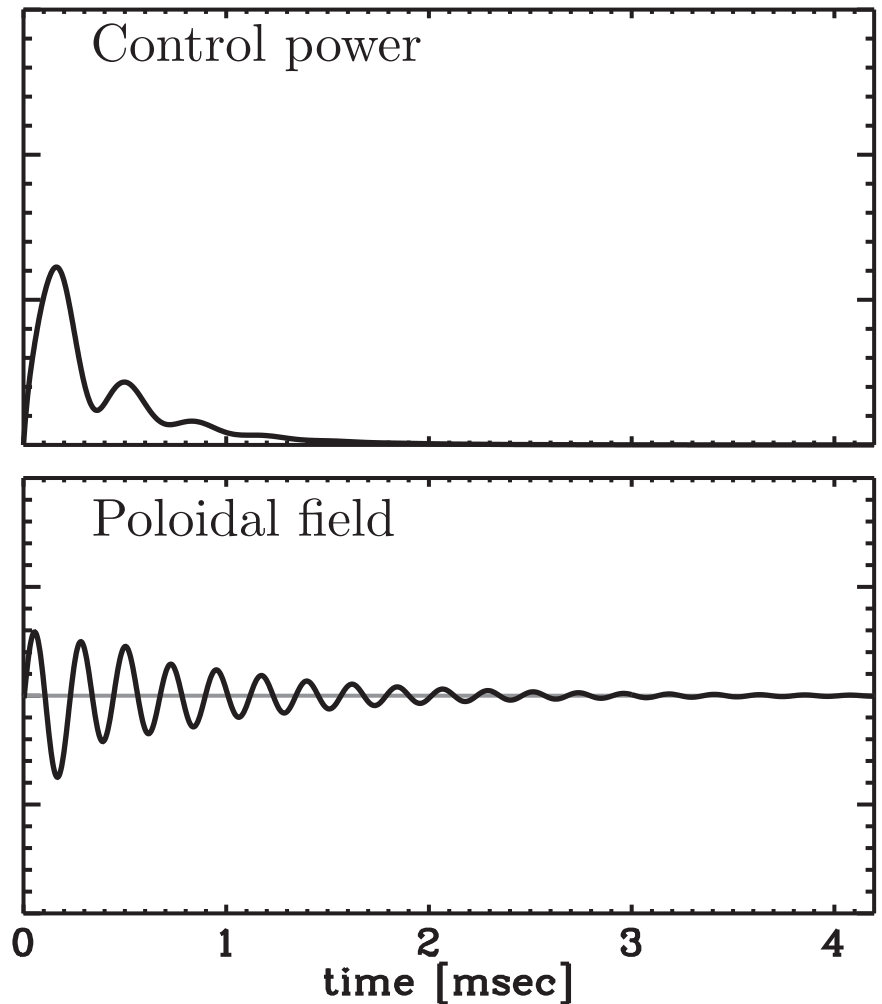
- Feedback still works, but quite a bit of noise makes it into the controller's output.
- Power consumption is high, even after the mode is stabilized.
- Because the simulation is *linear*, feedback works with arbitrary amounts of noise.
- In experiments, *non-linear* effects such as latency and saturation can make feedback performance much more sensitive to noise.

Stabilization is possible with noise, but power requirement is high

With noise



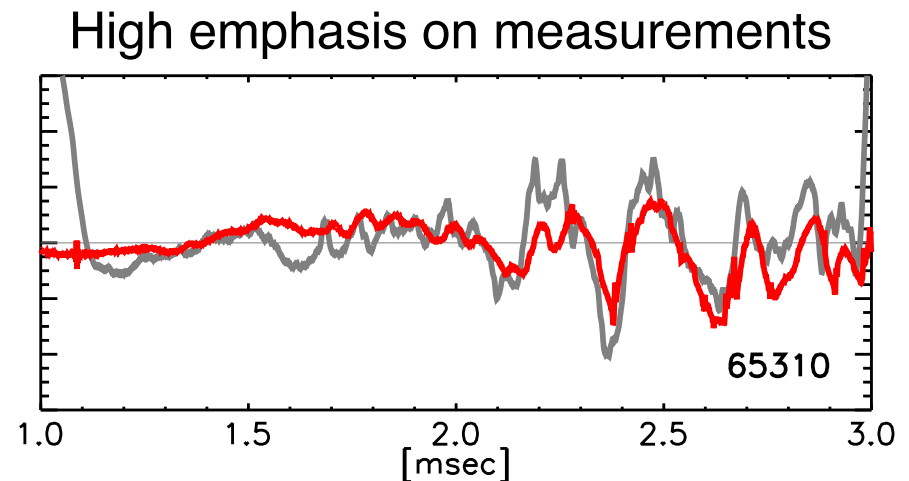
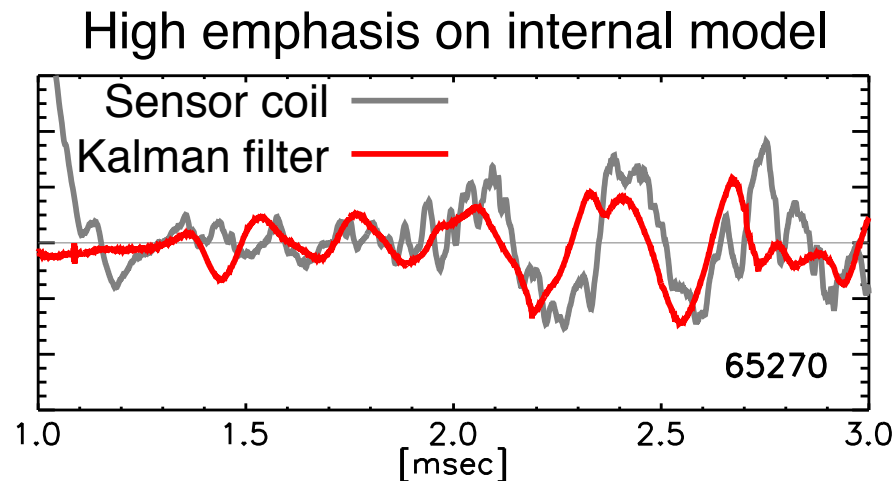
Without noise



The Kalman filter

What is a Kalman filter?

- The Kalman filter^a combines an internal, linear *model* for a system of interest with *measurements* to produce a real time estimate for the system's state.
- The internal model might be slightly inaccurate or incomplete.
- Likewise, measurements could be incomplete or noisy.
- With the Kalman filter, reliance on the model vs. the measurements can be adjusted.



- In simulation and experiments, we use a Kalman filter with a moderate amount of emphasis on the internal model.

^aR. E. Kalman, *Transactions of the ASME—Journal of Basic Engineering* **82**, (Series D), 35 (1960).

The Kalman filter is a simple matrix equation

$$\vec{x}_i = \Phi_i \vec{x}_{i-1} + K_i \vec{z}_i,$$

where \vec{x} is the optimal estimate of the system state and \vec{z} is a vector of measurements.

Here,

$$\Phi_i = (I - K_i H)(\mathbf{A} + B G H), \quad \text{and}$$
$$K_i = (\mathbf{A} P_i \mathbf{A}' + \mathbf{Q}) H' (H (\mathbf{A} P_i \mathbf{A}' + \mathbf{Q}) H' + \mathbf{R})^{-1}.$$

\mathbf{A}	A model for the system dynamics
B	System response to a control input
G	Gain
H	Model for measurement dynamics
P_i	Error covariance of estimate
\mathbf{Q}, \mathbf{R}	System and measurement noise covariances

- Increasing terms in \mathbf{Q} means the model is trusted less. Increasing terms in \mathbf{R} means measurements are trusted less.
- In experiments, we use a filter with a constant Kalman gain, $K_i \rightarrow K$.

The internal model depends only on the mode's growth and rotation rates

- The state-vector contains the $\cos \varphi$ and $\sin \varphi$ Fourier components of an $n = 1$ mode.

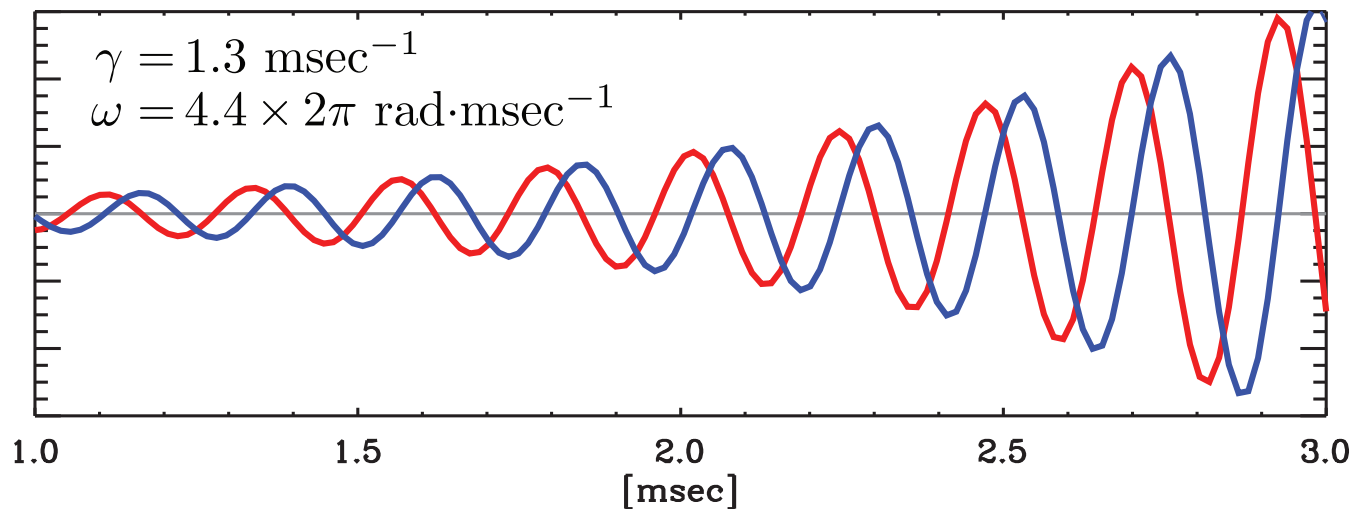
$$\vec{x} = [B_p^{\cos}, B_p^{\sin}]$$

- The internal model advances the mode at a prescribed growth and rotation rate.

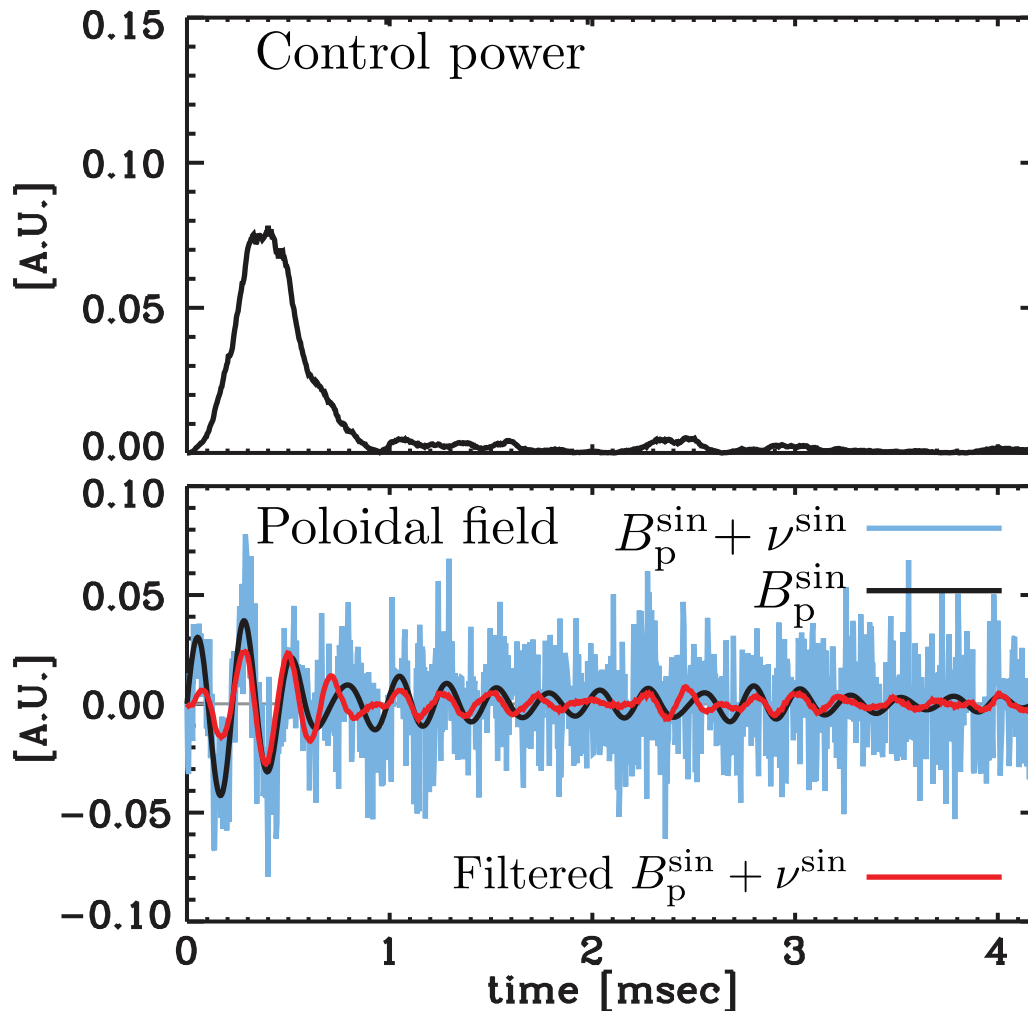
$$\frac{d\vec{x}}{dt} = \begin{pmatrix} \gamma & -\omega \\ \omega & \gamma \end{pmatrix} \vec{x}$$

- The solution is

$$\vec{B}_p(t) = \exp(\gamma t) \Re(\omega t) \vec{B}_p(0).$$



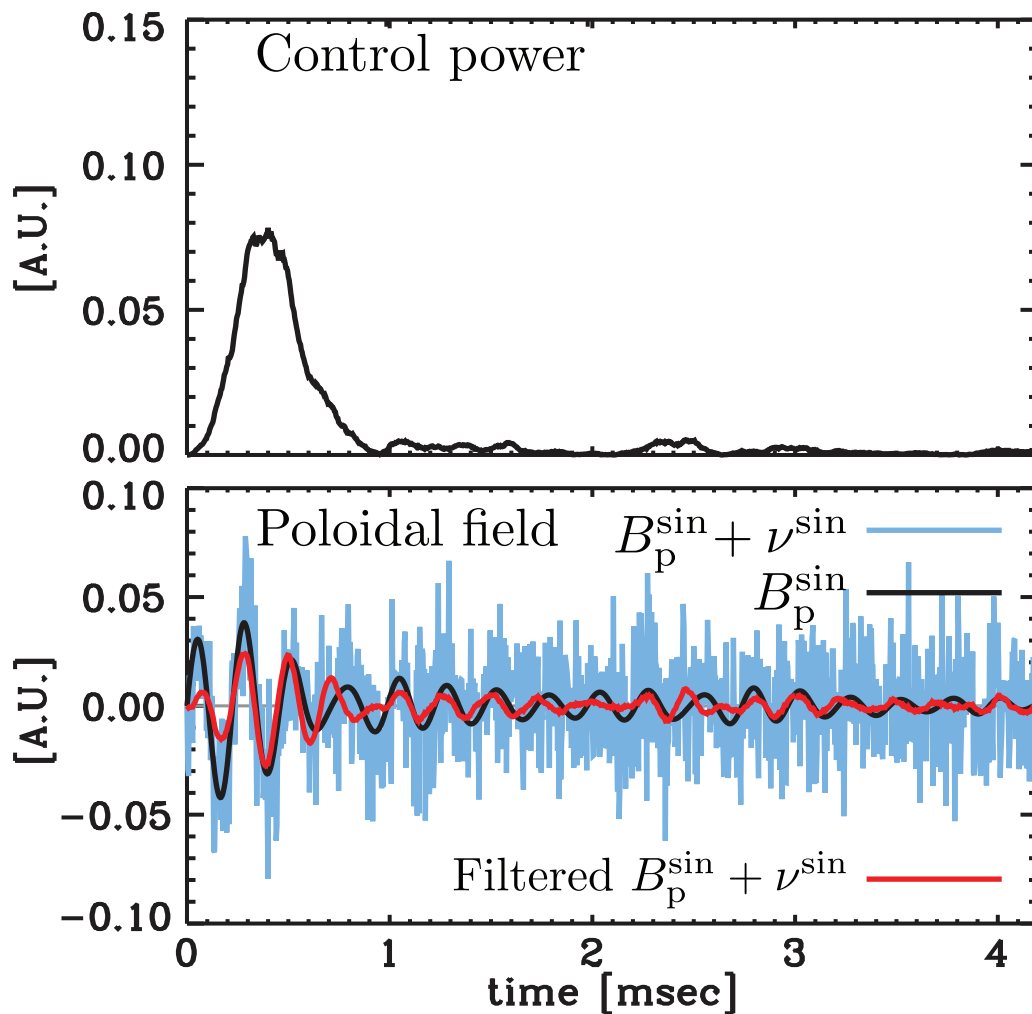
The Kalman filter stabilizes the mode quickly and efficiently



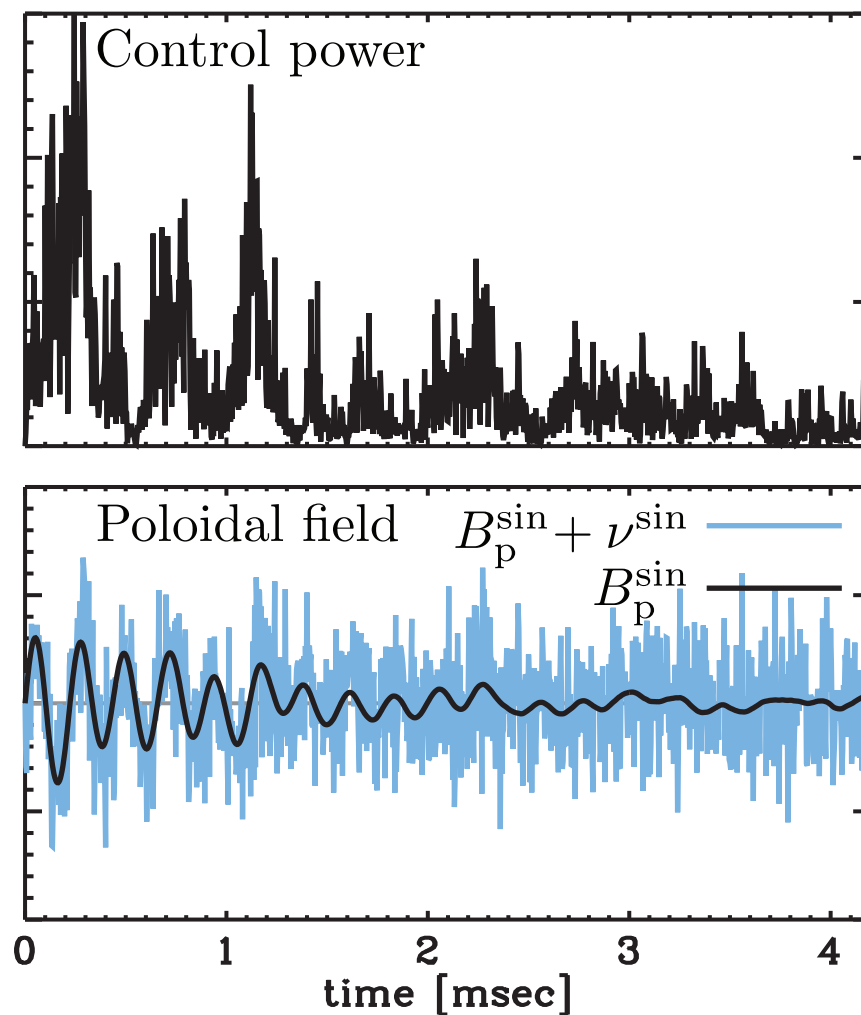
- With the Kalman filter, less control power is used, especially after the mode is stabilized.
- The mode is stabilized more quickly.
- The Kalman filter neatly removes the noise from the feedback signal.

The Kalman filter stabilizes the mode quickly and efficiently

With the Kalman filter

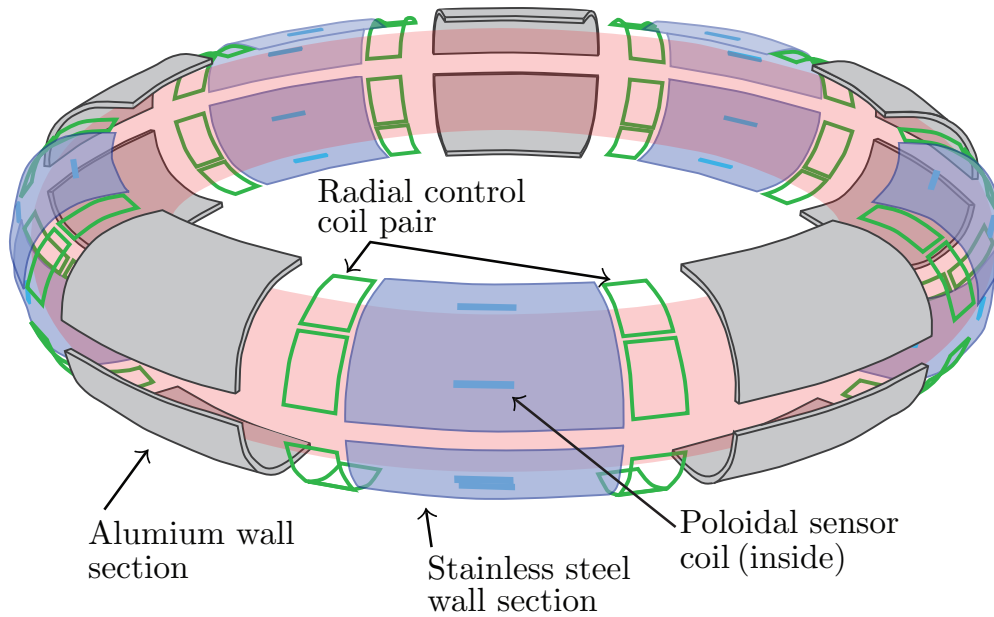


Without the Kalman filter



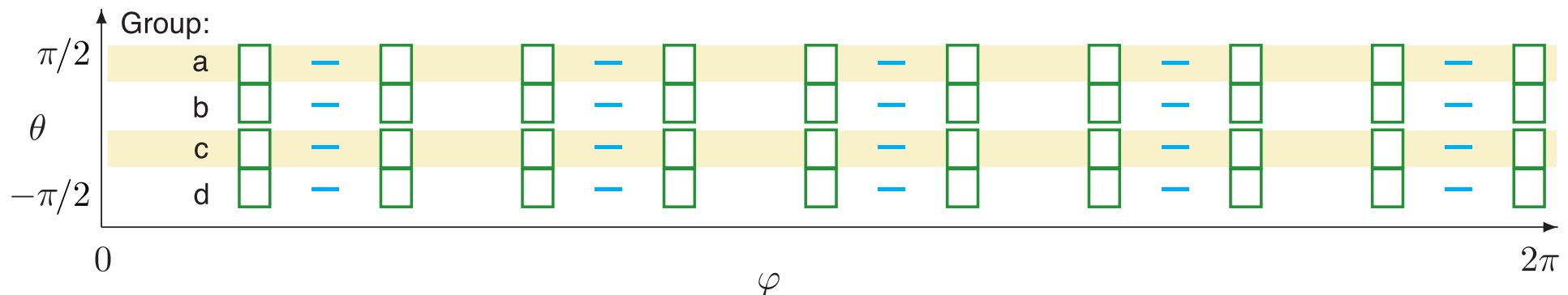
HBT-EP diagnostics and control hardware

HBT-EP has passive and active stabilization hardware

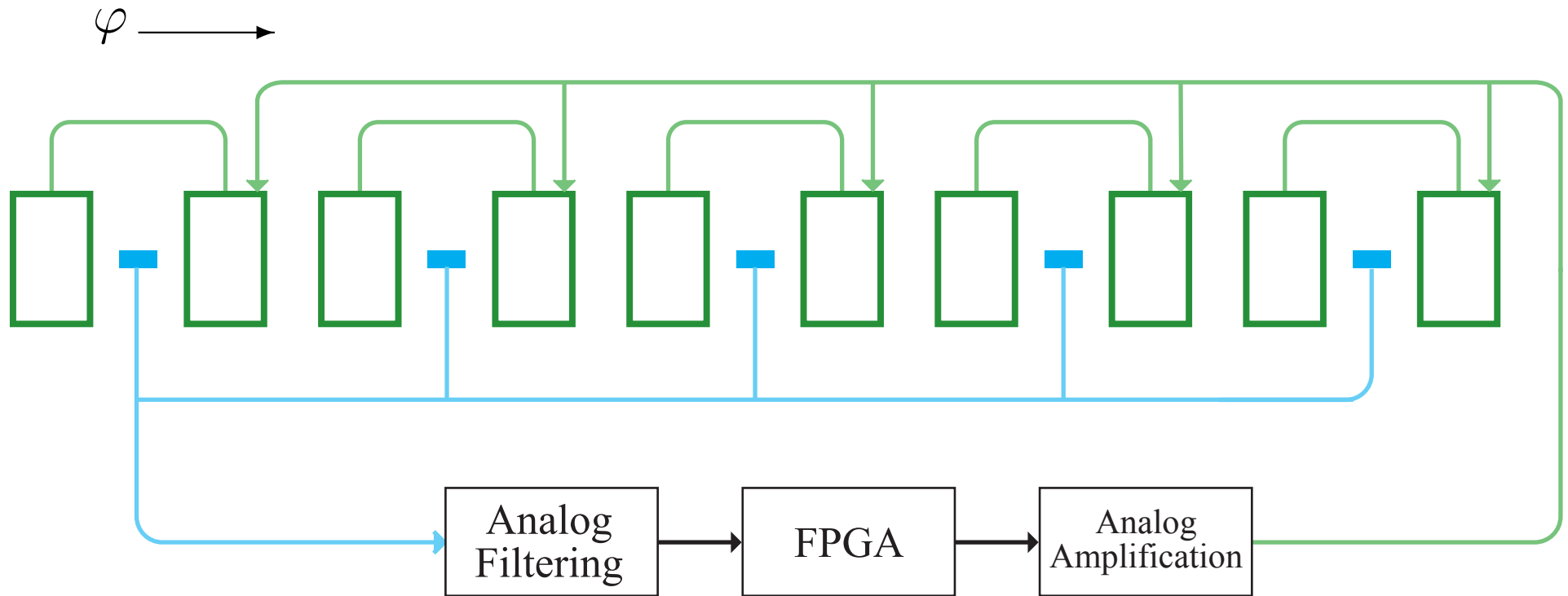


- There are 10 *thick aluminum shells* with a long wall time.
- There are 10 *thin stainless steel shells* with a short wall time.
- For feedback experiments, Al shells are pulled back 4 cm from the plasma surface, for $1/\gamma_w \approx 300 \mu\text{sec}$.

- We have 20 *poloidal sensor coils* and 20 pairs of *radial control coils*.
- The control coils are *small* and *localized*: they only cover 15% of the plasma surface.
- The coils are divided into four independent, parallel feedback loops.

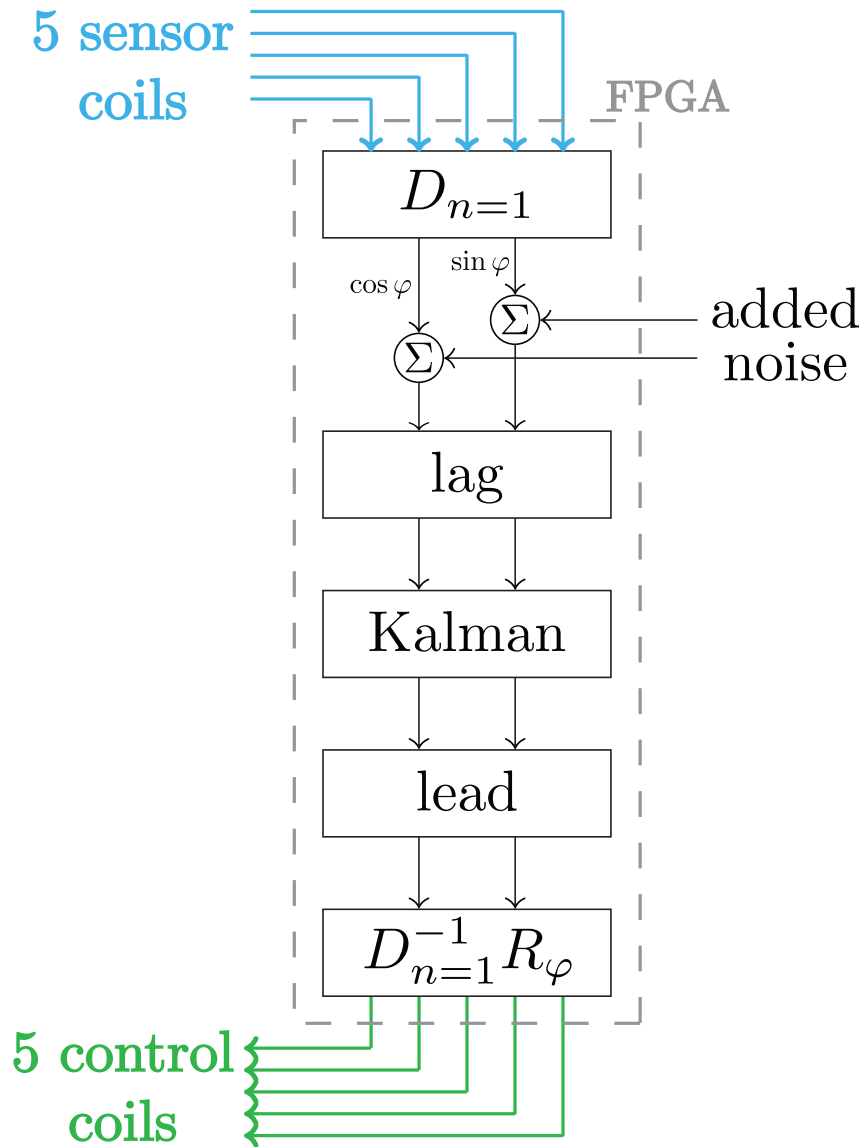


Each feedback loop consists of 5 sensor coils and control coil pairs



- Each feedback loop has its own field programmable gate array (FPGA) controller.
- With 5 evenly spaced sensors, $n = 1$ instabilities can be detected with Fourier analysis.

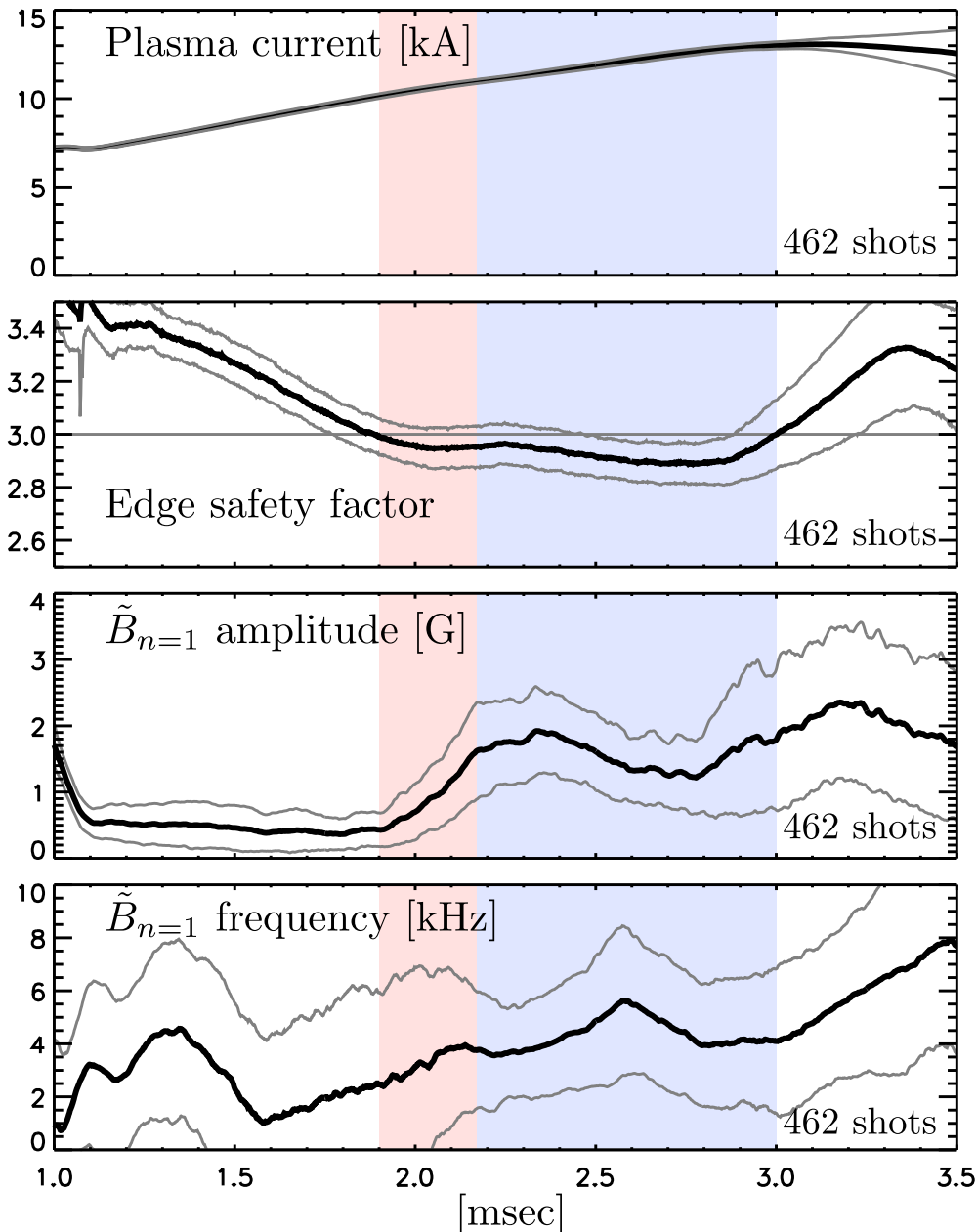
The feedback algorithm is implemented on low-latency field programmable gate array controllers



- A spatial discrete Fourier transform (DFT) is used to select the $n = 1$ mode.
- Phase lag and lead compensators correct for hardware transfer functions.
- Noise can be added after the DFT to test the robustness of control algorithms.
- The Kalman filter can be bypassed to get a conventional algorithm.
- The toroidal phase of the output is adjustable.
- Total latency is $\sim 10 \mu\text{sec}$, external kink instabilities grow and rotate on a 100–500 μsec timescale.

Experimental results

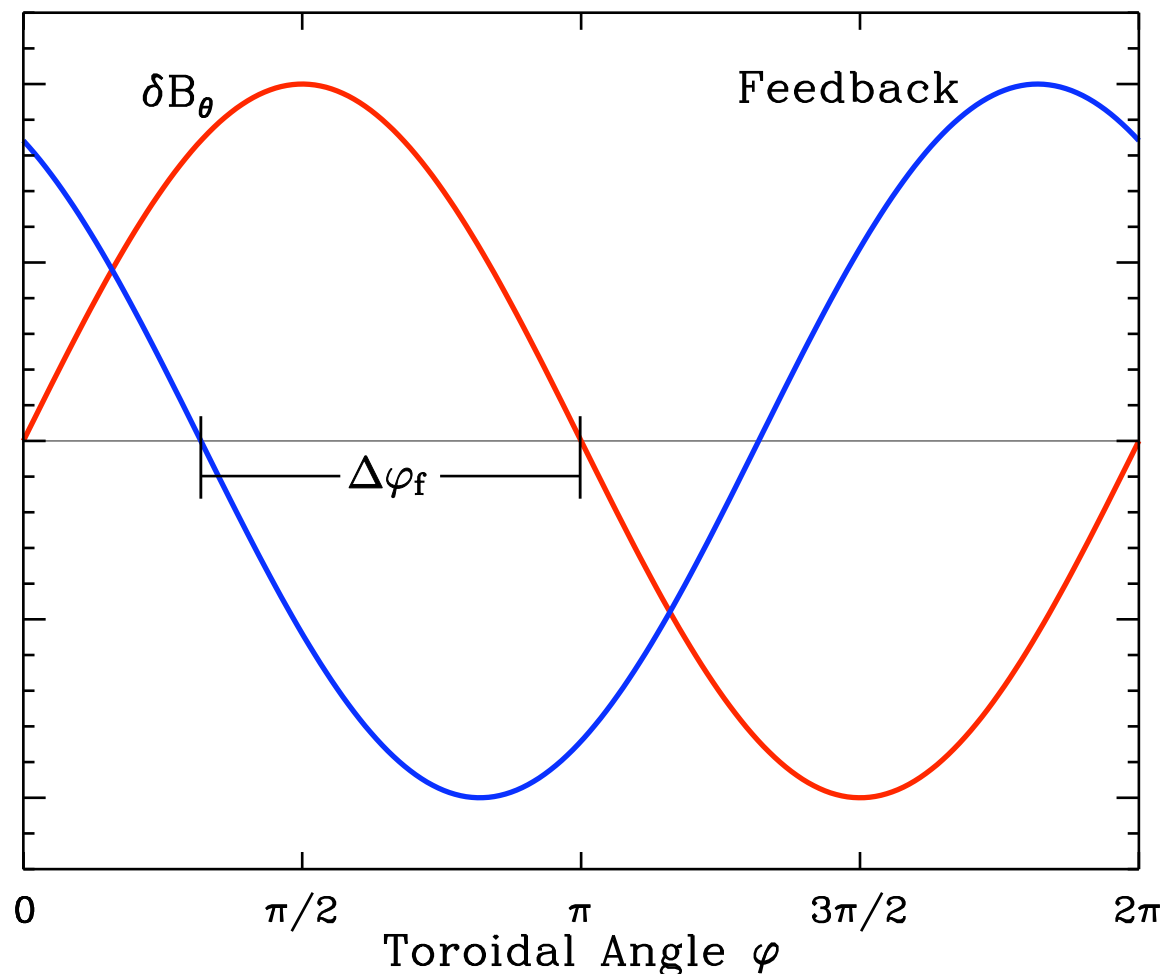
A current ramp is used to create external kink modes



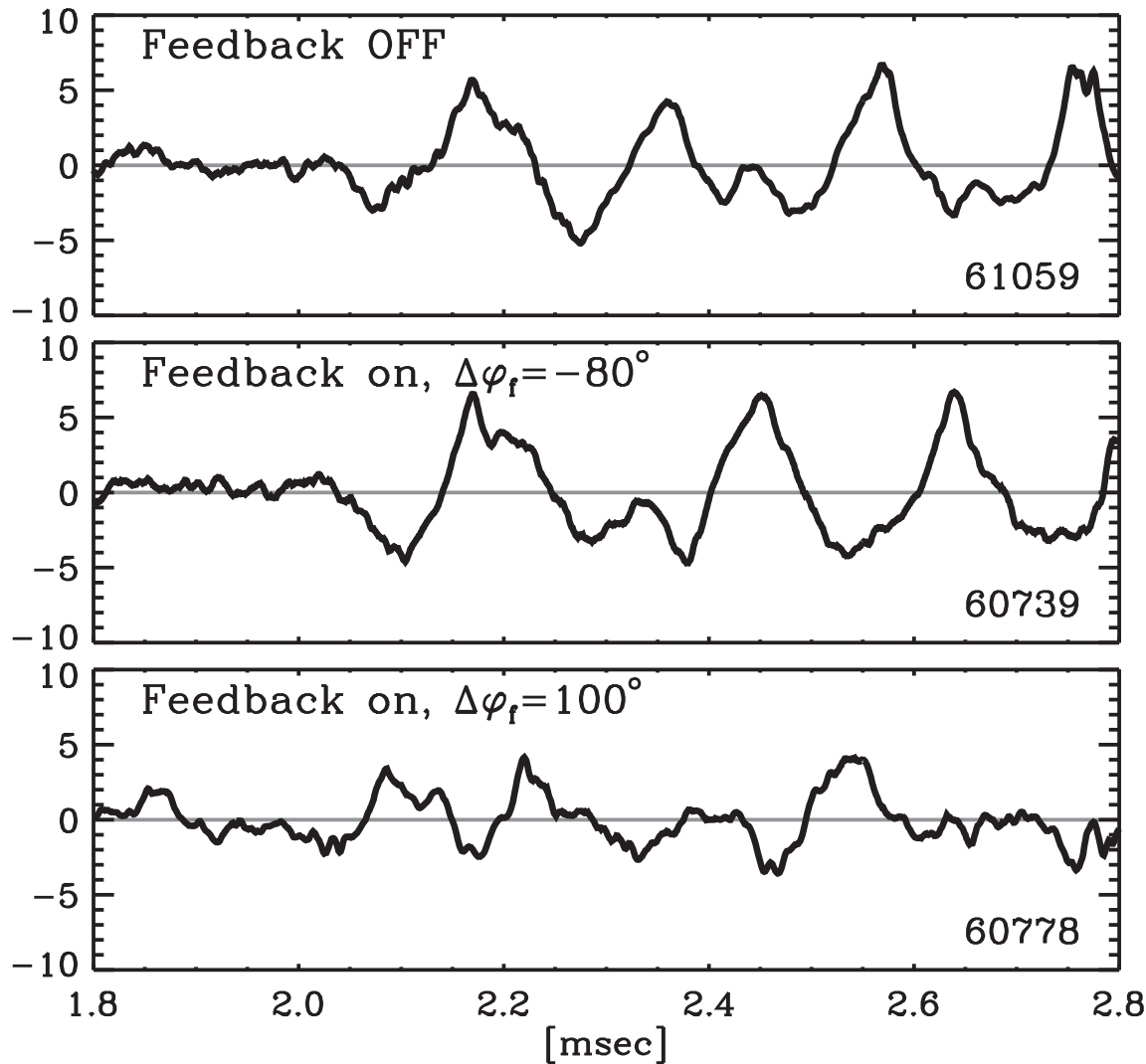
- The plasma current is ramped at ~ 3 MA/sec to create a current density gradient at the edge of the plasma.
- As the $q = 3$ surface goes external, a rotating $n = 1$ mode is observed in the magnetics.
- The mode grows exponentially, then saturates.
- Average growth rate is 5 msec^{-1} , but it varies shot to shot.
- Rotation frequency is near 3–5 kHz, and it often sweeps in time.

The toroidal phase of feedback is an adjustable control parameter

- Sensors measure the *poloidal* field, but feedback coils are *radial*. So a phase-shift is needed for negative feedback.
- Phase shifts also appear due to controller latency and imperfect optimization of the system transfer function.

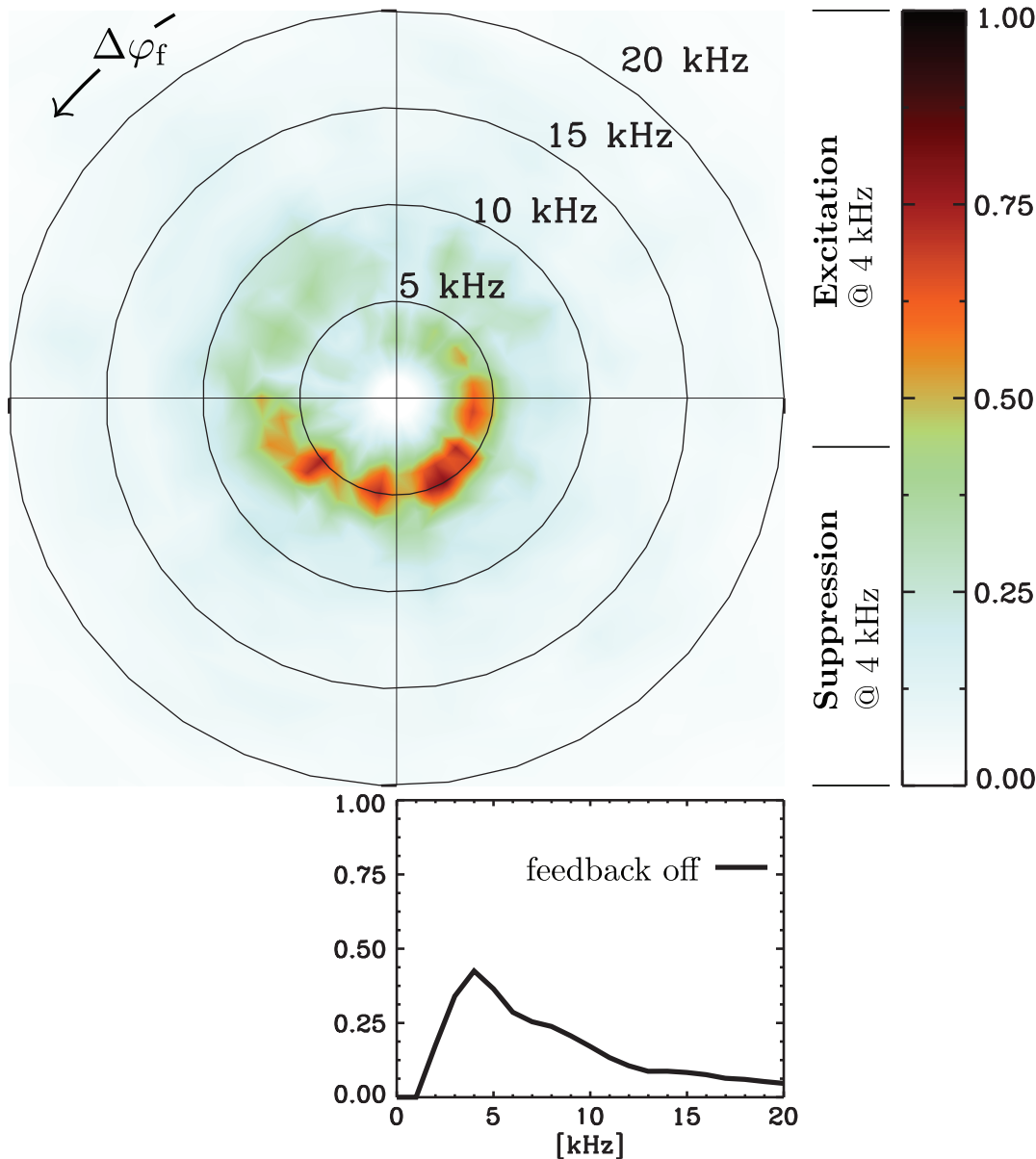


Feedback can be phased to either suppress or excite the mode



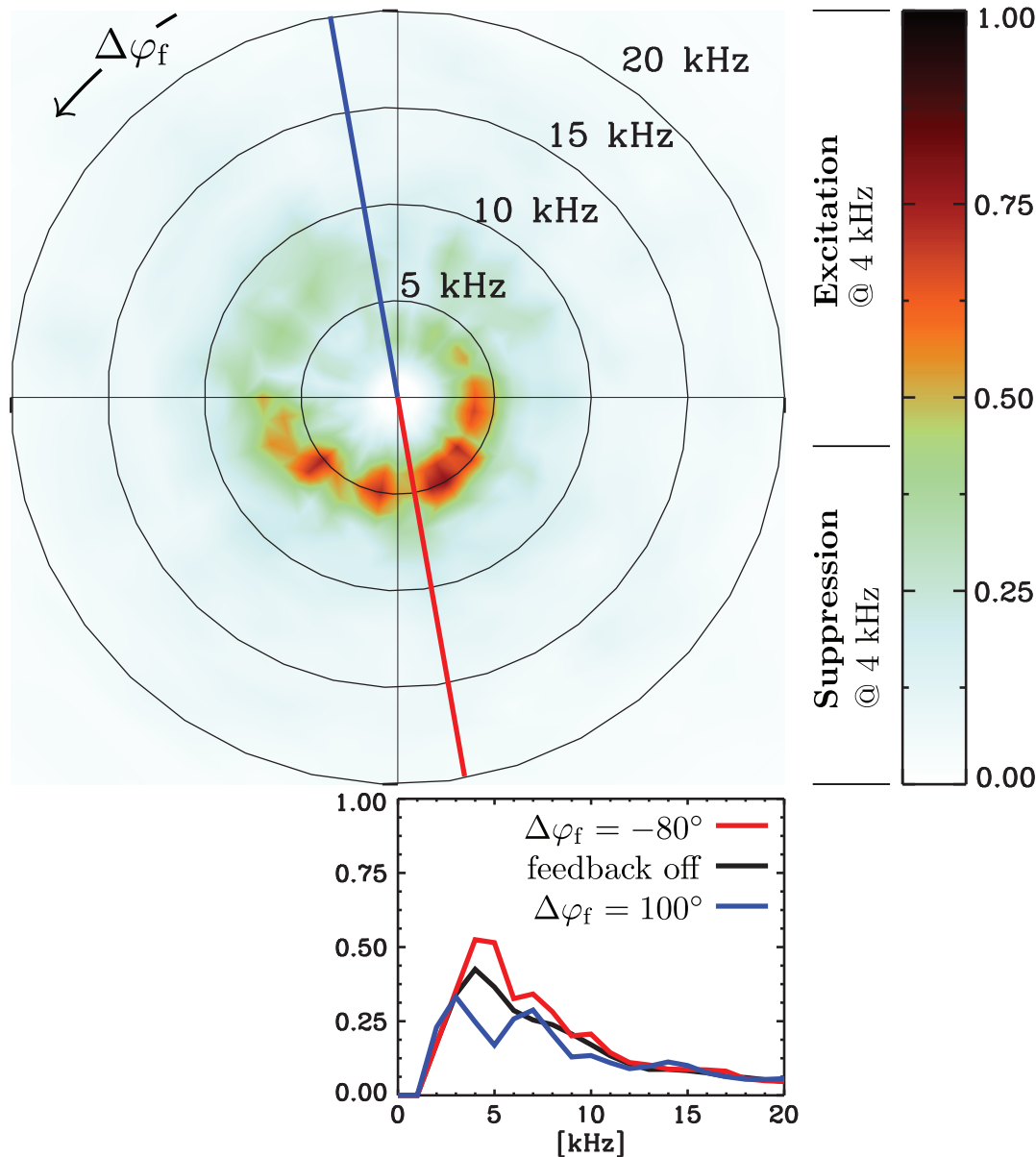
- With feedback off, fluctuations near 4 kHz are observed on a poloidal sensor coil.
- Positive feedback can be used to excite the mode.
- Negative feedback decreases mode's amplitude.

Feedback phase angle scan shows clear regions of excitation and suppression



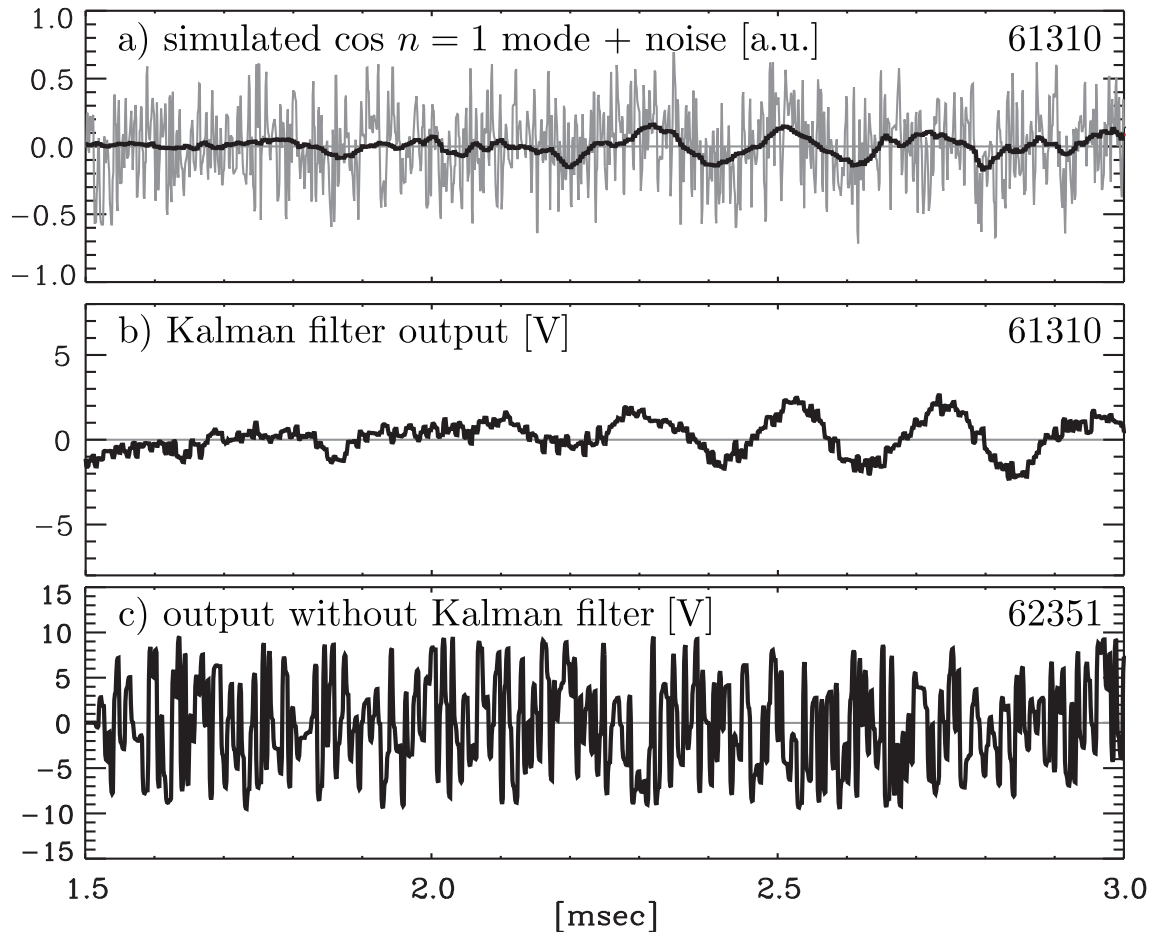
- As the feedback phase angle is scanned through 360° , the frequency spectrum of poloidal field fluctuations is observed.
- In the upper-left quadrant, suppression is observed relative to feedback off.
- Peak feedback excitation is about 180° away.

Feedback phase angle scan shows clear regions of excitation and suppression



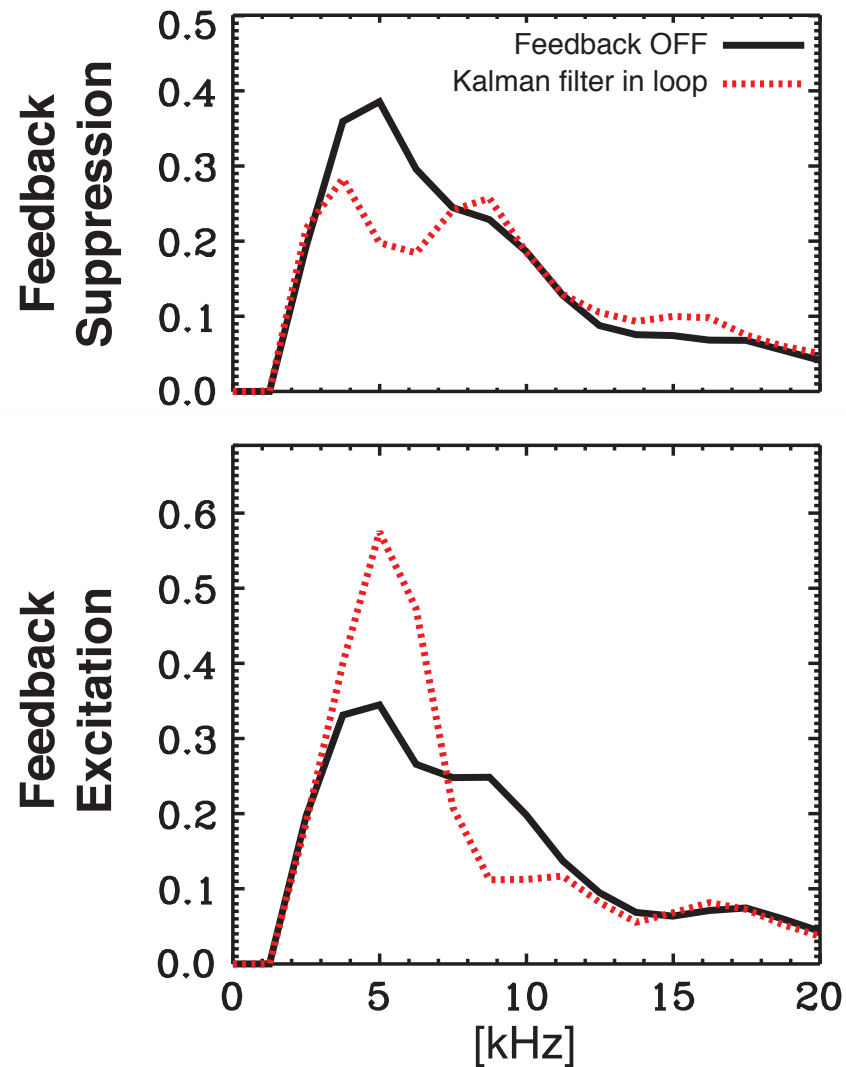
- As the feedback phase angle is scanned through 360° , the frequency spectrum of poloidal field fluctuations is observed.
- In the upper-left quadrant, suppression is observed relative to feedback off.
- Peak feedback excitation is about 180° away.

The Kalman filter removes added noise very effectively

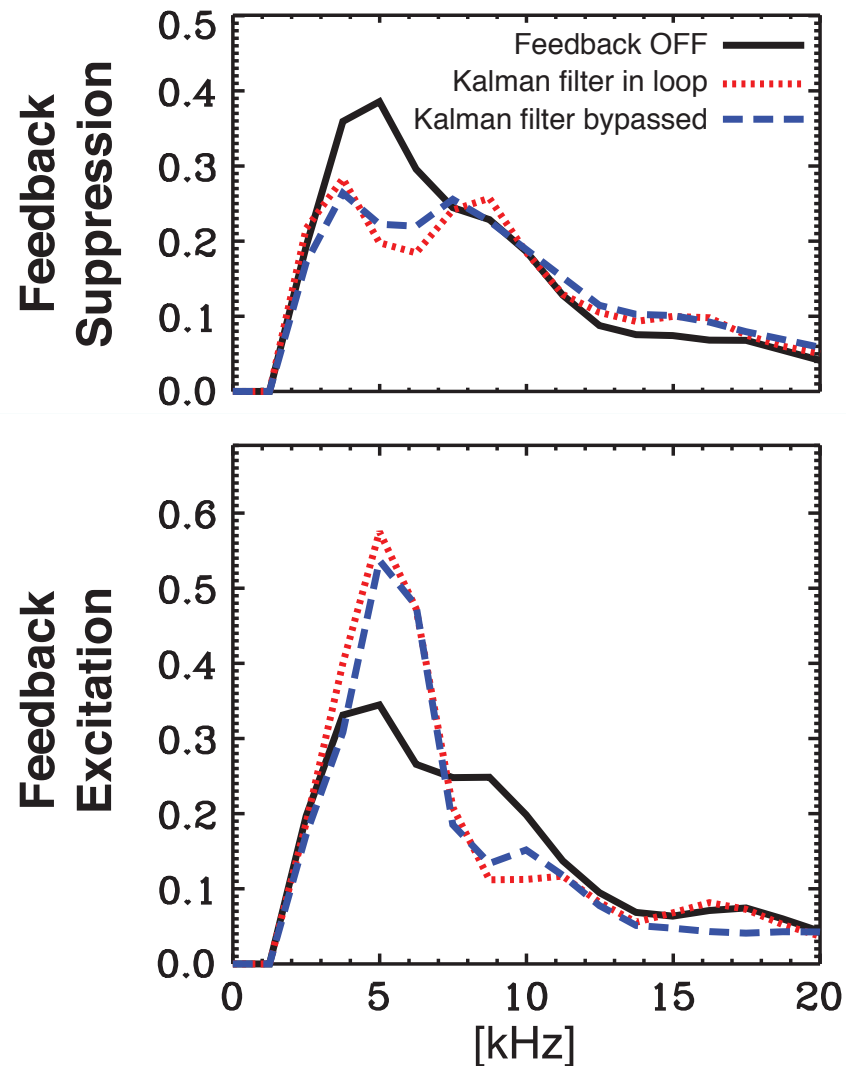


- White frequency spectrum, Gaussian noise was added to the algorithm after the DFT stage.
- This effectively added a random amplitude and phase to the $n = 1$ mode.
- The Kalman filter was able to track the mode well, even with large amplitude noise.

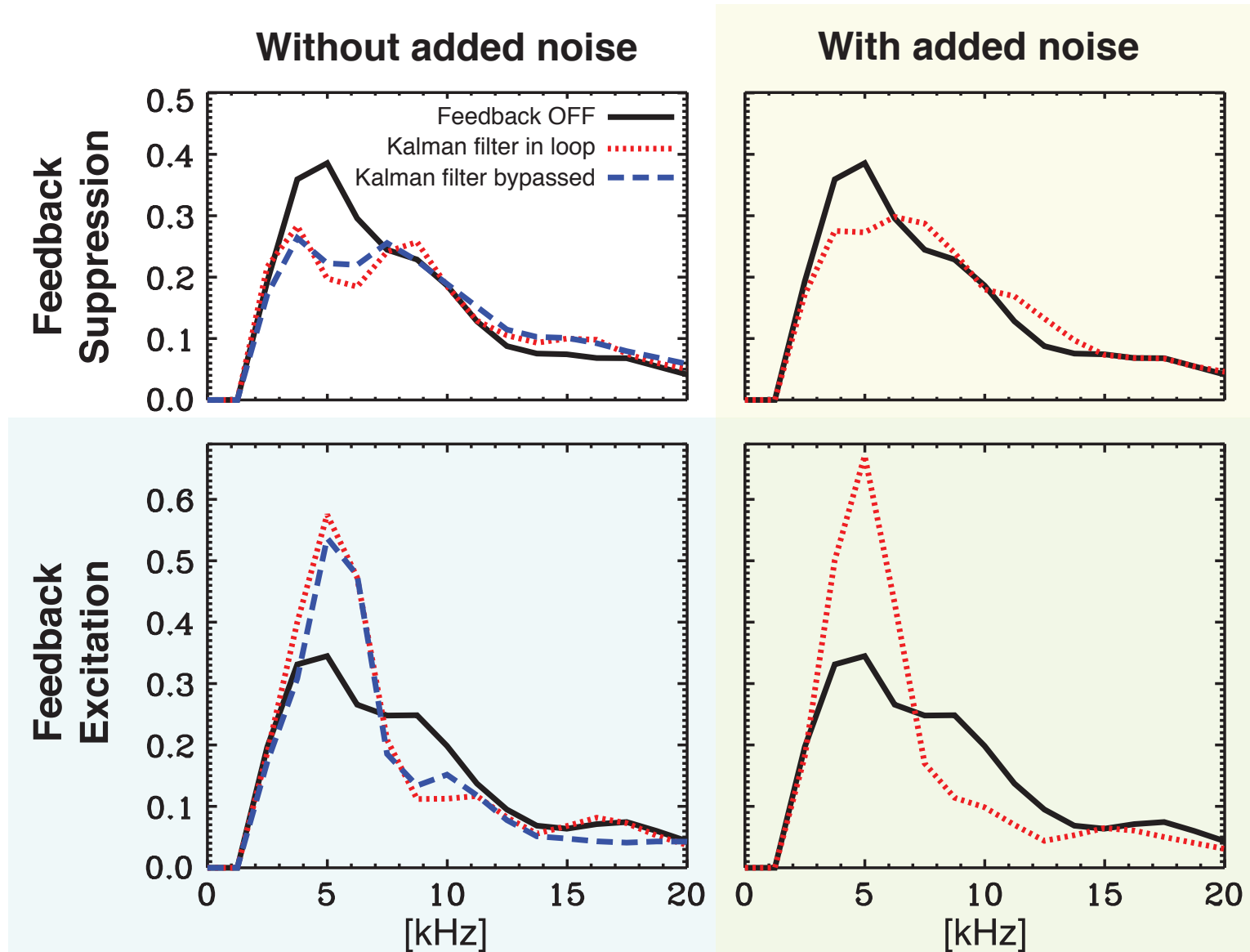
Kalman filter feedback remains robust when additional noise is added to the system



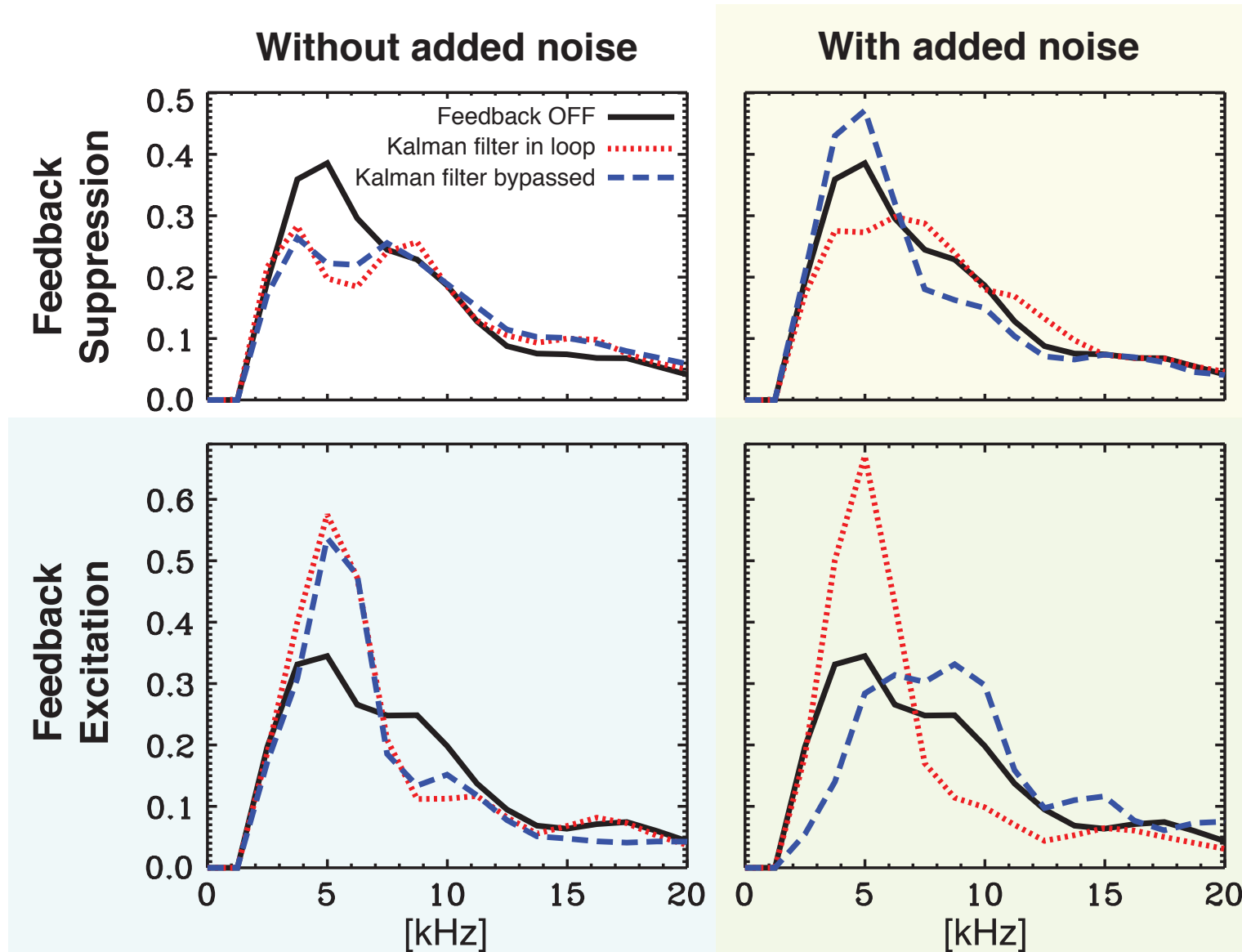
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Kalman filter feedback remains robust when additional noise is added to the system



Kalman filter parameter scans are used to determine best settings

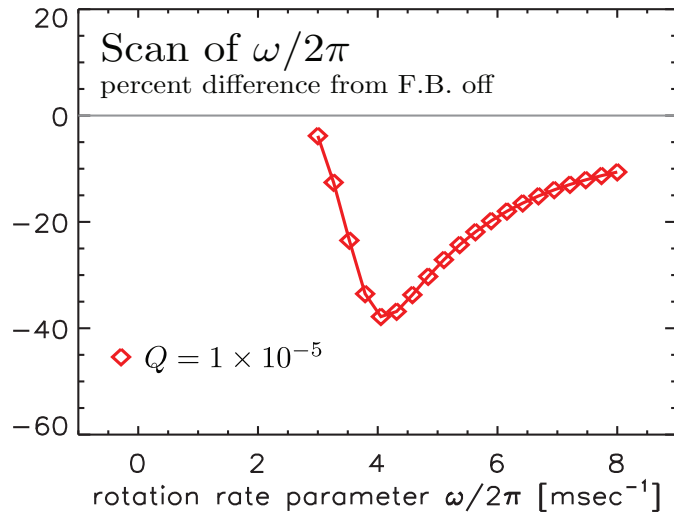
- We are interested in how the following parameters in the Kalman filter's system model affect feedback:

γ	Estimate of the mode's growth rate
ω	Estimate of the mode's rotation rate
Q	Uncertainty in the system model

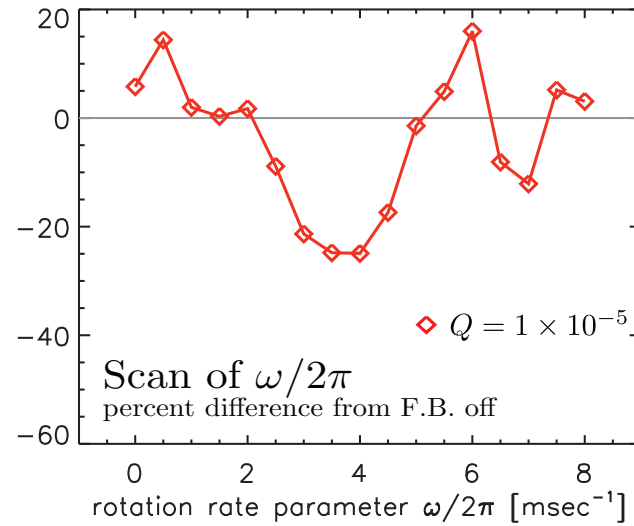
- The impact of these settings can be investigated in both the simulation and experiment by scanning one parameter at a time.
- For each scan point, the RMS average of the poloidal field is subtracted from feedback off average and normalized to a percentage.
- Percent differences greater than zero imply feedback excitation, percent differences less than zero imply suppression.
- This makes it straightforward to compare simulation results with those from the experiment.

Kalman filter parameter scans point to best settings

Simulation results

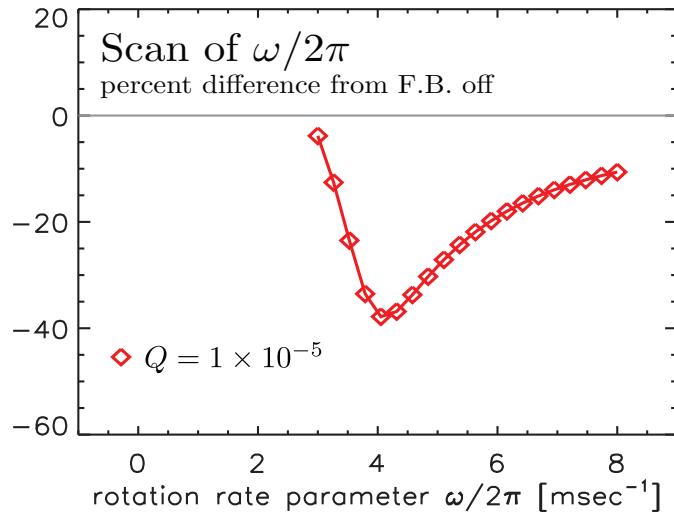


Experimental results

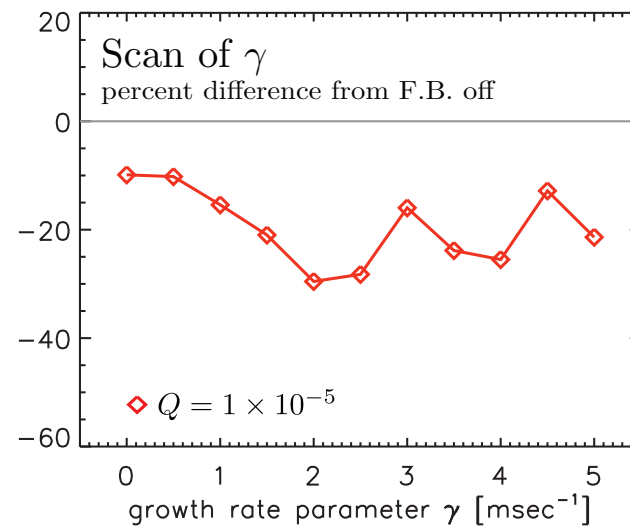
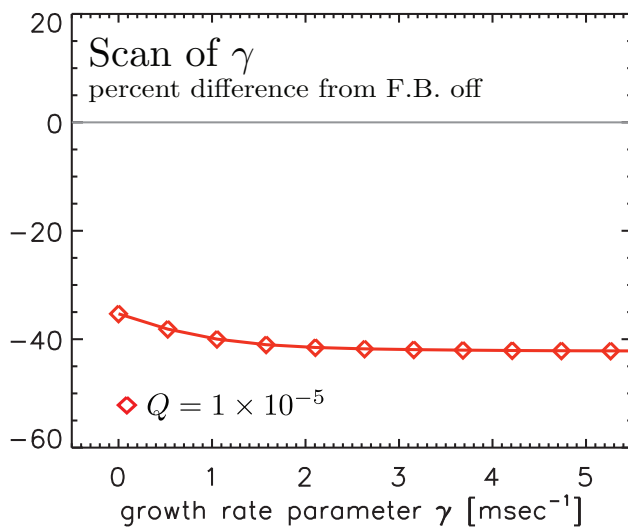
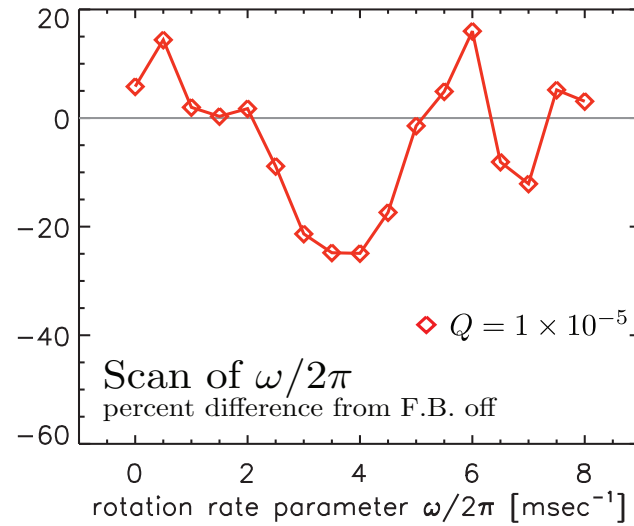


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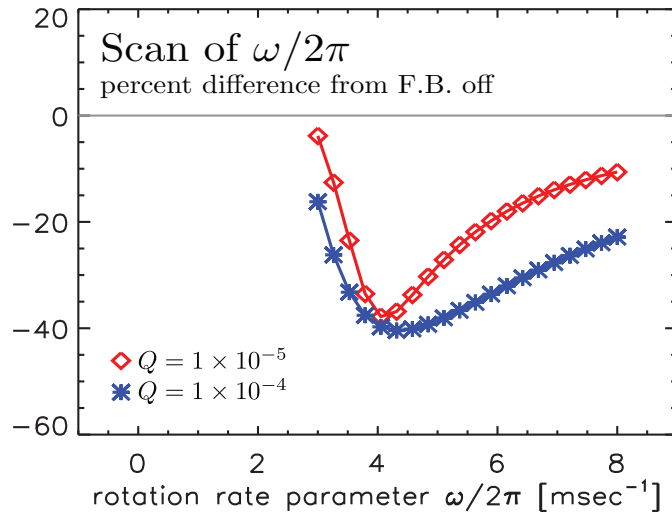


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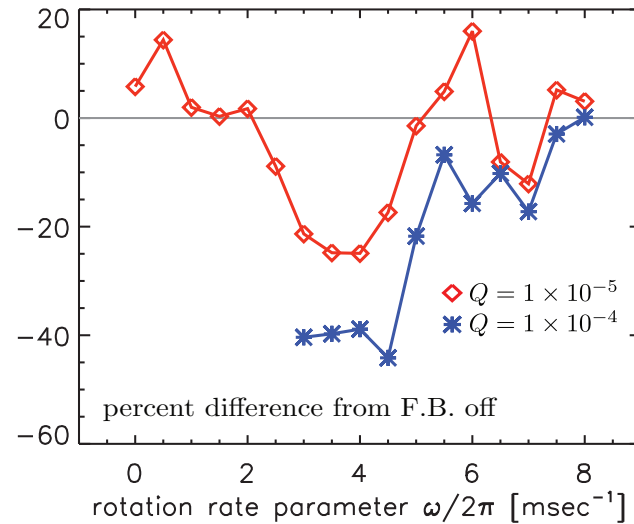


Kalman filter parameter scans point to best settings

Simulation results



Experimental results



- Scans of ω were done at two settings of Q
- Remember, Q is the amount of uncertainty in the Kalman filter's internal model.
- The larger value of Q leads more flexibility in the setting of ω and better suppression of the mode.

Key differences between simulation and experiment

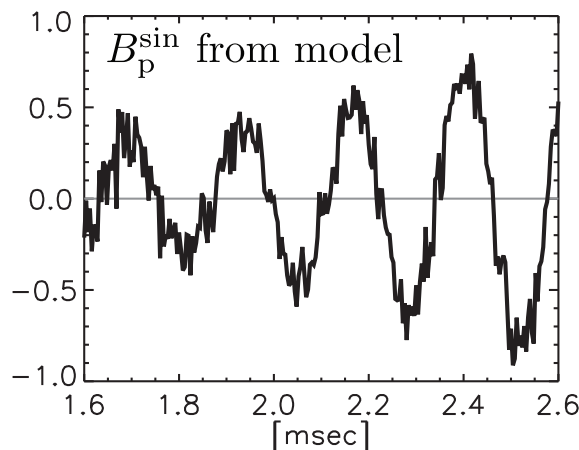
Simulation

Without feedback, instabilities grow infinitely large.

Mode lasts as long as we like.

Unique, fixed growth and rotation rates.

Mode rotation is smooth, fluctuations are sinusoidal.



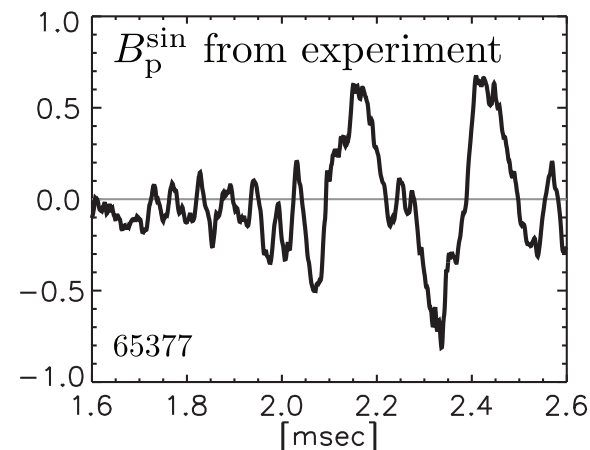
HBT-EP

Instabilities saturate at finite amplitude.

Can only maintain edge current gradient for ~ 1 msec.

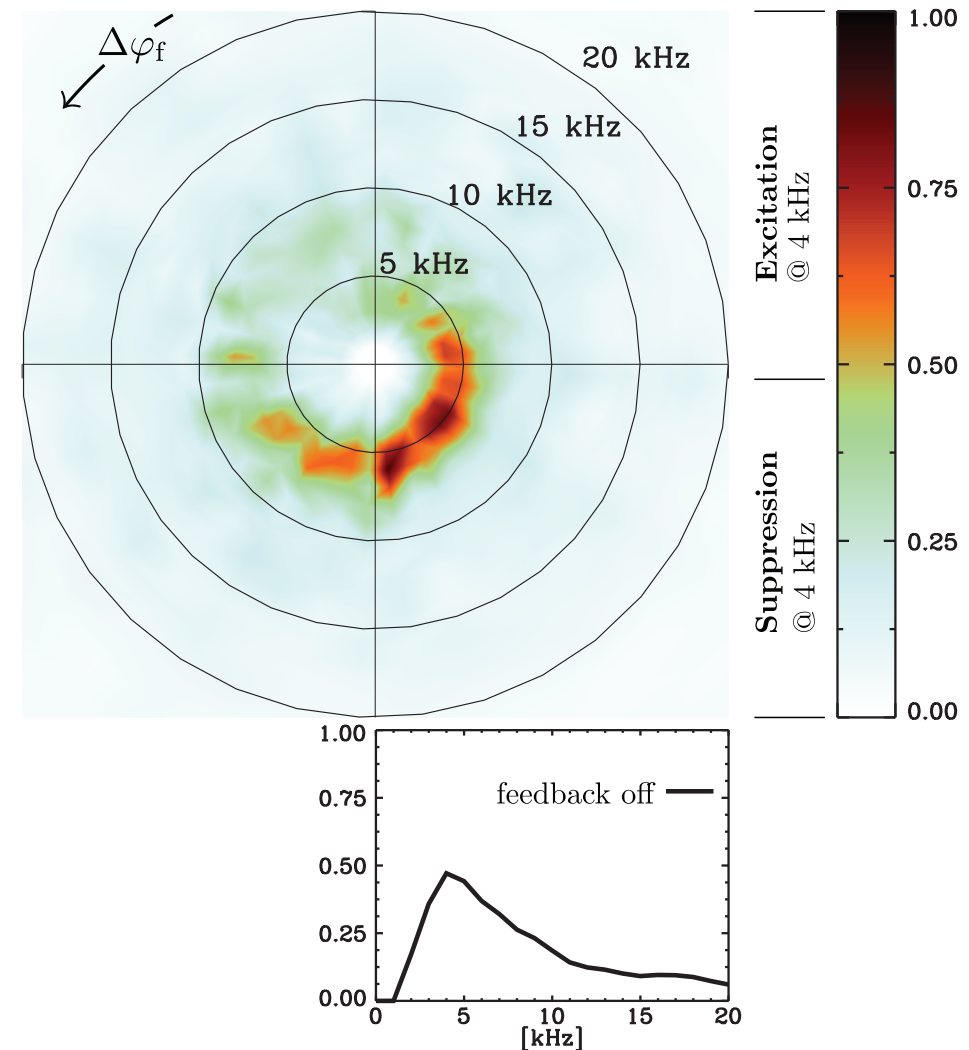
A range of growth and rotation rates are observed.

Fluctuations are not always sinusoidal, maybe due to interaction with a complex conducting boundary.



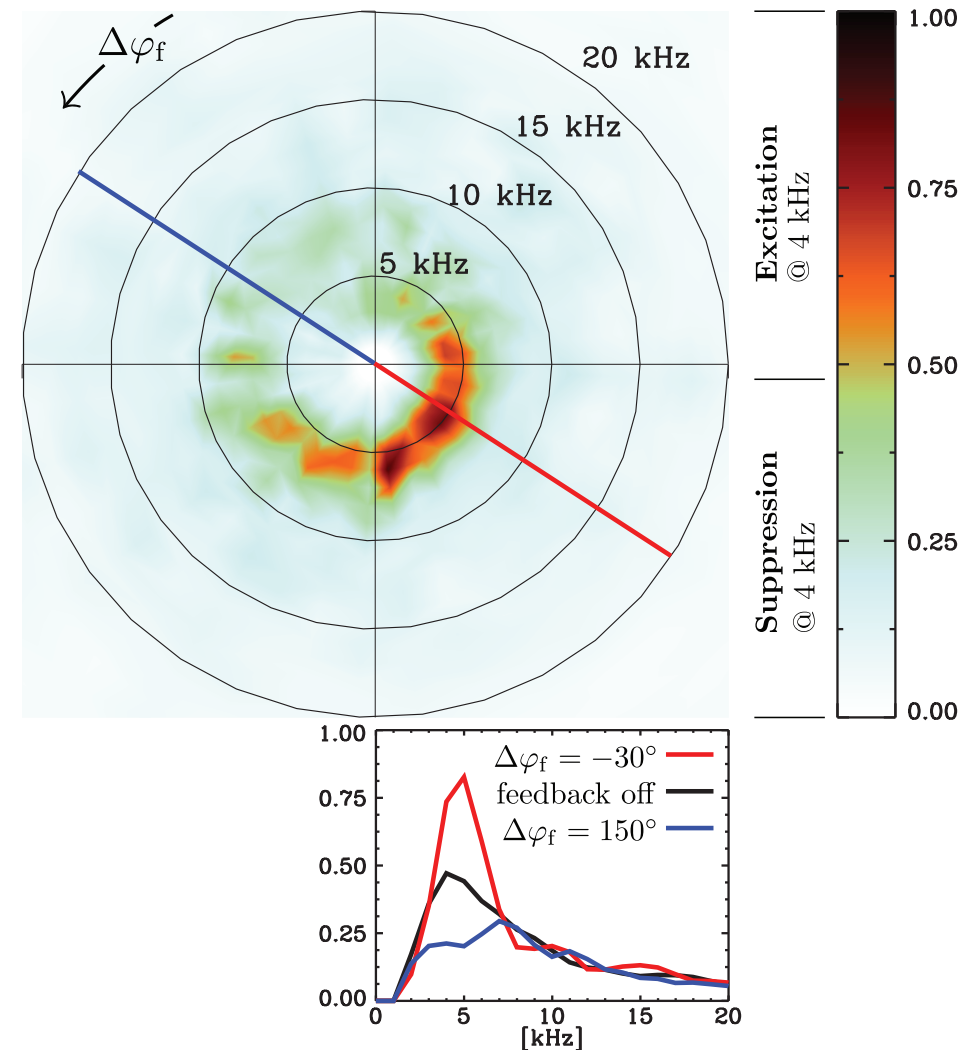
Choosing a more optimal set of filter parameters leads to improved performance

- The original filter worked quite well.
- With the new settings, feedback suppression and excitation are stronger.



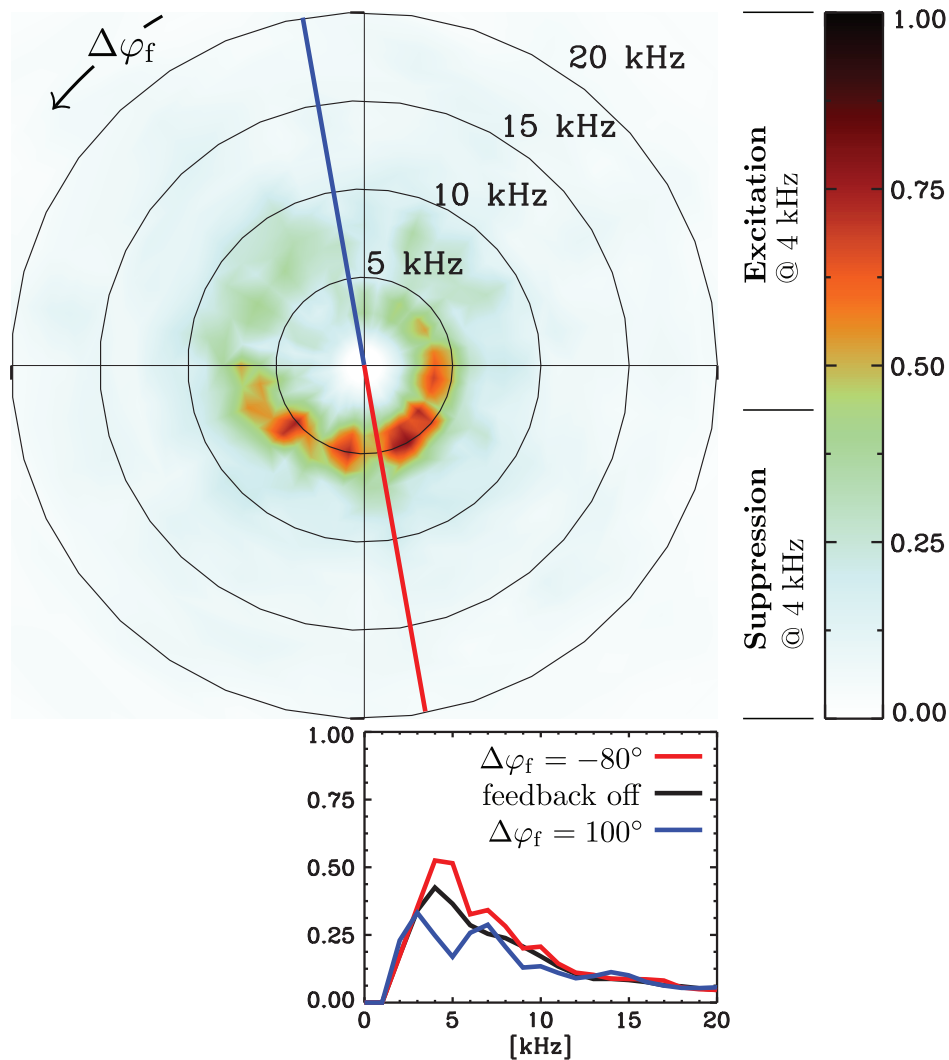
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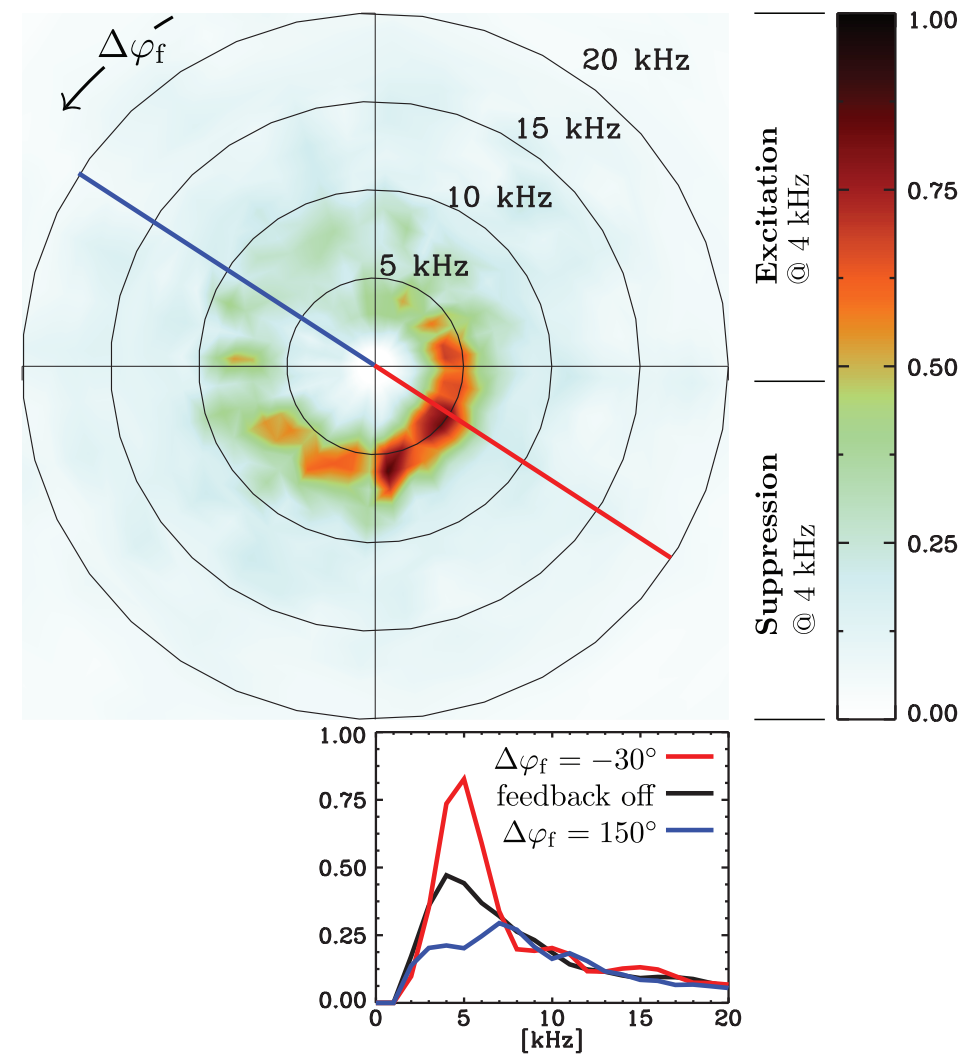


Choosing a more optimal set of filter parameters leads to improved performance

Before optimization



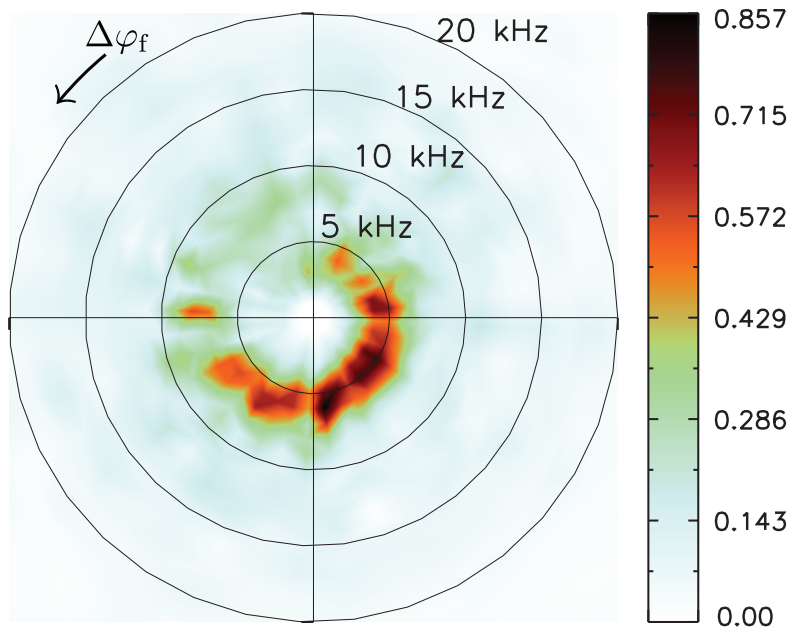
After optimization



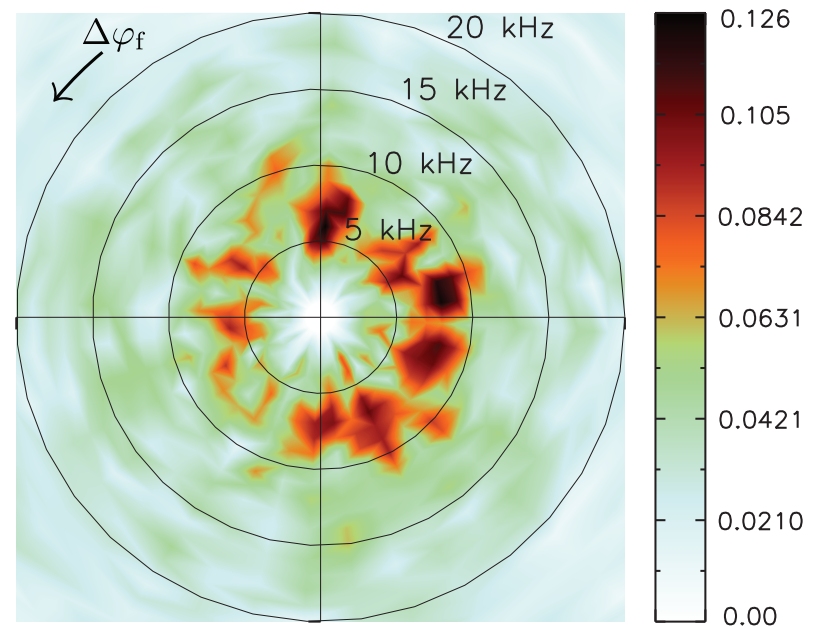
There's evidence of multiple simultaneous modes

- HBT-EP has a high-density poloidal array of pickup loops that can resolve high m -number fluctuations.
- A combined analysis of these and the sensor coils turned up evidence of a $(m, n) = (6, 2)$ mode.

$(m, n) = (3, 1)$ fluctuations



$(m, n) = (6, 2)$ fluctuations



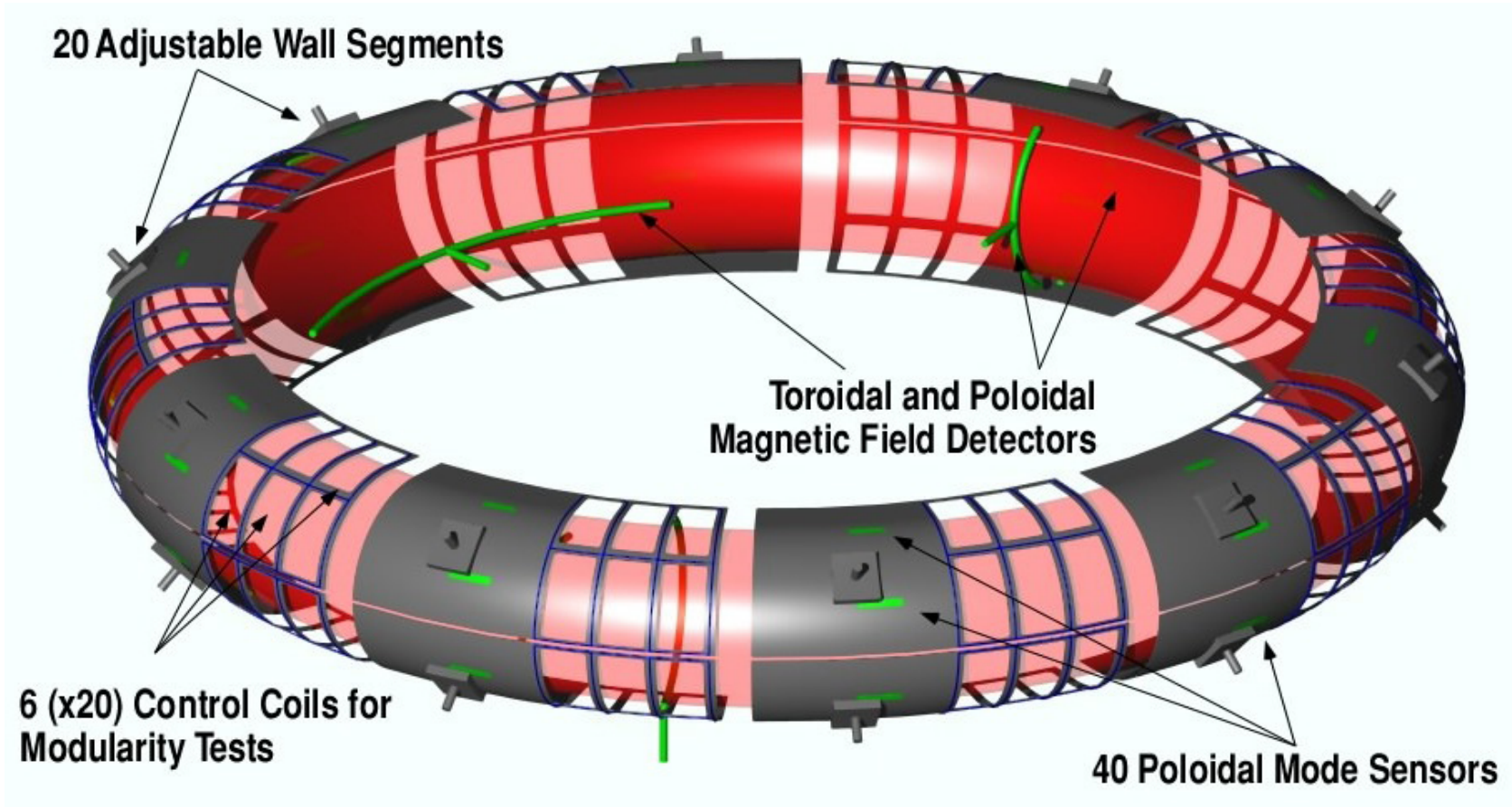
- The $(6, 2)$ mode is a lot smaller than the $(3, 1)$, and higher in frequency.
- It also seems to be mostly unaffected by feedback.

Conclusions and future work

Conclusions

- A **Kalman filter** algorithm has been implemented on a set of low-latency digital feedback controllers, and used to **excite** and **suppress** the $(m, n) = (3, 1)$ external kink instability on HBT-EP.
- The Kalman filter uses a simple, internal model for a growing, rotating mode.
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- Kalman filter feedback **works** under **noisy conditions** that disrupt feedback with conventional algorithms.

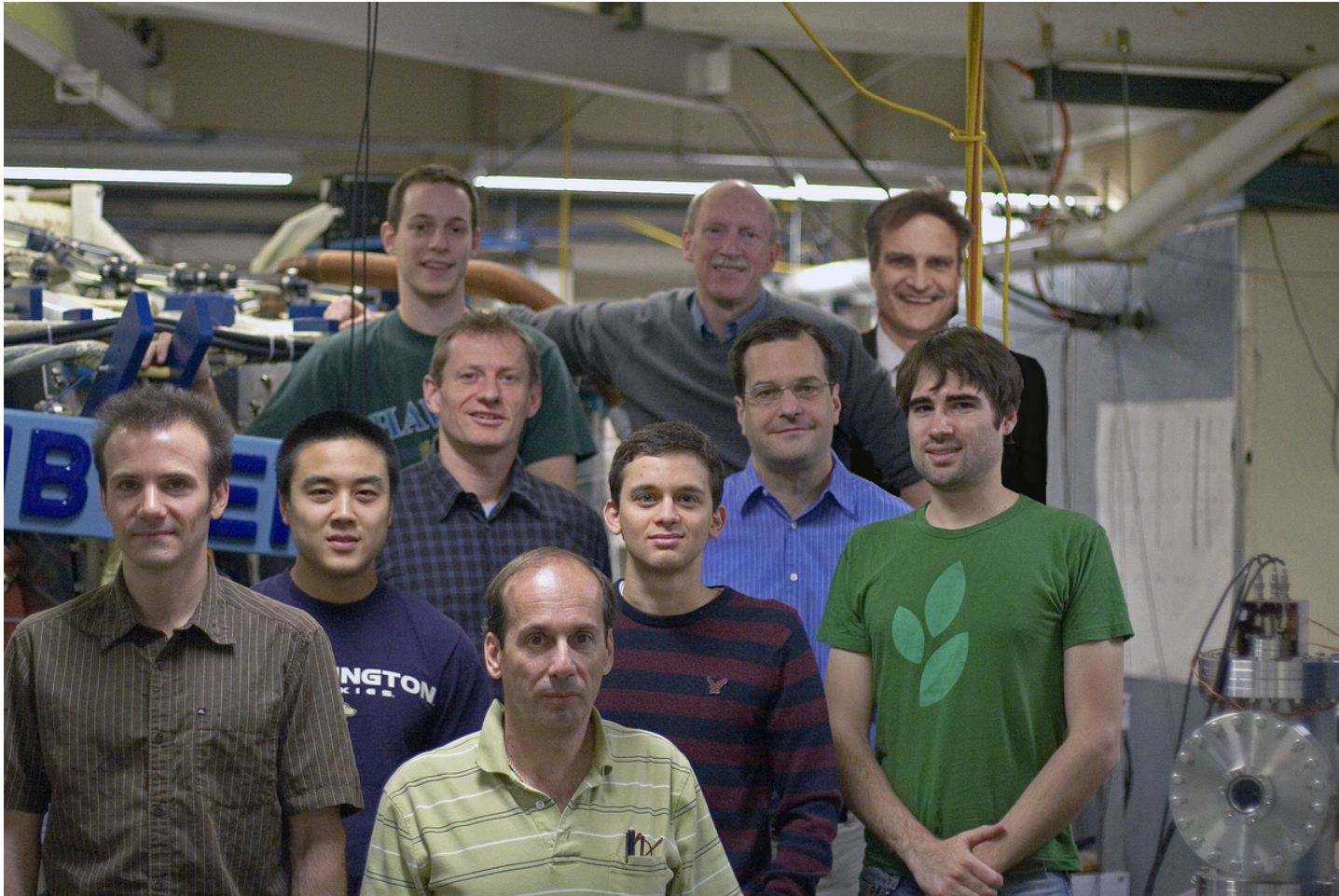
Future work



- A new wall will be installed in early 2009.
- There will be an increased number of small control coils for modularity and mode rigidity studies.
- ITER will also have small, modular control coils. We will address whether these types of coils can suppress low-wavelength modes.

HBT-EP Collaborators

James Bialek, Royce James (*Stevens Inst. Tech/USCG*), Bryan DeBono, Jeffrey Levesque, Michael Mauel, David Maurer, Gerald Navratil, Steve Paul (*Princeton University*), Thomas Pedersen, Daisuke Shiraki



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Extra slides

A Simple Control Coil Model

The control coils are modeled by^a

$$\frac{d\psi_c}{dt} + \frac{R_c}{L_c}\psi_c = \frac{M_c}{L_c}V_c$$

or, equivalently

$$\psi_{cn} = \epsilon\psi_{cn-1} + \frac{M_c}{R_c}(1 - \epsilon)V_{cn}$$

with $\epsilon = \exp(-R_c/L_c \delta t)$.

^aM. E. Mael, *et. al.*, *Bull. Amer. Phys. Soc. Paper* BP1.00007

The Time-varying Kalman Filter uses a simple, internal model

$$\begin{aligned}\vec{x}_n^* &= \hat{A}\vec{x}_{n-1} + B\vec{u}_n \\ \vec{x}_n &= \vec{x}_n^* + K_n(\vec{z}_n - H\vec{x}_n^*) \\ P_n^* &= \hat{A}P_{n-1}\hat{A}' + Q \\ K_n &= P_n^*H'(HP_n^*H' + R)^{-1} \\ P_n &= (I - K_nH)P_n^*\end{aligned}$$

The state vector is

$$\vec{x}(n) = (B_p^{\cos}(n), B_p^{\sin}(n), B_p^{\cos}(n-1), B_p^{\sin}(n-1)).$$

The system model A comes from the dynamics of a growing, rotating mode.

$$\frac{d}{dt} \begin{pmatrix} B_p^{\cos} \\ B_p^{\sin} \end{pmatrix} = \begin{pmatrix} \operatorname{Re}\gamma_k & -\operatorname{Im}\gamma_k \\ \operatorname{Im}\gamma_k & \operatorname{Re}\gamma_k \end{pmatrix} \begin{pmatrix} B_p^{\cos} \\ B_p^{\sin} \end{pmatrix}.$$

with $\gamma_k = 1.27 + 4.26i$ kHz.

Time-varying Kalman Filter

The $B\vec{u}$ term must give the response of the kink mode to a control flux.

$$B\vec{u} = 2\delta t \left(\frac{3}{1-c} \right) \text{Re} \left[((2\sqrt{c}, -(1+c)) \cdot \vec{\xi}_k) (\Xi^{-1} \cdot \vec{R}) \cdot \hat{e}_k \begin{pmatrix} 1 \\ e^{-i\pi/2} \end{pmatrix} \psi_c \right]$$

Here, Ξ contains the eigenvectors of the reduced Fitzpatrick-Aydemir system matrix in its columns, and k the index of the unstable eigenvalue.^a

Note: to solve this equation, we must measure the flux in the control coils.

^aM. E. Mauel, *et. al.*, *Bull. Amer. Phys. Soc. Paper* BP1.00007

The Steady-State Kalman Filter is easy to implement

The time-varying Kalman Filter is probably too large to implement on HBT-EP's present mode control system.

Take the limit of the time-varying Kalman filter in which $n \rightarrow \infty$.

This filter has a simple form – the controller does not need to compute a matrix inverse.

$$\vec{x}_n = \Phi \vec{x}_{n-1} + K \vec{z}_n$$

The matrices can be calculated in advance.

$$\begin{aligned}\Phi &= (I - KH)(\hat{\hat{A}} + BGH) \\ K &= (\hat{\hat{A}}P\hat{\hat{A}}' + Q)H'(H(\hat{\hat{A}}P\hat{\hat{A}}' + Q)H' + R)^{-1}\end{aligned}$$

The control flux ψ_c must be added to the state vector.

$$\vec{x}(n) = (\psi_c^{\cos}(n), \psi_c^{\sin}(n), B_p^{\cos}(n), B_p^{\sin}(n))$$

Steady-State Kalman Filter

There is a subtlety: if the control flux is not measured, it must be computed from the control voltage.

$$G = \frac{M_c}{R_c}(1 - \epsilon) \left(\begin{array}{cc|cc} \frac{\epsilon R_c}{M_c(1-\epsilon)} & 0 & g_p & i g_p \\ 0 & \frac{\epsilon R_c}{M_c(1-\epsilon)} & -i g_p & g_p \\ \hline & 0_{22} & & 0_{22} \end{array} \right)$$

The response of the system to the control flux must be calculated, too.

$$B = \left(\begin{array}{cc|c} \sigma & 0 & 0_{22} \\ 0 & \sigma & \\ \hline 0_{22} & & 0_{22} \end{array} \right)$$

Here, $\sigma = 2\delta t \frac{3}{1-c} ((2\sqrt{c}, -(1+c)) \cdot \vec{\xi}_i)(\Xi^{-1} \cdot \vec{R}) \cdot \hat{e}_i$.

When calculating the filter parameters, the real part of the product BG is used.