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Active noise control without tap length selection: a model order weighting method

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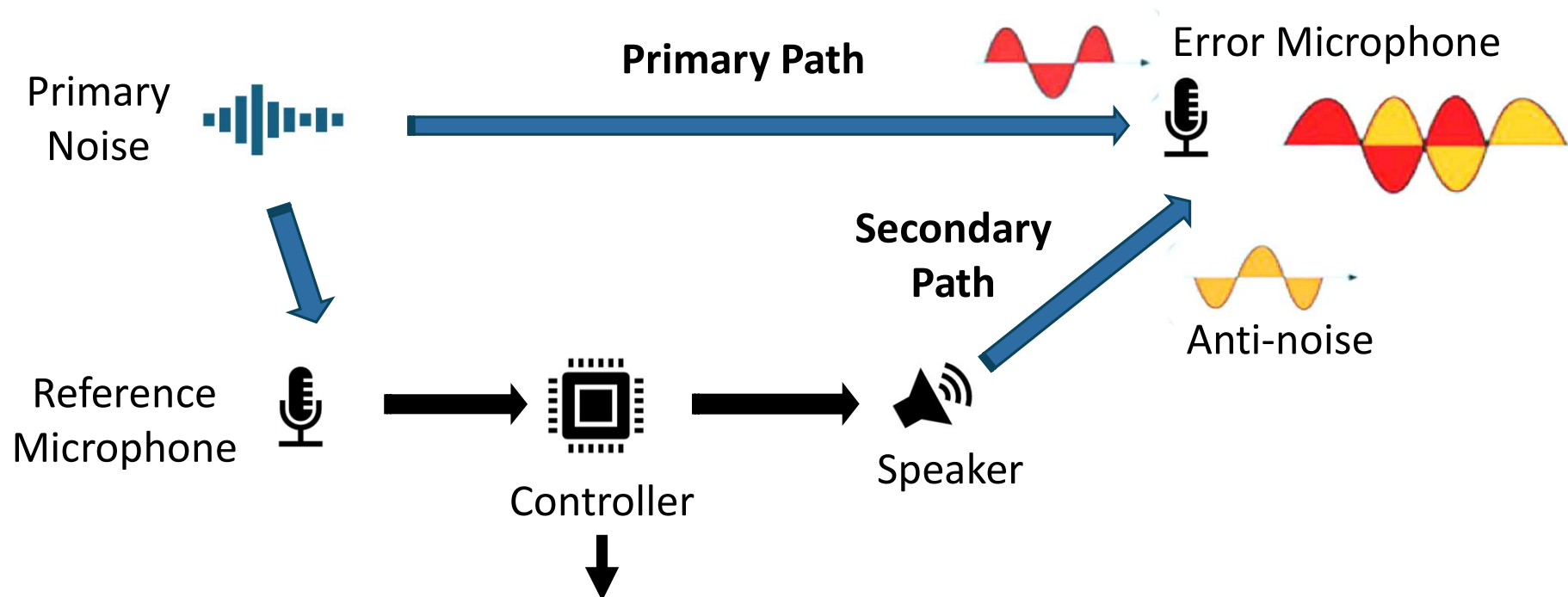
Andrew C. Singer - *Stony Brook University*



**LISTENING
TECHNOLOGY LAB**



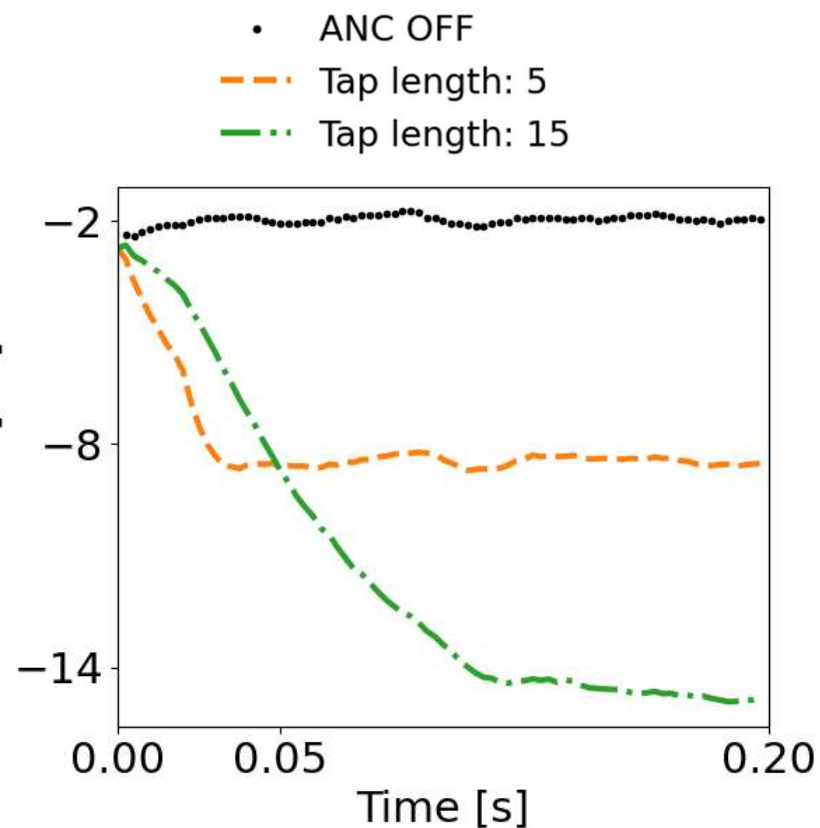
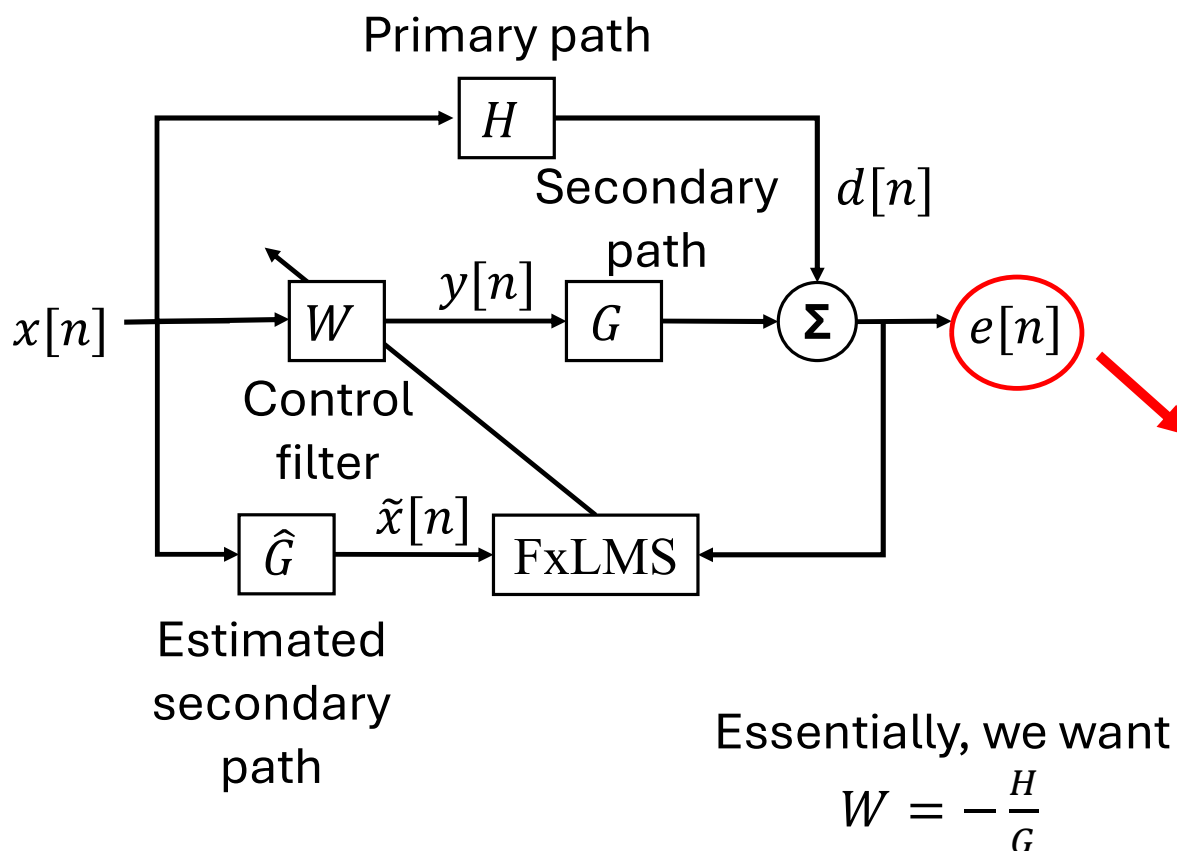
Active noise control (ANC) usually use fixed model order (tap length)



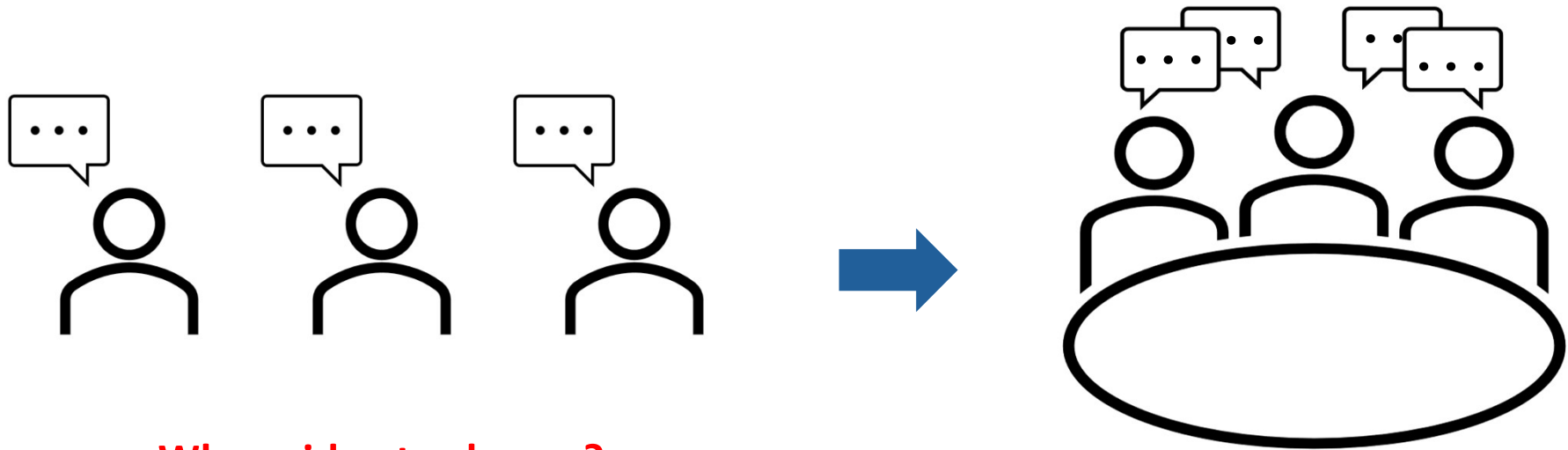
Usually, a fixed tap length finite impulse response (FIR) filter is used in the controller

Shorter tap length: faster convergence from eigenvalue analysis

Longer tap length: better steady-state performance



Intuition on the proposed method: a mixture of experts



Whose idea to choose?

**Blend their ideas based on
their previous performance!**

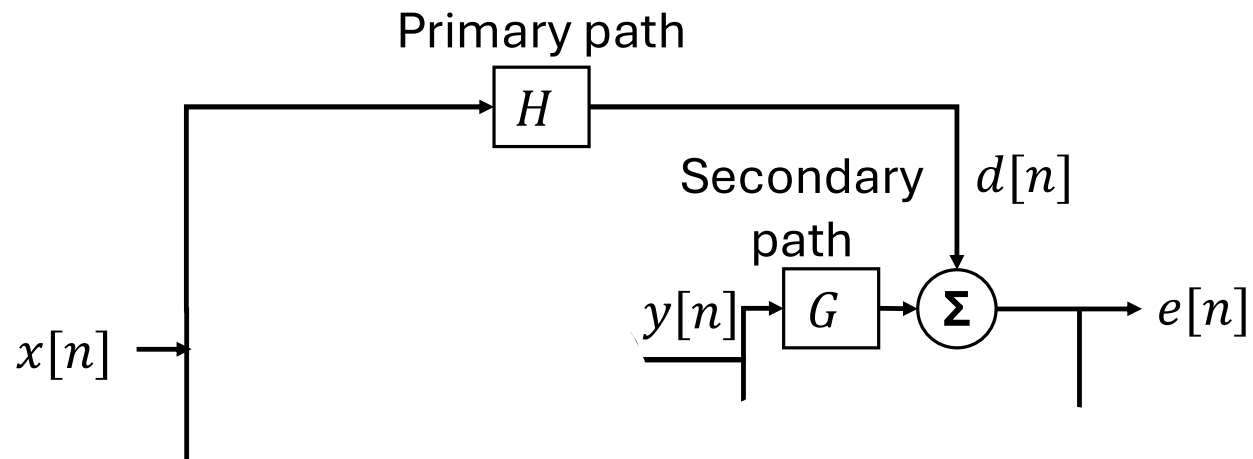
In real life:

- The trade-off between convergence rate and steady-state performance makes it difficult to determine the optimal tap length
- The optimal tap length may shift over time in time-varying environments

Instead of determining which model order to choose, blend different model orders.

In [Singer & Feder, 1999]:

- Linear predictors of different model orders are weighted to get the prediction.
- No need for tuning the model order.
- Their method is **universal**:
Asymptotically achieving the performance of the best candidate predictor

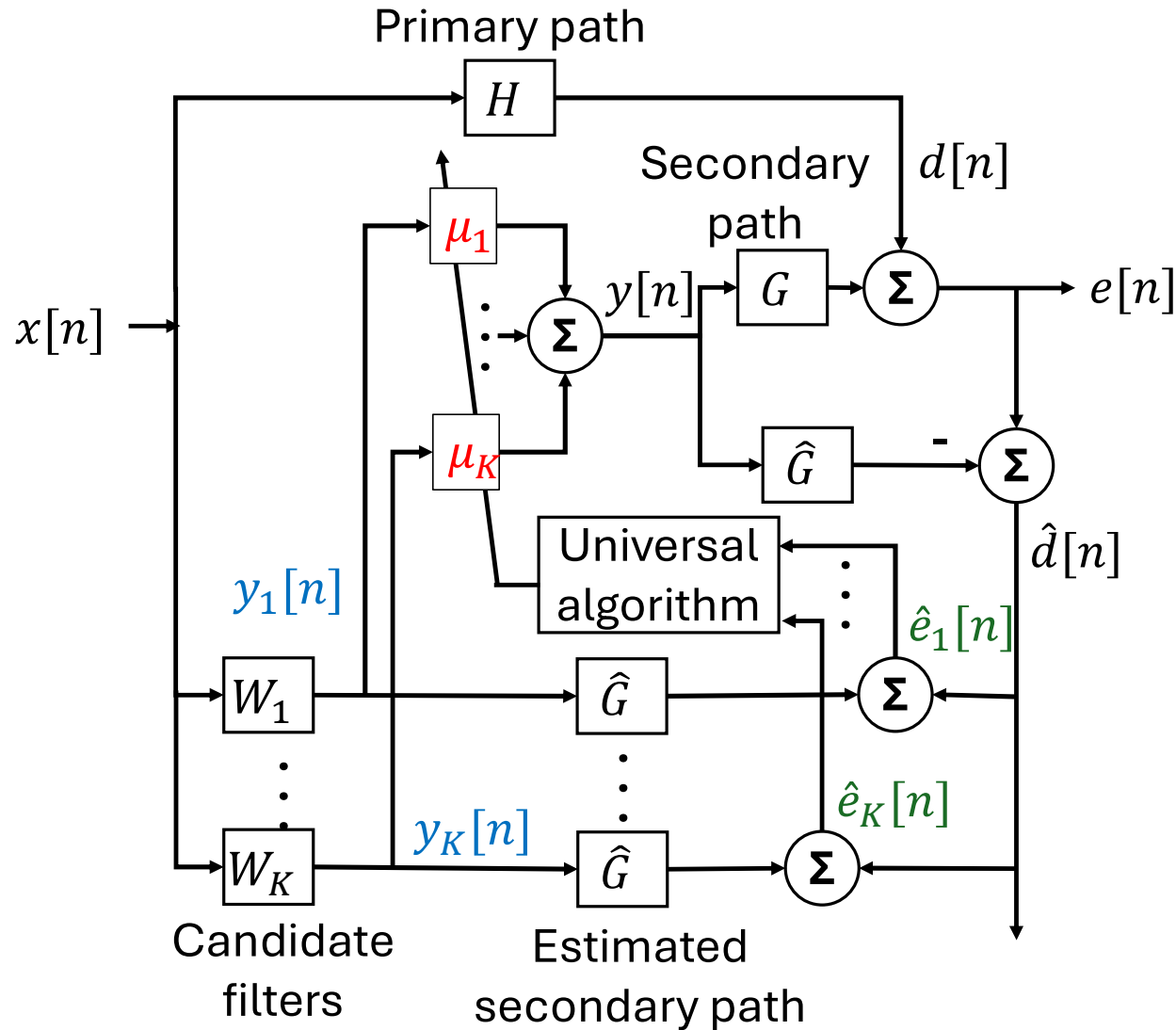


- The physical input of the speaker is:

$$y[n] = \sum_{k=1}^K \mu_k[n] y_k[n]$$

Candidate filter outputs

Mixture weights



- The mixture weights are computed based on each candidate filter's performance using softmax:

Performance of k th filter

$$\mu_k[n] = \frac{e^{-\alpha \ell_{n-1,k}}}{\sum_{j=1}^K e^{-\alpha \ell_{n-1,j}}}$$

Normalizing the weights

$\ell_{n-1,j}$: cumulative noise power at $\hat{e}_j[n-1]$ with forgetting factor

Universal method can track the best candidate filter in both transient and steady-state phase

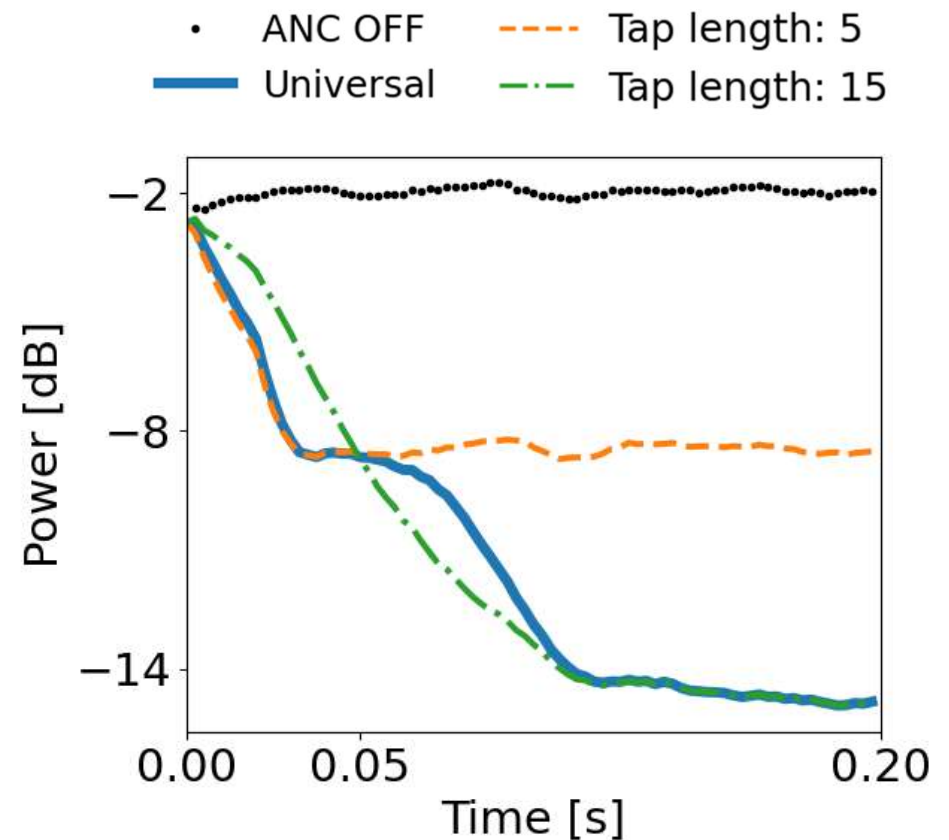
Apply the universal method on the previous example (100 Monte Carlo trials):

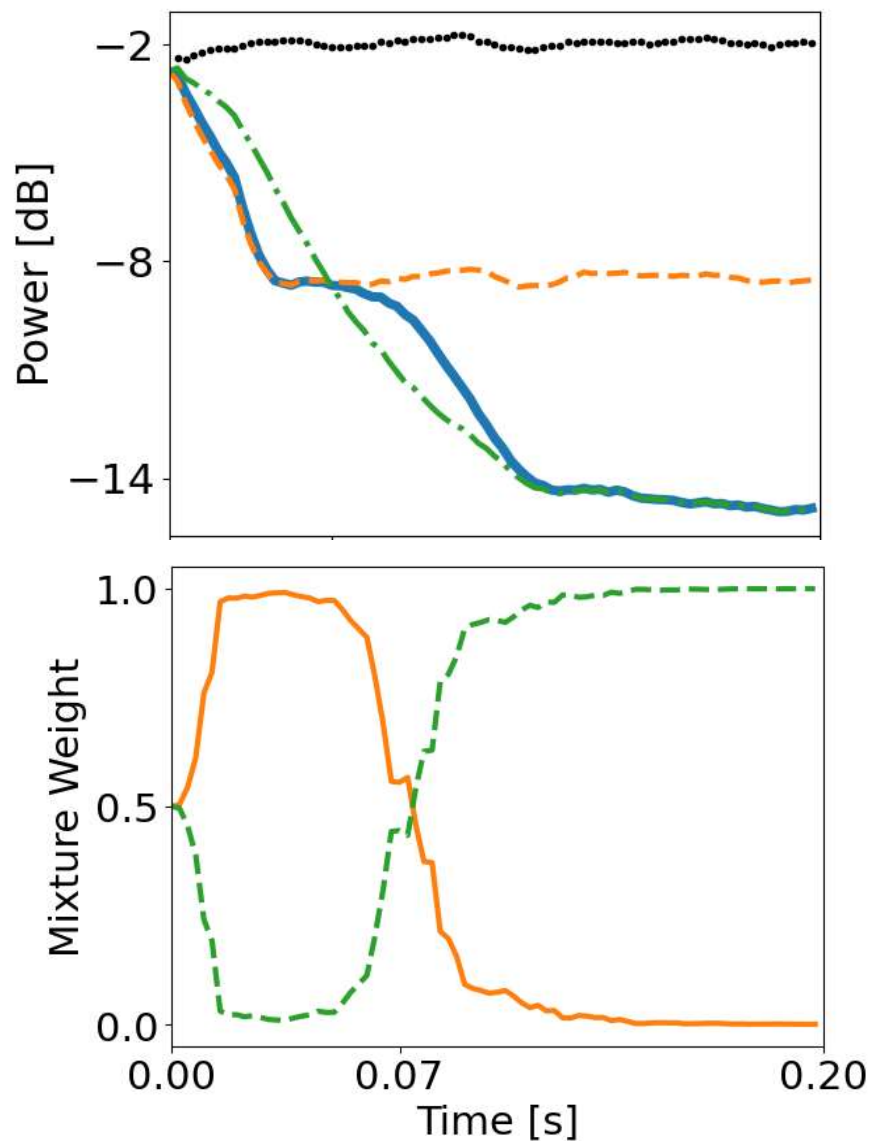
- Primary path:

$$H(z) = 1$$

- Secondary path:

$$G(z) = 1 + 0.5z^{-1}$$

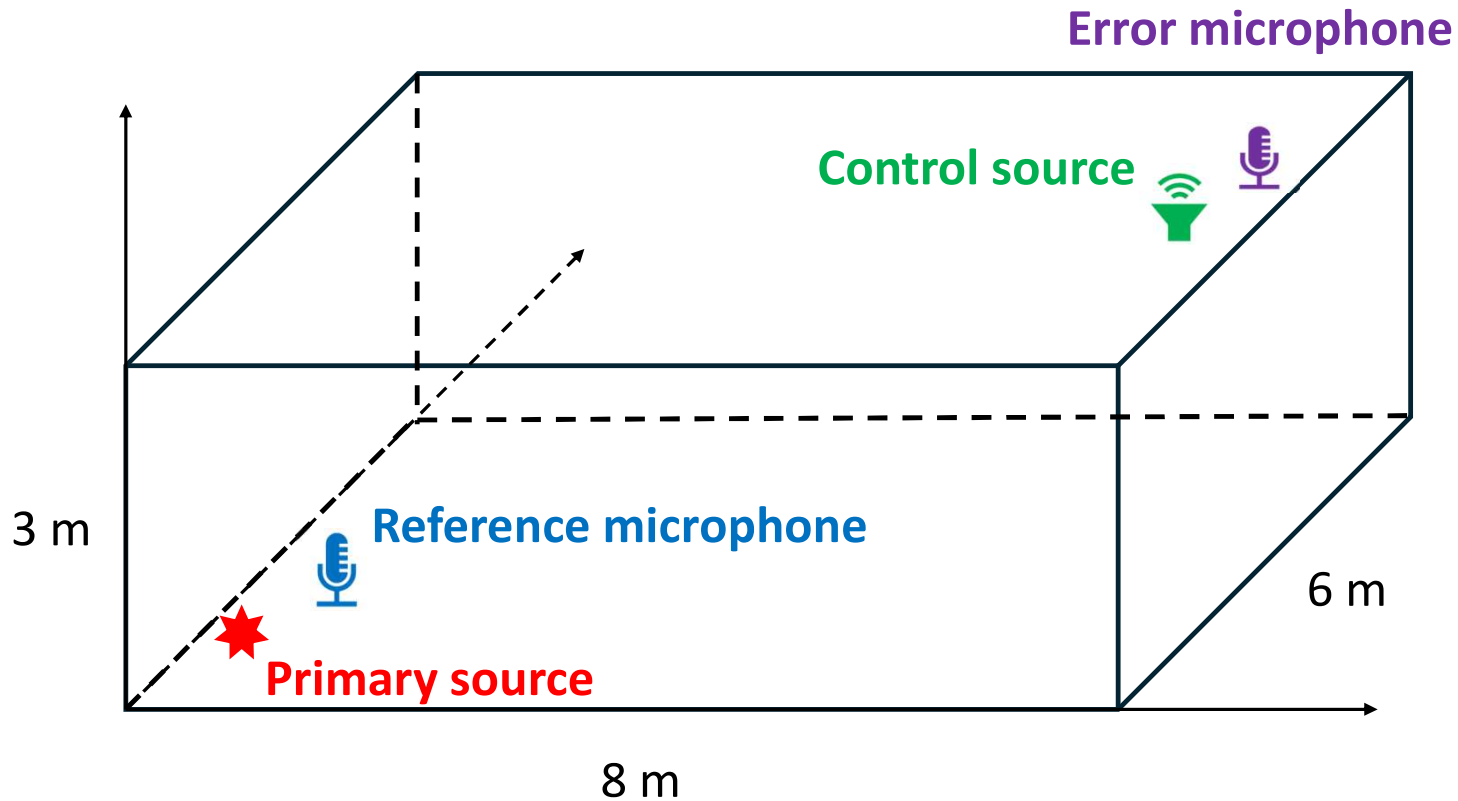




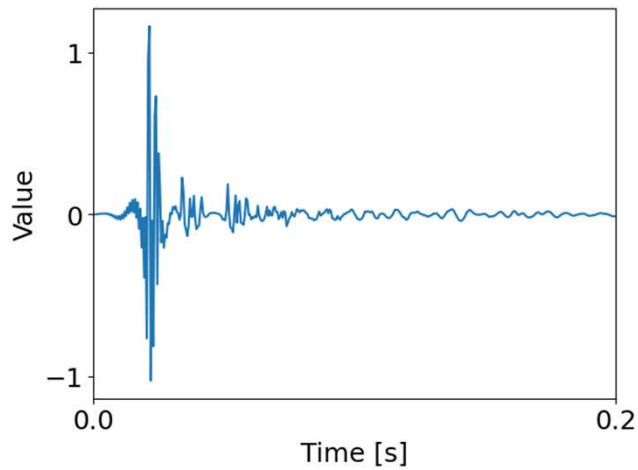
- ANC OFF
- Universal
- - Tap length: 5
- . Tap length: 15

Universal method adjusts the mixture weights based on the past performance of each candidate filter

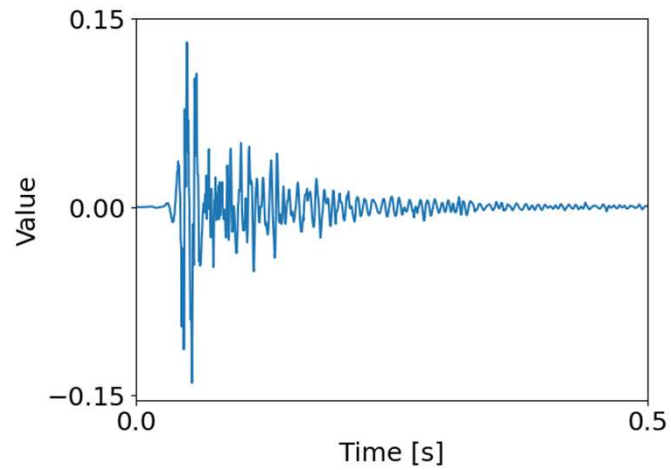
Using Pyroomacoustics to simulate a room response



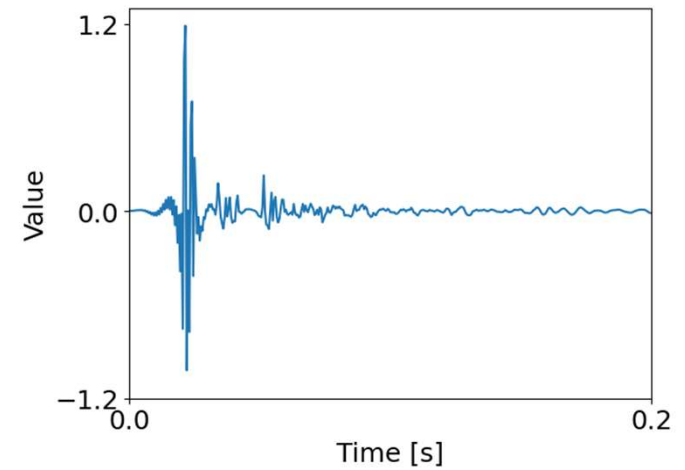
Simulated room responses



Noise source → Reference mic



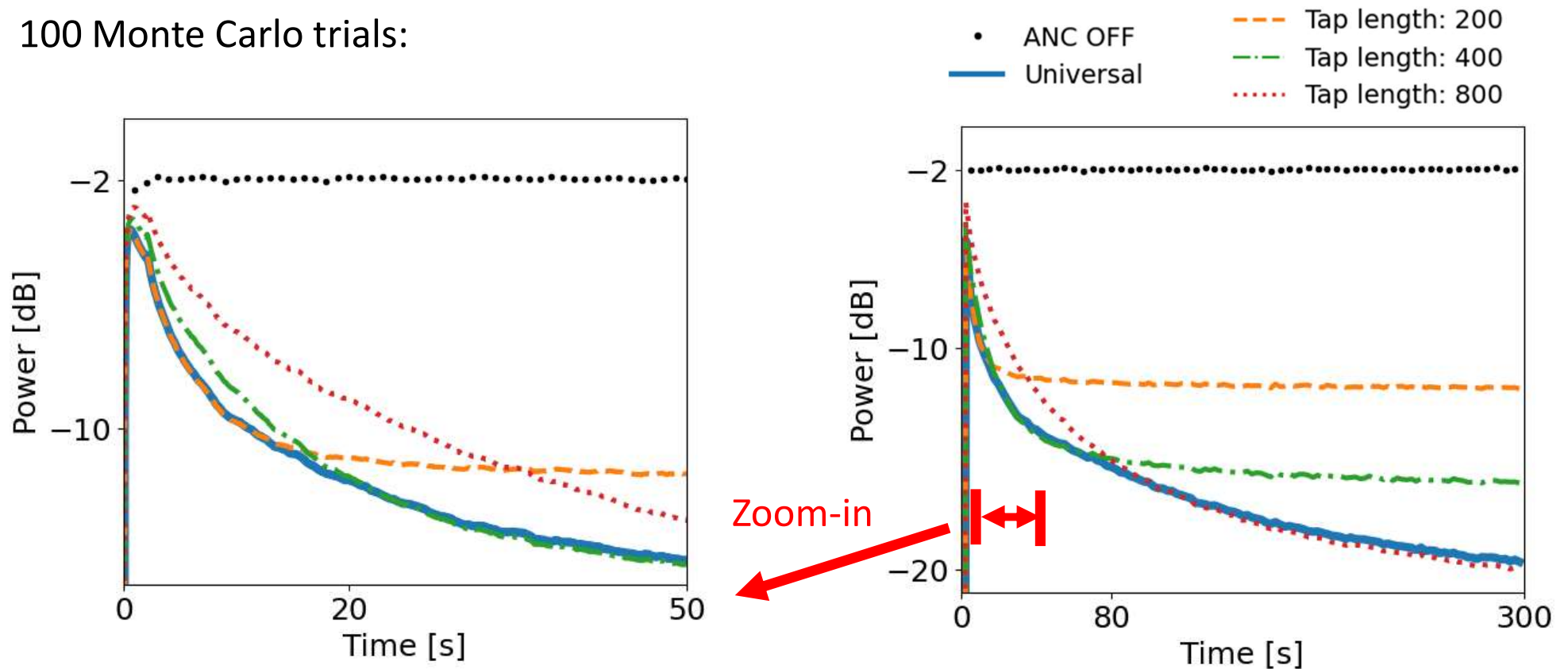
Noise source → Error mic

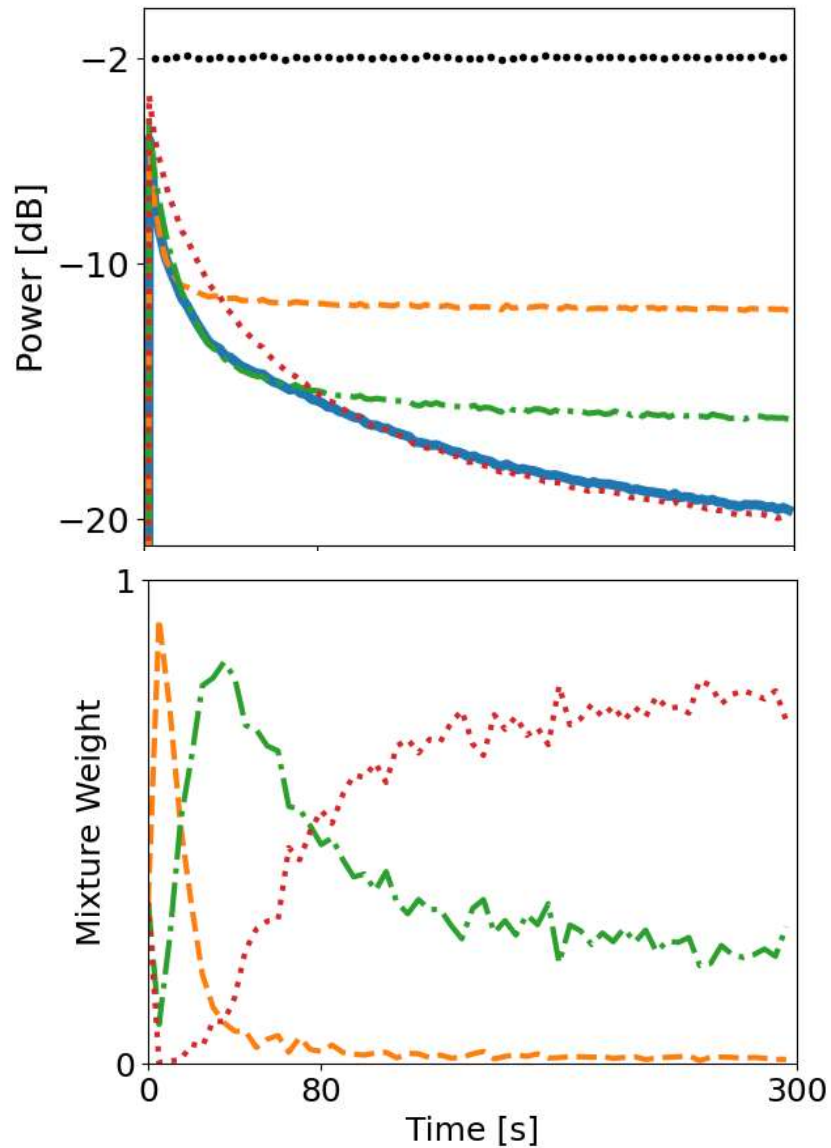


Control source → Error mic

Universal method can still track the best candidate filter in both transient and steady-state phase

100 Monte Carlo trials:



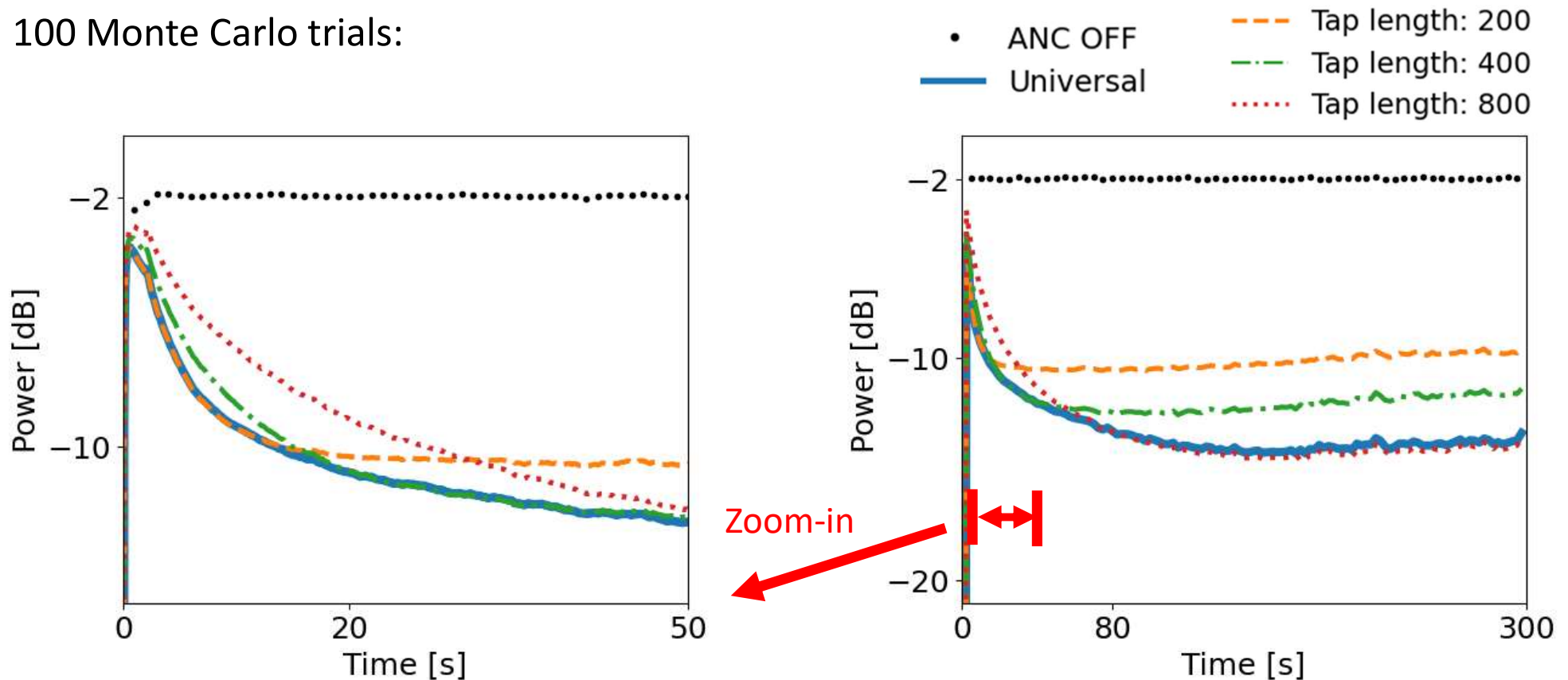


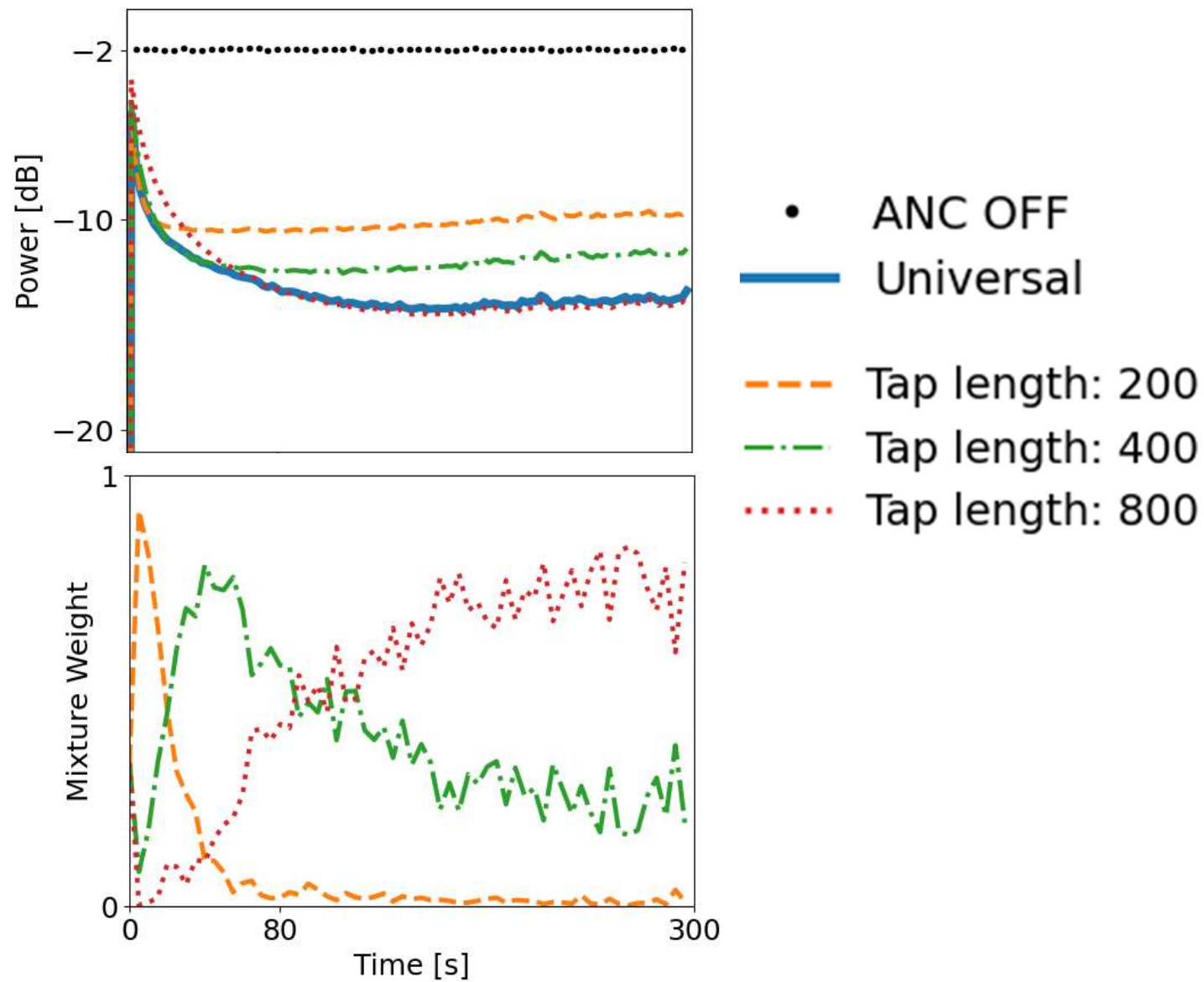
- ANC OFF
- Universal
- - - Tap length: 200
- . - Tap length: 400
- . . . Tap length: 800

Universal method adjusts the mixture weights based on the past performance of each candidate filter

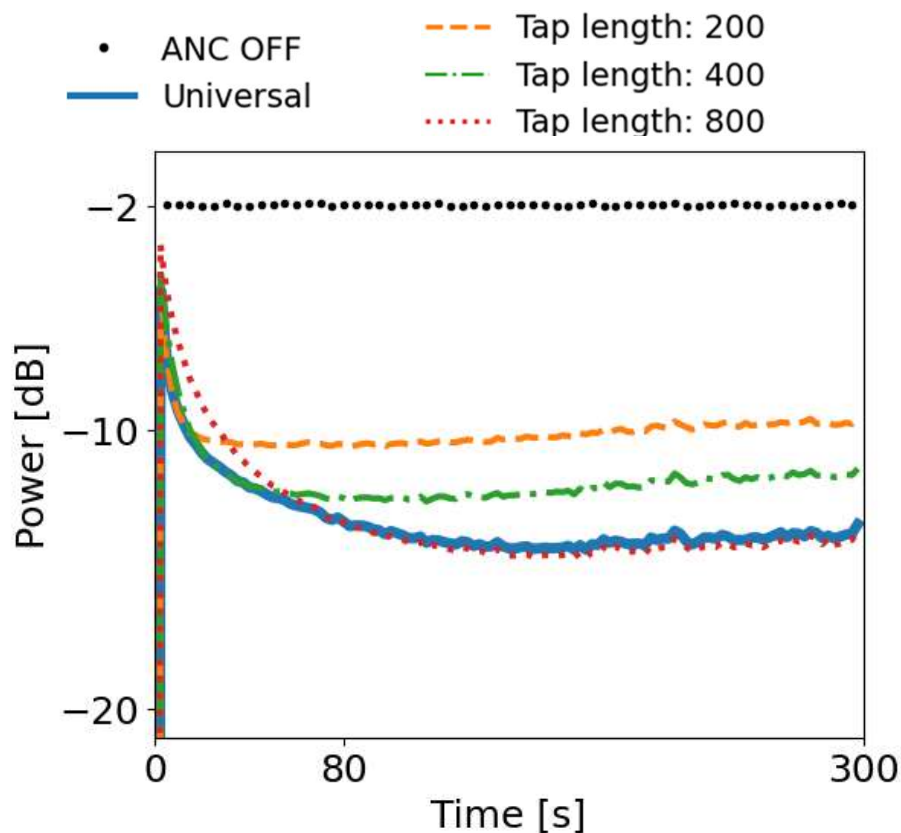
Universal method can still track the best candidate filter in a perturbed secondary path case

100 Monte Carlo trials:





Conclusion



- Blending the outputs of candidate filters based on their past performance
- Good performance under secondary path perturbation
- In the future:
 - Other filters
 - Efficient implementation
 - Real-time experiments