Adaptive Signal Processing (EQ2401)

Project Assignment II, Spring 2023

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Problem Formulation

This audio signal can be modeled as a combination of a clean speech signal and additive noise components:

$$y(n) = x(n) + e(n)$$

$y(n)$ - distorted audio signal
$x(n)$ - clean speech signal (to be retrieved)
$e(n)$ - background noise (obtained from microphone 2 recording)

Where $x(n)$ and $e(n)$ are uncorrelated; this is a valid assumption given that the speech signal and noise do not influence each other.

Wiener Filter Performance

Attempted filtering with order 30 Wiener solutions from the previous project:

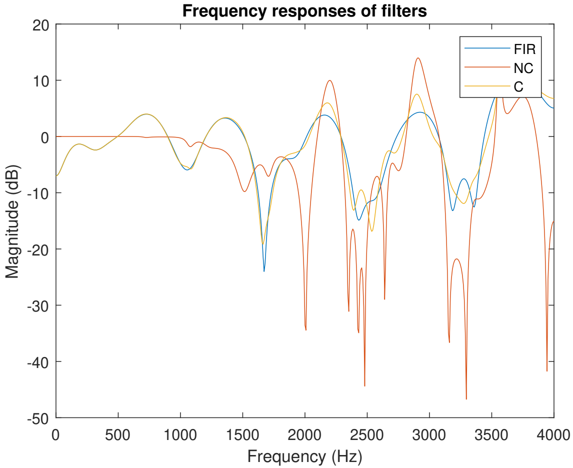


Figure. Wiener filter frequency responses

Generally poor performance: limited noise attenuation and fluctuating noise disturbance.

Algorithms

- LMS
- NLMS
- RLS

Approach

- Use microphone 2 recording as noise source ($v(n)$)
- Estimate noise in input with algorithm ($e(n) \approx F(n)v(n)$)
- Output difference between input and noise estimate ($x(n) = y(n) - e(n) \approx y(n) - F(n)v(n) = \hat{x}(n)$)

Solutions

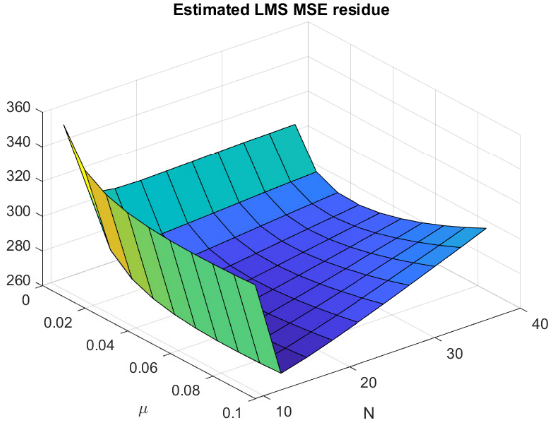
Parameter optimization

Parameter choice

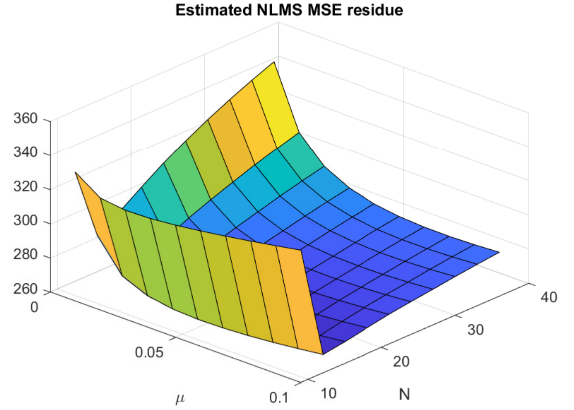
- Estimate MSE at every point in time ($(y(n) - F(n)v(n))^2 = \hat{x}(n)^2$)
- Sum MSE estimates to obtain scalar error metric
- Sweep parameters
- Minimize error metric

Solutions

Parameter optimization results (1)



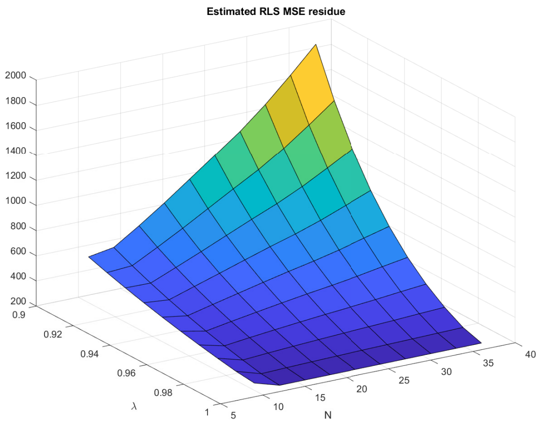
(a) LMS parameter sweep



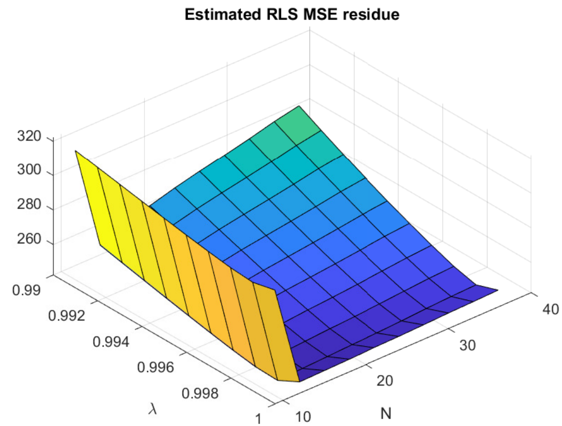
(b) NLMS parameter sweep

Solutions

Parameter optimization results (2)



(a) RLS parameter sweep



(b) RLS parameter sweep (extended)

SOLUTIONS

PARAMETERS

LMS

Parameters

- $order = 12$
- $\mu = 0.08$

NLMS

Parameters

- $order = 12$
- $\mu = 0.05$

RLS

Parameters

- $order = 12$
- $\lambda = 0.999$
- $P(0) = 1000I$ (error metric insensitive)

Solutions

Results

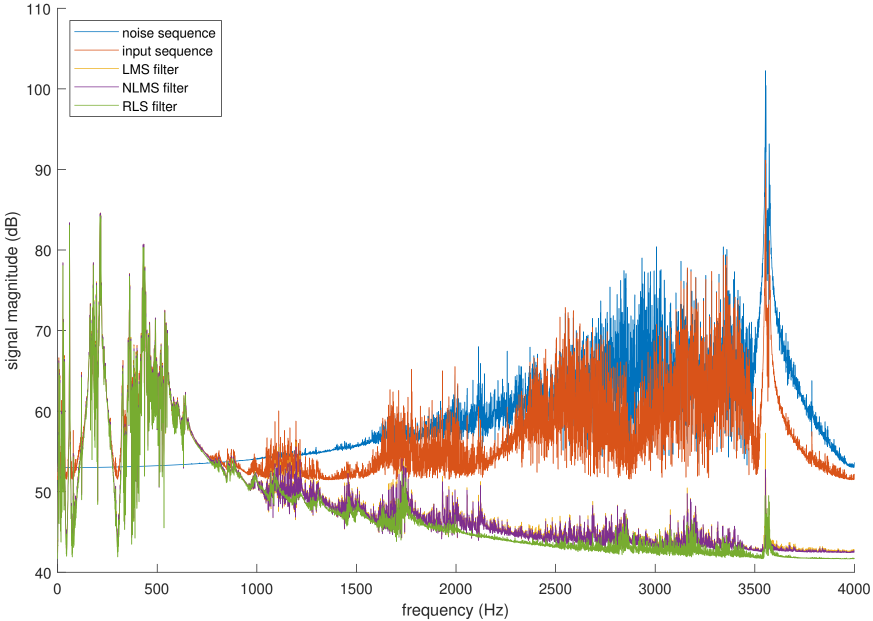


Figure. Input and filtered spectra

Solutions

Filter Responses

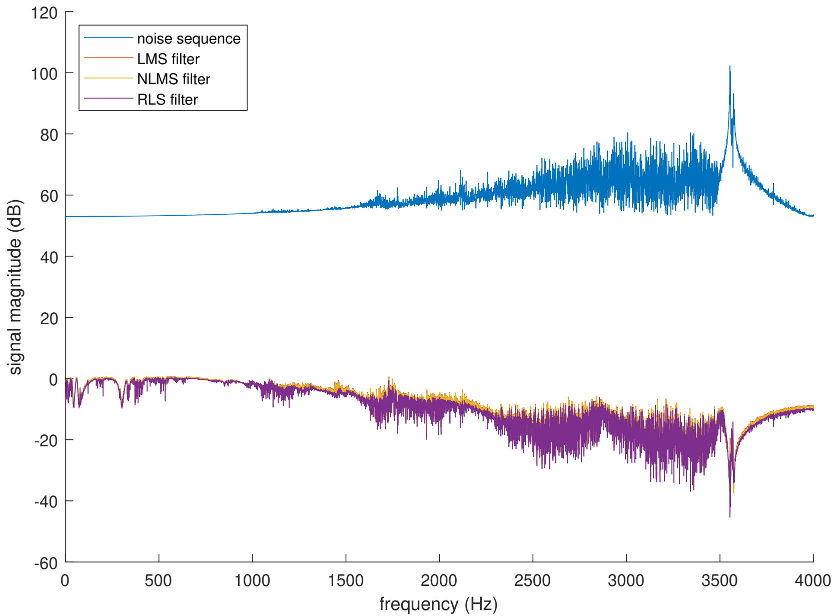


Figure. Effective frequency response ($\frac{\phi_{filt}}{\phi_{mic2}}$) vs noise spectrum

Solutions

Comparison with Wiener

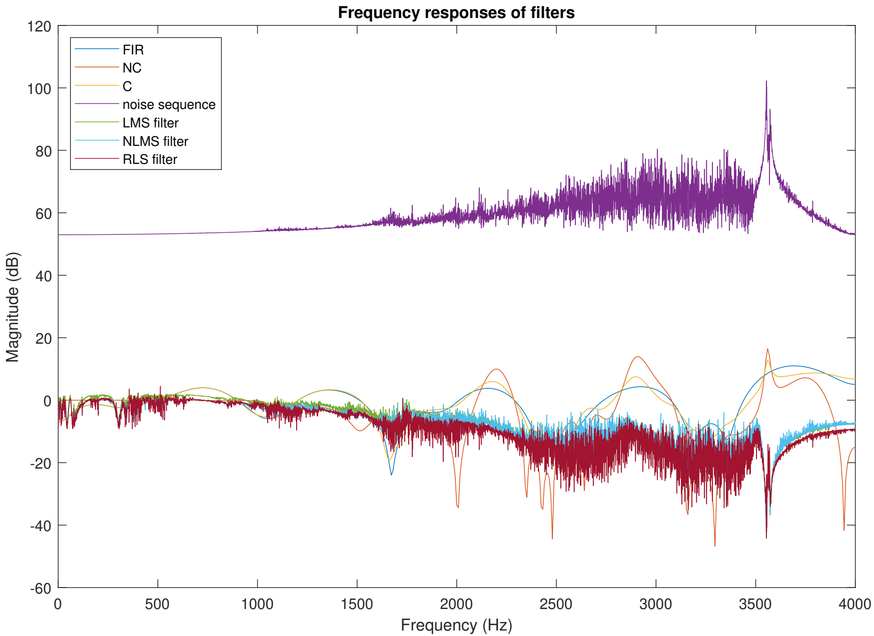


Figure. Effective filter frequency response ($\frac{\phi_{filt}}{\phi_{mic2}}$) vs Wiener vs noise spectrum

Solutions

Sliding window optimization

Conventional RLS

$$
\begin{aligned}
g &= \frac{P(n-1)Y(n)}{\lambda + Y(n)^T P(n-1)Y(n)} \\
P(n) &= \frac{P(n-1) - gY(n)^T P(n-1)}{\lambda} \\
\theta(n) &= \theta(n-1) + P(n)Y(n)(x(n) - \theta(n-1)^T Y(n))
\end{aligned}
$$

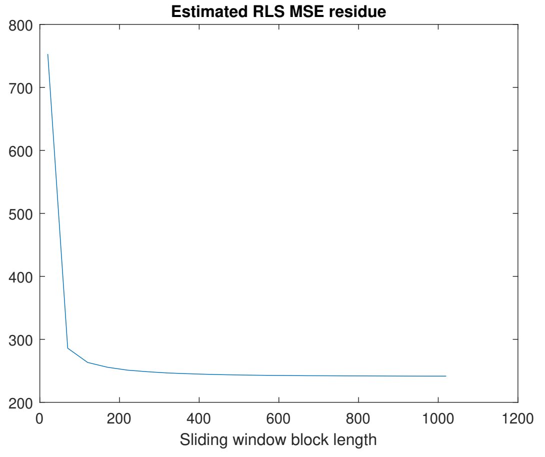
Sliding window RLS[1]
Additionally 'downdate' to remove effects outside sliding window (with k block length)

$$
\begin{aligned}
g &= \frac{P(n)\lambda^k Y(n-k)}{1 - Y(n-k)^T P(n)\lambda^k Y(n-k)} \\
P(n) &= P(n) + gY(n-k)^T P(n) \\
\theta(n) &= \theta(n) - P(n)Y(n-k)(x(n-k) - \theta(n)^T Y(n-k))
\end{aligned}
$$

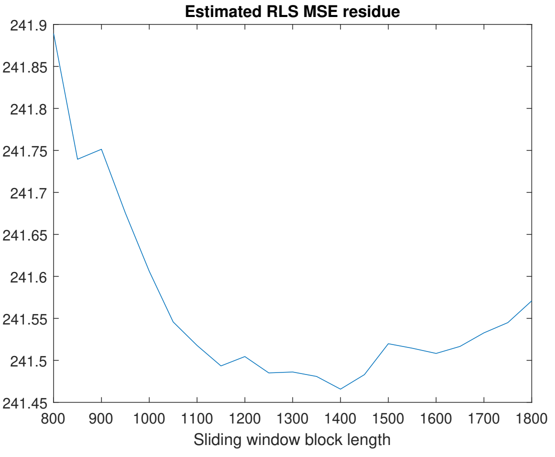
[1] Zhang, Q. (2000). Some implementation aspects of sliding window least squares algorithms.

Solutions

Sliding window optimization



(a) RLS sliding window block length sweep



(b) RLS sliding window block length sweep (extended)