Dually Regularized Recursive Prediction Error Identification for Acoustic Feedback and Echo Cancellation

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From Least-Squares to Prediction Error Identification

- Goal: identify a room impulse response (RIR) $F(q,t) = f_0(t) + f_1(t)q^{-1} + \ldots + f_{n_F}(t)q^{-n_F}$, given a far-end signal $u(t)$ and microphone signal $y(t)$, possibly disturbed by the presence of a near-end signal $v(t)$.
- Least-squares (LS) identification:

$$\text{data model: } y(t) = F(q,t)u(t) + v(t)$$

$$\text{LS criterion: } \min_{\hat{\mathbf{f}}(t)} \frac{1}{2N} \sum_{k=1}^{t} \lambda^{t-k} [y(k) - \hat{F}(q,t)u(k)]^2$$

- Prediction error (PE) identification: include a time-varying AR (TVAR) near-end signal model

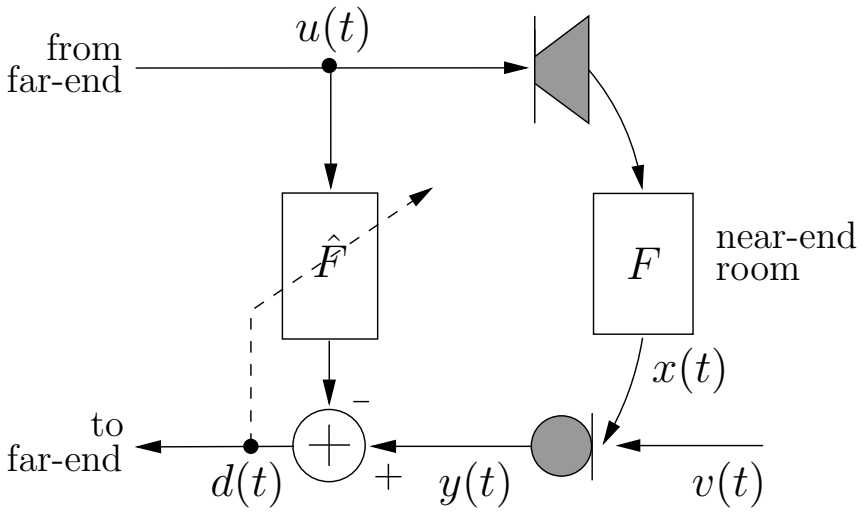
$$\text{data model: } y(t) = F(q,t)u(t) + \frac{1}{A(q,t)}e(t)$$

$$\text{PE criterion: } \min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N} \sum_{k=1}^{t} \frac{\lambda^{t-k}}{\hat{\sigma}_k^2} \{\hat{A}(q,t)[y(k) - \hat{F}(q,t)u(k)]\}^2$$

Application 1: Double-talk-robust Acoustic Echo Cancellation

Double-talk in Acoustic Echo Cancellation:

- **bursting** double-talk [double-talk detector (DTD) imperfections]: increase double-talk-robustness of adaptive filtering algorithms
- **continuous** double-talk (noisy near-end conditions): enable adaptive filter to operate without DTD



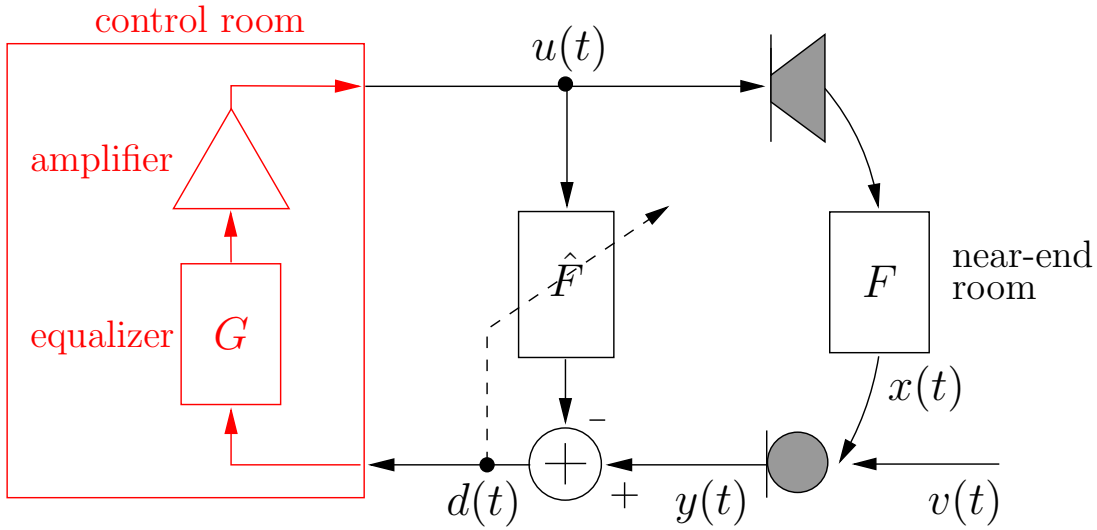
- global solution to PE criterion (under some conditions)
  = Best (**minimum-variance**) Linear Unbiased Estimate (BLUE) of RIR [1]

[1] T. van Waterschoot, G. Rombouts, P. Verhoeve, and M. Moonen, "Double-talk-robust prediction error identification algorithms for acoustic echo cancellation," *IEEE Trans. Signal Process.*, vol. 55, no. 3, pp. 846–858, Mar. 2007.

Application 2: Unbiased Acoustic Feedback Cancellation

Bias in Acoustic Feedback Cancellation (AFC):

- closed-loop signal correlation: **bias** in LS RIR estimate
- PE identification provides signal **decorrelation** without affecting closed-loop signal quality [2]



[2] G. Rombouts, T. van Waterschoot, K. Struyve, and M. Moonen, "Acoustic feedback suppression for long acoustic paths using a nonstationary source model," *IEEE Trans. Signal Process.*, vol. 54, no. 9, pp. 3426–3434, Sept. 2006.

Core Problem: Scaling Ambiguity in the RPE Algorithm

- State-of-the-art stochastic gradient RPE algorithm: produces estimates of
  - primary variables (RIR coefficients vector $\hat{\mathbf{f}}(t) = \begin{bmatrix} \hat{f}_0(t) & \dots & \hat{f}_{n_F}(t) \end{bmatrix}$)
  - auxiliary variables (TVAR coefficients vector $\hat{\mathbf{a}}(t) = \begin{bmatrix} \hat{a}_1(t) & \dots & \hat{a}_{n_A}(t) \end{bmatrix}$, PE variance $\hat{\sigma}_t^2$, ...)
- Scaling ambiguity: if some of the auxiliary variables are replaced by their scaled counterparts

$$\left\{\hat{\mathbf{a}}(t), \hat{\mathbf{a}}(t-1), \hat{\sigma}_t^2, \hat{\sigma}_{t-1}^2, \boldsymbol{\psi}_F[t, \hat{\mathbf{a}}(t-1)], \varepsilon[t, \hat{\boldsymbol{\theta}}(t-1)], \mathbf{R}_A(t), \mathbf{R}_A(t-1)\right\}$$

$$\downarrow$$

$$\left\{K\hat{\mathbf{a}}(t), K\hat{\mathbf{a}}(t-1), K^2\hat{\sigma}_t^2, K^2\hat{\sigma}_{t-1}^2, K\boldsymbol{\psi}_F[t, \hat{\mathbf{a}}(t-1)], K\varepsilon[t, \hat{\boldsymbol{\theta}}(t-1)], K^{-2}\mathbf{R}_A(t), K^{-2}\mathbf{R}_A(t-1)\right\}$$

and if the scaling factor is large enough

$$K >> \|\hat{\mathbf{a}}(t-1)\|_2^{-1}$$

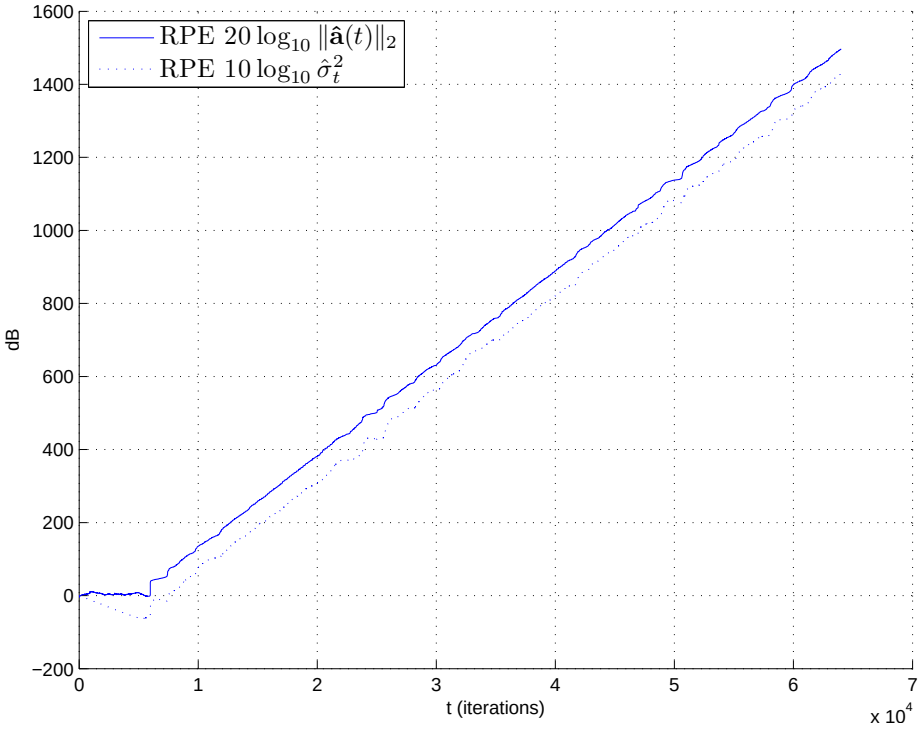
then the RPE algorithm yields **the same solution $\hat{\mathbf{f}}(t)$ as in the case without scaling**

Consequences of the Scaling Ambiguity

- Consequences:
  - in many RPE simulations, the auxiliary variables undergo an **exponentially increasing scaling**, until numerical overflow occurs
  - this effect renders the RPE algorithm **numerically inaccurate and unstable**
- Example: log-scale plot of the squared norm of two auxiliary variables for an AFC simulation

TVAR coefficients norm: $\|\hat{\mathbf{a}}(t)\|_2^2$

prediction error variance: $\hat{\sigma}_t^2$



Regularizing the Auxiliary Variables Identification

- Proposed solution: regularize the identification of one of the auxiliary variables, i.e., the TVAR coefficients identification.
- Tikhonov Regularization: includes a minimum-norm constraint in the PE criterion, featuring one regularization parameter β

$$\min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N} \sum_{k=1}^{t} \frac{\lambda^{t-k}}{\hat{\sigma}_k^2} \left\{ \hat{A}(q,t)[y(k) - \hat{F}(q,t)u(k)] \right\}^2 + \beta \|\hat{\mathbf{a}}(t)\|_2^2$$

- Bayesian Regularization: adds a more flexible regularization term in the PE criterion

$$\min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N} \left\{ \sum_{k=1}^{t} \frac{\lambda^{t-k}}{\hat{\sigma}_k^2} \left\{ \hat{A}(q,t)[y(k) - \hat{F}(q,t)u(k)] \right\}^2 + [\hat{\mathbf{a}}(t) - \mathbf{a_0}]^T \mathbf{R_a}^{-1} [\hat{\mathbf{a}}(t) - \mathbf{a_0}] \right\}$$

which may incorporate prior knowledge on true TVAR process generating the near-end signal:

$$\mathbf{a_0} \triangleq E\{\mathbf{a}\}, \quad \mathbf{R_a} \triangleq \text{cov}\{\mathbf{a}\} = E\left\{ (\mathbf{a} - \mathbf{a_0})(\mathbf{a} - \mathbf{a_0})^T \right\}$$

Dual Regularization: Combined RIR and TVAR Regularization

- Combined RIR and TVAR Regularization:

$$\min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N}\Bigg\{\sum_{k=1}^{t}\frac{\lambda^{t-k}}{\hat{\sigma}_k^2}\{\hat{A}(q,t)[y(k)-\hat{F}(q,t)u(k)]\}^2 + \underbrace{[\hat{\mathbf{f}}(t)-\mathbf{f_0}]^T\mathbf{R_f}^{-1}[\hat{\mathbf{f}}(t)-\mathbf{f_0}]}_{\text{RIR regularization}} + \underbrace{[\hat{\mathbf{a}}(t)-\mathbf{a_0}]^T\mathbf{R_a}^{-1}[\hat{\mathbf{a}}(t)-\mathbf{a_0}]}_{\text{TVAR regularization}}\Bigg\}$$

- Special cases [3]:
  - if $\mathbf{a_0} = \mathbf{0}$ the dual regularization corresponds to a generalized, MSE-optimal type of Tikhonov regularization (**TR**)
  - if $\mathbf{a_0} = \hat{\mathbf{a}}(t-1)$ the dual regularization corresponds to a generalized, MSE-optimal type of Levenberg-Marquardt regularization (**LMR**)

[3] T. van Waterschoot, G. Rombouts, and M. Moonen, "Optimally regularized adaptive filtering algorithms for room acoustic signal enhancement," *Signal Processing*, to appear.

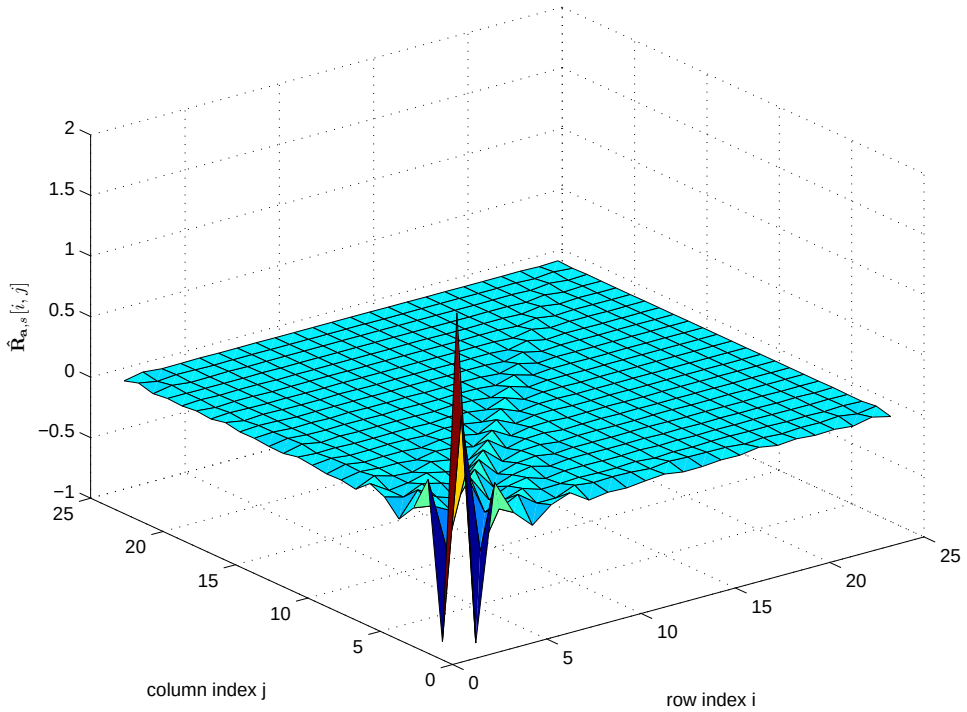
Simulations: TVAR Regularization Matrix Construction

How to construct an appropriate TVAR regularization matrix $\mathbf{R_a}$?

- using no prior knowledge: $\mathbf{R_a} = \mathbf{I}$, which leads to traditional TR/LMR regularization

- using prior knowledge: $\mathbf{R_a} = \hat{\mathbf{R}}_{\mathbf{a},s}$
  - TVAR models $\hat{\mathbf{a}}_i$ of 310929 different 20 ms speech frames from the TIMIT database were identified
  - the corresponding TVAR coefficient vector outer products were ensemble-averaged:

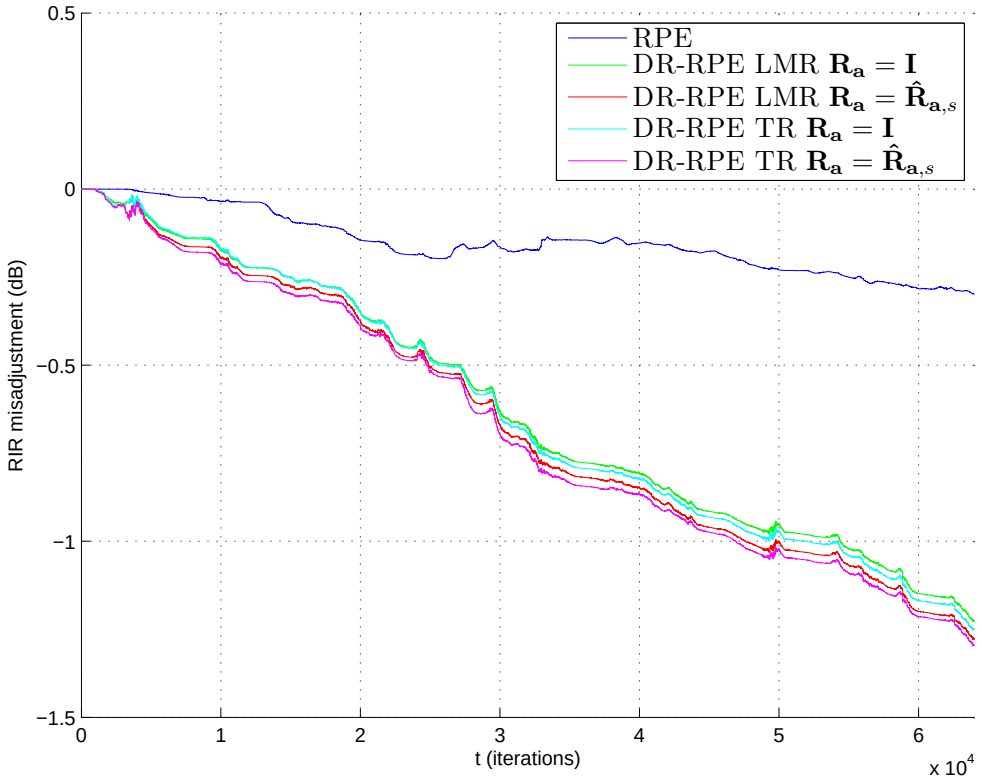
$$\hat{\mathbf{R}}_{\mathbf{a},s} = E\{\hat{\mathbf{a}}_i \hat{\mathbf{a}}_i^T\},$$
$$i = 1, \ldots, 310929$$



Simulation 1: AFC with real near-end speech (1)

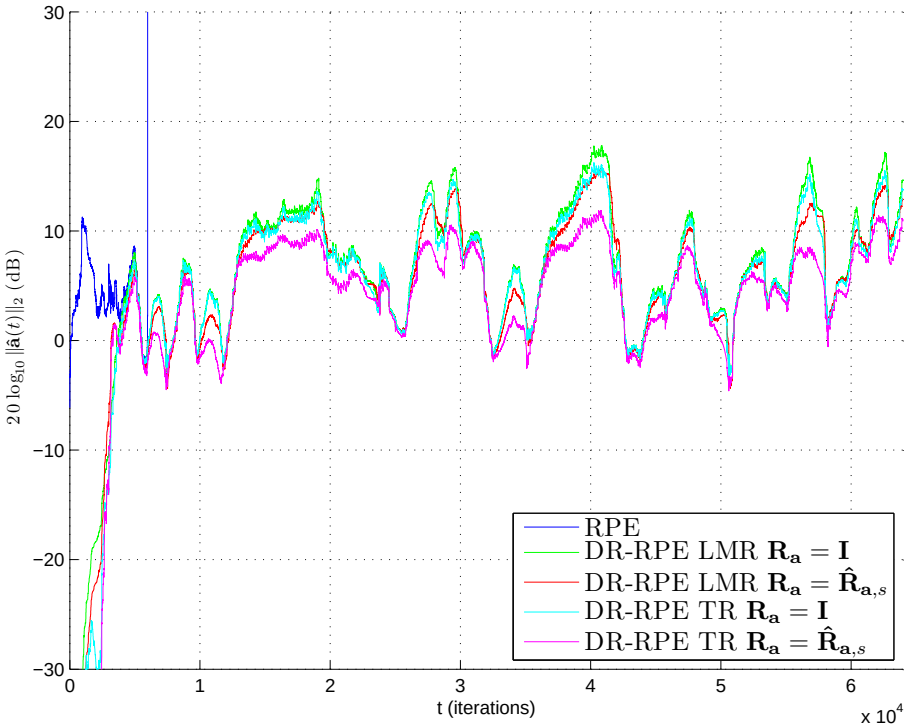
Acoustic Feedback Cancellation (AFC):

- sampling frequency: 16 kHz
- amplifier gain: -9 dB (gain margin $= 3$ dB)
- equalizer: pure time delay of 320 samples
- near-end signal: 4 s male speech (not from TIMIT database!)
- RIR order: $n_F = 2000$
- TVAR model order: $n_A = 24$
- TVAR forgetting factor: $\lambda_A = 0.9971$
- step size: $\mu_F = 10^{-3}$ (RPE), $\mu_F = 10^{-2}$ (DR-RPE)
- RIR regularization matrix: $\mathbf{R}_\mathbf{f} = \mathbf{I}$

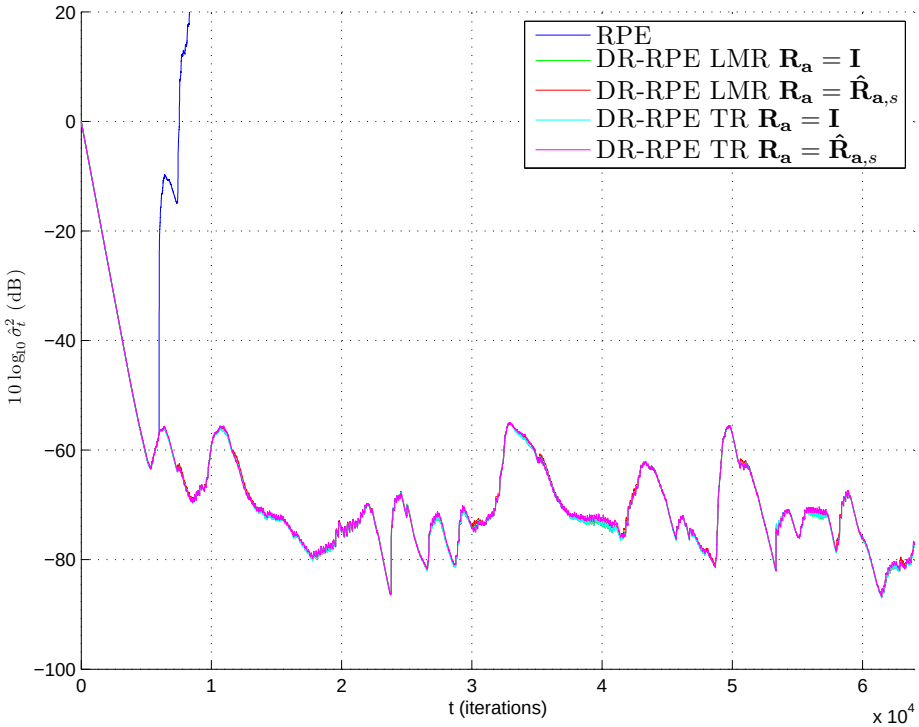


$$\text{RIR misadjustment (dB)} = 20 \log_{10} \frac{\|\hat{\mathbf{f}}(t) - \mathbf{f}\|_2}{\|\mathbf{f}\|_2}.$$

Simulation 1: AFC with real near-end speech (2)



TVAR coefficients norm (dB) $= 20 \log_{10} \|\hat{\mathbf{a}}(t)\|_2$



Prediction error variance (dB) $= 10 \log_{10} \hat{\sigma}_t^2$

Simulation 2: AFC with synthetic near-end speech

- Synthetic speech generation: passing GWN through time-varying all-pole filter of order $n_A = 24$, whose coefficients $\mathbf{a}(t)$ change every 20 ms and are computed by linear prediction of real speech
- AFC simulation: same simulation parameters as in Simulation 1, except for near-end signal = 60 s synthetic speech (data record length $M = 960 \cdot 10^3$ samples)
- Results: we compare the accuracy of the TVAR coefficients identification using TR/LMR and with/without prior knowledge

Regularization method	$\mathbf{R_a}$	TVAR misadjustment
Levenberg-Marquardt	$\mathbf{I}$	-1.5322 dB
Levenberg-Marquardt	$\hat{\mathbf{R}}_{\mathbf{a},s}$	-1.9629 dB
Tikhonov	$\mathbf{I}$	-1.9814 dB
Tikhonov	$\hat{\mathbf{R}}_{\mathbf{a},s}$	-3.5738 dB

$$\text{TVAR misadjustment (dB)} = 20 \log_{10} \left(\frac{1}{M} \sum_{k=1}^{M} \frac{\|\hat{\mathbf{a}}(k) - \mathbf{a}(k)\|_2}{\|\mathbf{a}(k)\|_2} \right)$$

Conclusions

- **Recursive prediction error (RPE) identification** algorithms are attractive alternatives to traditional least-squares-based adaptive filtering algorithms for RIR identification, e.g., to deliver double-talk-robust AEC or unbiased AFC solutions.
- The state-of-the-art stochastic gradient RPE algorithm suffers from a scaling ambiguity in the calculation of the auxiliary variables, which leads to **numerical inaccuracy and instability** being observed in many computer simulations.
- The proposed solution consists in regularizing the identification of the TVAR auxiliary variables, which may be combined with RIR regularization to obtain **Dual Regularization**.
- A class of **Dually Regularized RPE (DR-RPE) Algorithms** is then obtained, with different choices of regularization methods (Tikhonov/Levenberg-Marquardt) and matrices (possibly incorporating prior knowledge).
- Simulation results confirm that, regardless of the choice of regularization method or matrix, the scaling ambiguity is solved by using the DR-RPE algorithm in an AFC application with real near-end speech, and the **RIR misadjustment is improved**.
- AFC simulations with synthetic near-end speech moreover illustrate that the **accuracy of the TVAR coefficients identification is increased** by using prior knowledge, and that the Tikhonov method is preferred over the Levenberg-Marquardt method.