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DUALLY REGULARIZED RECURSIVE PREDICTION ERROR IDENTIFICATION FOR ACOUSTIC FEEDBACK AND ECHO CANCELLATION

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ABSTRACT

Recursive prediction error (RPE) identification algorithms are attractive alternatives to the traditional least-squares-based adaptive filtering algorithms for, e.g., room impulse response identification, in such applications as acoustic feedback and echo cancellation. It has however been observed that a recently proposed RPE algorithm suffers from numerical problems due to a scaling ambiguity in the calculation of the auxiliary variables. This problem is tackled by regularizing the identification of some of the auxiliary variables, which is called "dual regularization". This leads to a class of Dually Regularized Recursive Prediction Error (DR-RPE) identification algorithms, with different choices of regularization methods (Tikhonov or Levenberg-Marquardt) and matrices (possibly incorporating prior knowledge). Simulation results confirm that the DR-RPE algorithms do not exhibit numerical problems, and as a consequence produce more accurate estimates of the room impulse response and of the auxiliary variables.

1. INTRODUCTION

Recently, recursive prediction error (RPE) identification algorithms have been proposed as robust and efficient solutions to such problems as adaptive feedback cancellation (AFC) [1], [2] and acoustic echo cancellation (AEC) [3]. In these applications, the cancellation of interfering feedback or echo signals is based on the identification of an unknown room impulse response (RIR), see Fig. 1. Since both the AFC and AEC problems can be described by a linear data model,

$$y(t) = F(q,t)u(t) + v(t), \tag{1}$$

with the finite-order and possibly time-varying RIR defined as

$$F(q,t) = f_0(t) + f_1(t)q^{-1} + \ldots + f_{n_F}(t)q^{-n_F} \tag{2}$$

and q denoting the time shift operator, i.e., $q^{-k}u(t) = u(t-k)$, they have traditionally been solved using least-squares(LS)-based adaptive filtering algorithms such as the recursive least squares (RLS), normalized least mean squares (NLMS), and affine projection algorithm (APA). However, due to the non-whiteness of the near-end signal $v(t)$, which is a disturbing signal w.r.t. the RIR identification, the LS-based algorithms are suboptimal and perform poorly, especially in the stochastic gradient (NLMS) case [3]. In the AFC application, the non-whiteness of $v(t)$ moreover produces a bias in the solution of LS-based identification algorithms, which is due to the correlation between the signals $u(t)$ and $v(t)$ in the closed-loop system [1].

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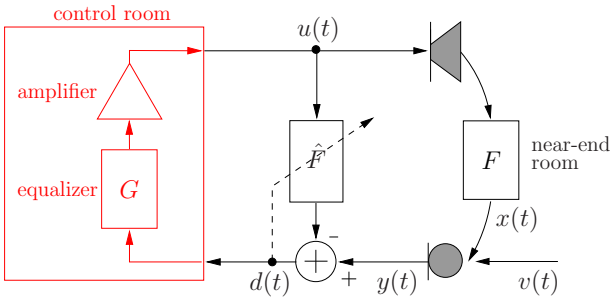


Figure 1: The black part of the figure depicts a typical acoustic echo cancellation (AEC) scenario. Taking also into account the red part of the figure, turns the AEC problem into an adaptive feedback cancellation (AFC) problem.

This is where recursive prediction error (RPE) identification algorithms outperform the traditional adaptive filtering algorithms. By including a time-varying autoregressive (TVAR) model for the near-end signal in the linear data model of (1),

$$y(t) = F(q,t)u(t) + \frac{1}{A(q,t)}e(t), \tag{3}$$

with

$$A(q,t) = 1 + a_1(t)q^{-1} + \ldots + a_{n_A}(t)q^{-n_A}, \tag{4}$$

one can obtain a transformed problem [by multiplying both sides of (3) with $A(q,t)$, and subsequently changing the order of the filters $A(q,t)$ and $F(q,t)$ in the cascade $A(q,t)F(q,t)$]

$$A(q,t)y(t) = F(q,t)A(q,t)u(t) + e(t), \tag{5}$$

which has a white disturbance signal $e(t)$ and transformed (i.e., prefiltered) input and output signals $A(q,t)u(t)$ and $A(q,t)y(t)$, respectively. Due to the whiteness of the disturbance, a LS-based algorithm applied to the transformed problem in (5) can yield an unbiased and optimal (mimimum-variance) RIR estimate [4]. It should however be pointed out that the TVAR polynomial $A(q,t)$ is also unknown and time-varying. The concept of RPE identification lies in the joint identification of the RIR and of the TVAR near-end signal model by recursively minimizing the sum of squared prediction errors,

$$\min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N}\sum_{k=1}^{t}\frac{\lambda^{t-k}}{\hat{\sigma}_k^2}\left\{\hat{A}(q,t)[y(k) - \hat{F}(q,t)u(k)]\right\}^2, \tag{6}$$

where $\hat{A}(q,t)$ and $\hat{F}(q,t)$ represent estimates of $A(q,t)$ and $F(q,t)$, respectively, and weighting is performed using the inverse predic-

tion error power $\hat{\sigma}_k^{-2}$ to account for energy variations in the disturbance $e(t)$ in the transformed data model (5), and using λ^{t-k} to discount old data with an exponential forgetting profile. The effective window length $N = 1/(1-\lambda)$ is then determined by the forgetting factor λ.

It has been observed that the RPE identification algorithm proposed in [3] performs very well in AFC and AEC computer simulations, yet sometimes runs into numerical problems. In this paper, we will reveal the origin of this numerical shortcoming and propose a theoretically well-founded solution. In Section 2, we will show that the RPE algorithm exhibits a so-called scaling ambiguity, in that it may theoretically produce the correct RIR estimate, even when the TVAR coefficients and some of the other auxiliary variables are scaled with an arbitrary scaling factor (that is significantly larger than the inverse of the norm of the estimated TVAR coefficients). Since the auxiliary variables are not of direct interest to the user, this should not be a problem, unless the scaling becomes so large that numerical overflow occurs. In some simulation scenarios such numerical overflow has indeed been observed.

Hence, even if the TVAR coefficients are not of direct interest, we may benefit by improving their identification, since then numerical problems will be avoided and the resulting RIR estimate will have a higher numerical accuracy. In Section 3, we will indicate how the accuracy of the estimated TVAR coefficients can be increased using regularization. To distinguish between the regularization of the estimated TVAR coefficients and the regularization of the estimated RIR coefficients, we will use the term "dual regularization" to denote the former, and "primal regularization" for the latter. We will apply both the Tikhonov and Levenberg-Marquardt regularization methods to the dual regularization problem, with a regularization matrix that may incorporate prior knowledge on the true TVAR coefficients [5]. We will see how such prior knowledge can be constructed for near-end speech signals. The performance of the Dually Regularized RPE (DR-RPE) algorithms is then illustrated using results from computer simulations in Section 4, and finally Section 5 concludes the paper.

2. SCALING AMBIGUITY IN THE RPE ALGORITHM

For convenience, the RPE algorithm with stochastic gradient RIR weight update as proposed in [3], is reproduced in Table 1. The parameter vectors and data matrices are defined as:

$$\theta(t) \triangleq \begin{bmatrix} \mathbf{f}(t) \\ \mathbf{a}(t) \end{bmatrix}_{(n_F+n_A+1)\times 1}, \tag{7}$$

$$\mathbf{f}(t) \triangleq [f_0(t) \quad f_1(t) \quad \dots \quad f_{n_F}(t)]^T_{(n_F+1)\times 1}, \tag{8}$$

$$\mathbf{a}(t) \triangleq [a_1(t) \quad a_2(t) \quad \dots \quad a_{n_A}(t)]^T_{n_A\times 1}, \tag{9}$$

$$\mathbf{y}(t) \triangleq [y(t-1) \quad \dots \quad y(t-n_A)]^T_{n_A\times 1}, \tag{10}$$

$$\mathbf{u}(t) \triangleq [u(t) \quad \dots \quad u(t-n_F)]^T_{(n_F+1)\times 1}, \tag{11}$$

$$\mathbf{U}(t) \triangleq \begin{bmatrix} u(t-1) & \dots & u(t-n_A) \\ \vdots & \ddots & \vdots \\ u(t-n_F-1) & \dots & u(t-n_F-n_A) \end{bmatrix}_{(n_F+1)\times n_A} \tag{12}$$

The TVAR coefficient vector $\mathbf{a}(t)$ and the prediction error variance σ_t^2 are estimated on an exponential data window with a forgetting factor λ_A, chosen such that the effective data window length equals approximately 20 ms (which is the average time interval on which a speech signal can be considered stationary). The stochastic gradient RIR weight update features a step size μ_F.

The scaling ambiguity is explained as follows: if the auxiliary variables $\hat{\mathbf{a}}(t)$, $\hat{\mathbf{a}}(t-1)$, $\hat{\sigma}_t^2$, $\hat{\sigma}_{t-1}^2$, $\psi_F[t,\hat{\mathbf{a}}(t-1)]$, $\varepsilon[t,\hat{\theta}(t-1)]$, $\mathbf{R}_A(t)$, and $\mathbf{R}_A(t-1)$, are replaced by their scaled counterparts $K\hat{\mathbf{a}}(t)$, $K\hat{\mathbf{a}}(t-1)$, $K^2\hat{\sigma}_t^2$, $K^2\hat{\sigma}_{t-1}^2$, $K\psi_F[t,\hat{\mathbf{a}}(t-1)]$, $K\varepsilon[t,\hat{\theta}(t-1)]$, $K^{-2}\mathbf{R}_A(t)$, and $K^{-2}\mathbf{R}_A(t-1)$, respectively, then the RPE algorithm will produce the same solution $\hat{\mathbf{f}}(t)$ as in the case without scaling, provided that $K >> \|\hat{\mathbf{a}}(t-1)\|_2^{-1}$. For such large scaling factors, the unit coefficient preceding the estimated TVAR coefficients in the calculation of $\varepsilon[t,\hat{\theta}(t-1)]$ and $\psi_F[t,\hat{\mathbf{a}}(t-1)]$ becomes negligible as compared to $K\hat{\mathbf{a}}(t-1)$, and as a consequence, the prediction error filter $\hat{A}(q,t-1)$ approximately has a zero at infinity,

$$\begin{aligned}\hat{A}(q,t-1) &= 1 + K\hat{a}_1(t-1)q^{-1} + \dots + K\hat{a}_{n_A}(t-1)q^{-n_A}, \\ &\approx Kq^{-1}[\hat{a}_1(t-1) + \dots + \hat{a}_{n_A}(t-1)q^{-n_A+1}].\end{aligned}$$

In computer simulations using the RPE algorithm, it appears that starting at some iteration, and without any outliers occuring in the data, the aforementioned auxiliary variables undergo an exponentially increasing scaling. This is illustrated in Fig. 2, where the norm of the TVAR coefficients $20\log_{10}\|\hat{\mathbf{a}}(t)\|_2$ and the prediction error power $10\log_{10}\hat{\sigma}_t^2$ are drawn on a dB-scale, as a function of the number of RPE iterations. In some simulations, the numerical divergence of the auxiliary variables is hardly visible in the convergence curves of the RIR estimate until overflow occurs (see, e.g., [3, Fig. 4(c)]), yet in other simulations, it is clear that even before numerical overflow occurs, the accuracy of the RIR estimate is already severely affected by the numerical problems in the auxiliary variable estimation (see Fig. 4).

Table 1: Stochastic gradient RPE algorithm [3]

Prediction error:

$$\varepsilon[t,\hat{\theta}(t-1)] = \begin{bmatrix}1 & \hat{\mathbf{a}}^T(t-1)\end{bmatrix}\left(\begin{bmatrix}y(t)\\ \mathbf{y}(t)\end{bmatrix} - \begin{bmatrix}\mathbf{u}^T(t)\\ \mathbf{U}^T(t)\end{bmatrix}\hat{\mathbf{f}}(t-1)\right)$$

Prediction error variance:

$$\hat{\sigma}_t^2 = \lambda_A\hat{\sigma}_{t-1}^2 + (1-\lambda_A)\varepsilon^2[t,\hat{\theta}(t-1)]$$

Regression vectors:

$$\psi_F[t,\hat{\mathbf{a}}(t-1)] = [\mathbf{u}(t) \quad \mathbf{U}(t)]\begin{bmatrix}1\\ \hat{\mathbf{a}}(t-1)\end{bmatrix}$$

$$\psi_A[t,\hat{\mathbf{f}}(t-1)] = \mathbf{U}^T(t)\hat{\mathbf{f}}(t-1) - \mathbf{y}(t)$$

TVAR regression vector correlation matrix update:

$$\mathbf{R}_A(t) = \lambda_A\mathbf{R}_A(t-1) + \frac{1}{\hat{\sigma}_t^2}\psi_A[t,\hat{\mathbf{f}}(t-1)]\psi_A^T[t,\hat{\mathbf{f}}(t-1)]$$

TVAR and RIR weight updates:

$$\hat{\mathbf{a}}(t) = \hat{\mathbf{a}}(t-1) + \frac{1}{\hat{\sigma}_t^2}\mathbf{R}_A^{-1}(t)\psi_A[t,\hat{\mathbf{f}}(t-1)]\varepsilon[t,\hat{\theta}(t-1)]$$

$$\hat{\mathbf{f}}(t) = \hat{\mathbf{f}}(t-1) + \mu_F\frac{\psi_F[t,\hat{\mathbf{a}}(t-1)]\varepsilon[t,\hat{\theta}(t-1)]}{\psi_F^T[t,\hat{\mathbf{a}}(t-1)]\psi_F[t,\hat{\mathbf{a}}(t-1)] + \hat{\sigma}_t^2}$$

3. DUAL REGULARIZATION

A simple and intuitive solution to prevent the TVAR coefficients from diverging as in the above example, is to include a minimum-norm constraint into the prediction error criterion (6), i.e.,

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

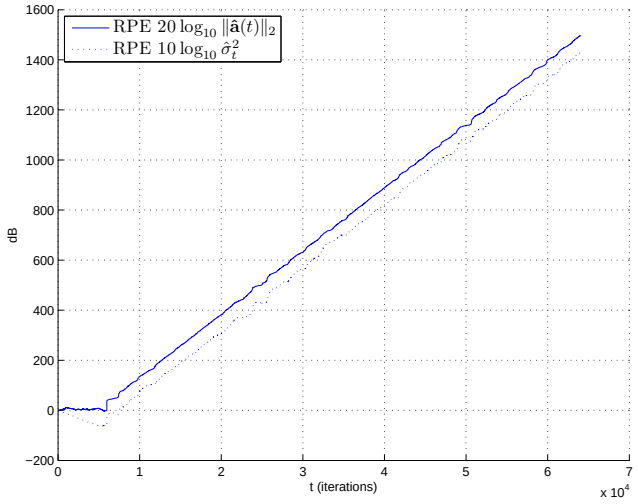


Figure 2: RPE scaling problem: from $t \approx 6000$ iterations, the auxiliary variables start growing at an exponential rate.

which corresponds to performing a Tikhonov regularization with regularization parameter β. We will denote the TVAR coefficients' regularization as "dual regularization", for pointing out the difference with the ("primal") RIR coefficients' regularization. A more thorough regularization approach would be to perform a "generalized" type of regularization, by considering the true TVAR coefficient vectors $\mathbf{a}(k), k = 1, \ldots, t$ as different realizations of the same stochastic variable $\mathbf{a}$ on which some prior knowlegde may be available through its mean and covariance matrix, i.e.,

$$\begin{cases} E\{\mathbf{a}\} \triangleq \mathbf{a_0}, & (13) \\ \text{cov}\{\mathbf{a}\} = E\{(\mathbf{a}-\mathbf{a_0})(\mathbf{a}-\mathbf{a_0})^T\} \triangleq \mathbf{R_a}. & (14) \end{cases}$$

An optimal approach to the dual regularization problem can then be suggested in accordance with the optimal primal regularization approach in [5], and consists in minimizing

$$\min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N}\Bigg\{\sum_{k=1}^{t}\frac{\lambda^{t-k}}{\hat{\sigma}_k^2}\{\hat{A}(q,t)[y(k)-\hat{F}(q,t)u(k)]\}^2 + [\hat{\mathbf{a}}(t)-\mathbf{a_0}]^T\mathbf{R_a}^{-1}[\hat{\mathbf{a}}(t)-\mathbf{a_0}]\Bigg\}. \quad (15)$$

Finally, also adding a primal regularization term results in

$$\min_{\hat{\mathbf{f}}(t),\hat{\mathbf{a}}(t)} \frac{1}{2N}\Bigg\{\sum_{k=1}^{t}\frac{\lambda^{t-k}}{\hat{\sigma}_k^2}\{\hat{A}(q,t)[y(k)-\hat{F}(q,t)u(k)]\}^2 \quad (16)$$
$$+[\hat{\mathbf{f}}(t)-\mathbf{f_0}]^T\mathbf{R_f}^{-1}[\hat{\mathbf{f}}(t)-\mathbf{f_0}]+[\hat{\mathbf{a}}(t)-\mathbf{a_0}]^T\mathbf{R_a}^{-1}[\hat{\mathbf{a}}(t)-\mathbf{a_0}]\Bigg\},$$

where the true RIR $\mathbf{f}(t)$ is considered to be a realization of the stochastic variable $\mathbf{f}$, with mean and covariance matrix

$$\begin{cases} E\{\mathbf{f}\} \triangleq \mathbf{f_0}, & (17) \\ \text{cov}\{\mathbf{f}\} = E\{(\mathbf{f}-\mathbf{f_0})(\mathbf{f}-\mathbf{f_0})^T\} \triangleq \mathbf{R_f}. & (18) \end{cases}$$

Minimizing (16) w.r.t. $\hat{\mathbf{f}}(t)$ and $\hat{\mathbf{a}}(t)$ results in the so-called Dually Regularized Recursive Prediction Error (DR-RPE) identification algorithm, shown in Table 2. It should be noted that the user has the choice of using either the Tikhonov regularized TVAR weight update (corresponding to $\mathbf{a_0} = \mathbf{0}$), or the Levenberg-Marquardt regularized TVAR weight update (corresponding to $\mathbf{a_0} = \hat{\mathbf{a}}(t-1)$). As for the stochastic gradient RIR weight update, the Levenberg-Marquardt regularization (corresponding to $\mathbf{f_0} = \hat{\mathbf{f}}(t-1)$) is the only relevant choice [5].

Table 2: Dually Regularized RPE (DR-RPE) algorithm

Prediction error:

$$\varepsilon[t,\hat{\theta}(t-1)] = \begin{bmatrix}1 & \hat{\mathbf{a}}^T(t-1)\end{bmatrix}\left(\begin{bmatrix}y(t)\\ \mathbf{y}(t)\end{bmatrix} - \begin{bmatrix}\mathbf{u}^T(t)\\ \mathbf{U}^T(t)\end{bmatrix}\hat{\mathbf{f}}(t-1)\right)$$

Prediction error variance:

$$\hat{\sigma}_t^2 = \lambda_A\hat{\sigma}_{t-1}^2 + (1-\lambda_A)\varepsilon^2[t,\hat{\theta}(t-1)]$$

Regression vectors:

$$\psi_F[t,\hat{\mathbf{a}}(t-1)] = [\mathbf{u}(t) \quad \mathbf{U}(t)]\begin{bmatrix}1\\ \hat{\mathbf{a}}(t-1)\end{bmatrix}$$
$$\psi_A[t,\hat{\mathbf{f}}(t-1)] = \mathbf{U}^T(t)\hat{\mathbf{f}}(t-1) - \mathbf{y}(t)$$

Regularized TVAR regression vector correlation matrix update [dual]:

$$\mathbf{R}_A(t) = \lambda_A\mathbf{R}_A(t-1) + \frac{1}{\hat{\sigma}_t^2}\psi_A[t,\hat{\mathbf{f}}(t-1)]\psi_A^T[t,\hat{\mathbf{f}}(t-1)] + (1-\lambda_A)\mathbf{R_a}^{-1}$$

Tikhonov Regularized TVAR weight update [dual]:

$$\hat{\mathbf{a}}(t) = \hat{\mathbf{a}}(t-1) + \mathbf{R}_A^{-1}(t) \times\Big\{\frac{1}{\hat{\sigma}_t^2}\psi_A[t,\hat{\mathbf{f}}(t-1)]\varepsilon[t,\hat{\theta}(t-1)] - (1-\lambda_A)\mathbf{R_a}^{-1}\hat{\mathbf{a}}(t-1)\Big\}$$

Levenberg-Marquardt Regularized TVAR weight update [dual]:

$$\hat{\mathbf{a}}(t) = \hat{\mathbf{a}}(t-1) + \frac{1}{\hat{\sigma}_t^2}\mathbf{R}_A^{-1}(t)\psi_A[t,\hat{\mathbf{f}}(t-1)]\varepsilon[t,\hat{\theta}(t-1)]$$

Levenberg-Marquardt Regularized RIR weight update [primal]:

$$\hat{\mathbf{f}}(t) = \hat{\mathbf{f}}(t-1) + \mu_F\frac{\mathbf{R_f}\psi_F[t,\hat{\mathbf{a}}(t-1)]\varepsilon[t,\hat{\theta}(t-1)]}{\psi_F^T[t,\hat{\mathbf{a}}(t-1)]\mathbf{R_f}\psi_F[t,\hat{\mathbf{a}}(t-1)]+\hat{\sigma}_t^2}$$

4. SIMULATION RESULTS

Computer simulations were carried out to compare the performance of the unregularized RPE algorithm with the performance of the proposed DR-RPE algorithm for different choices of the regularization matrix $\mathbf{R_a}$, and for both Tikhonov (TR) and Levenberg-Marquardt (LMR) regularization methods. Since the focus of this paper is on the dual regularization, the primal regularization matrix is set to $\mathbf{R_f} = \mathbf{I}$. A first choice for the dual regularization matrix is $\mathbf{R_a} = \mathbf{I}$, which yields a traditional (identity matrix) Tikhonov or Levenberg-Marquardt regularization. A second choice for $\mathbf{R_a}$ allows for incorporating prior knowledge on speech signal characteristics. To this end, we have identified a TVAR model on 310929 different 20 ms speech frames read from the TIMIT database [6], and ensemble-averaged the TVAR coefficient vector outer product to obtain

$$\hat{\mathbf{R}}_{\mathbf{a},s} = E\{\hat{\mathbf{a}}_i\hat{\mathbf{a}}_i^T\}, \quad i = 1,\ldots,310929. \quad (19)$$

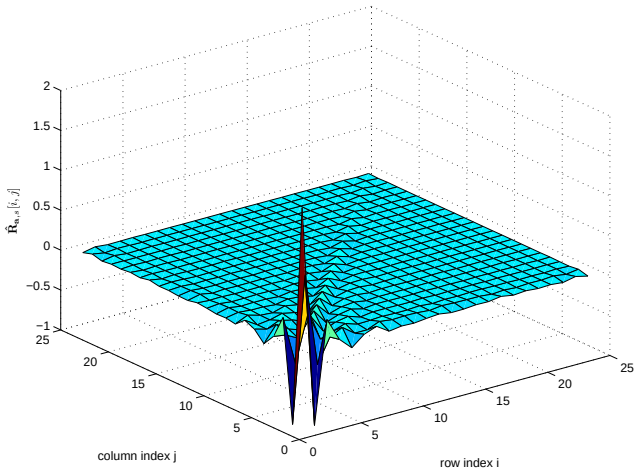


Figure 3: 3D surface plot of regularization matrix $\hat{\mathbf{R}}_{\mathbf{a},s}$.

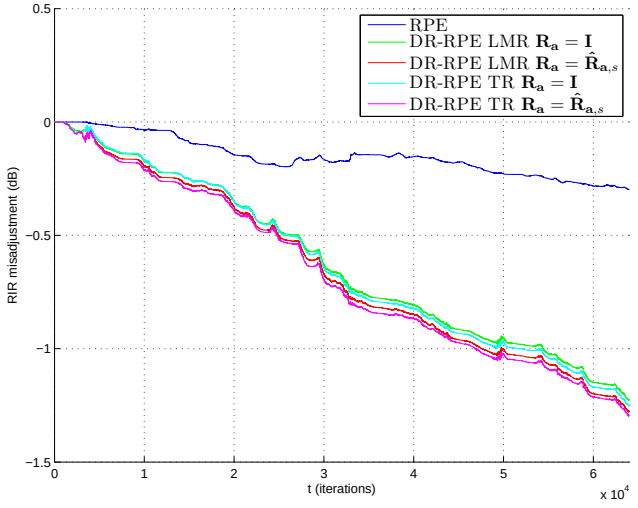


Figure 4: RIR misadjustment convergence curves for speech simulation.

A 3D surface plot of the resulting regularization matrix $\hat{\mathbf{R}}_{\mathbf{a},s}$ is shown in Fig. 3.

The algorithms were tested in an adaptive feedback cancellation (AFC) scenario at a sampling frequency of 16 kHz. Referring to Fig. 1, the amplifier is modelled as a broadband gain L cascaded with a saturation function, and the equalizer is a pure time delay, i.e., $G(q) = q^{-d}$, needed for identifiability of $\mathbf{f}(t)$ and $\mathbf{a}(t)$ [1]. The closed-loop system is kept at an average gain margin of 3 dB, by setting $L = -9$ dB and $d = 320$ samples. The near-end signal is a 4 s male speech signal (not from the TIMIT database), while the true RIR is measured in a typical recording studio and is of known order $n_F = 2000$. The TVAR model order is chosen as $n_A = 24$, the forgetting factor for estimating the TVAR coefficients and the prediction error variance is set to $\lambda_A = 0.9971$, and the step size is optimized for each of the algorithms, resulting in $\mu_F = 10^{-3}$ for the unregularized RPE algorithm and $\mu_F = 10^{-2}$ for the DR-RPE algorithms.

The convergence of the RIR estimate is depicted in Fig. 4 by plotting the so-called RIR misadjustment, defined as

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

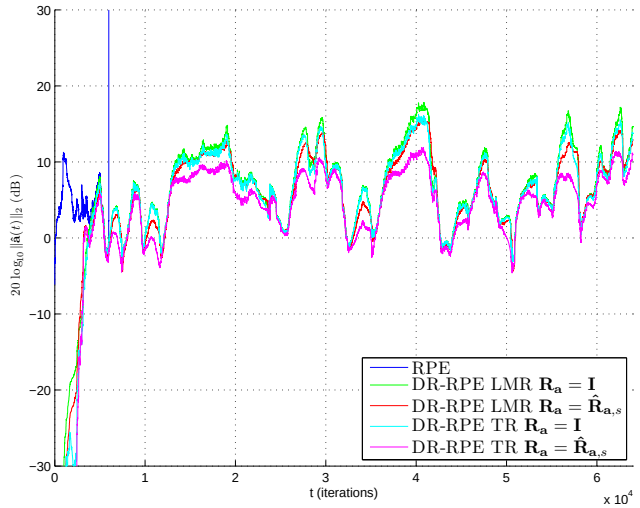


Figure 5: Estimated TVAR coefficient norm for speech simulation.

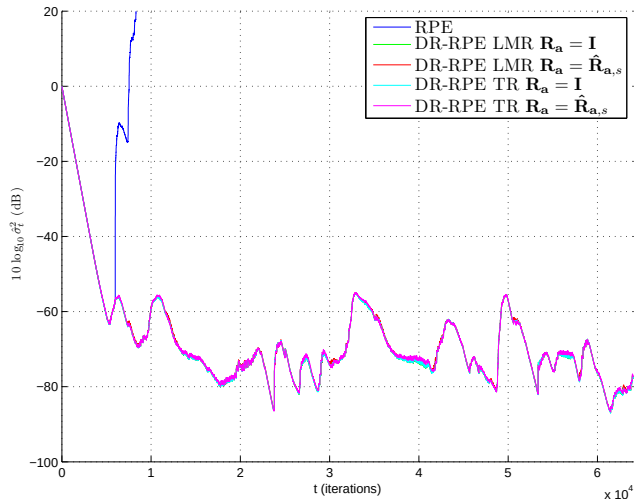


Figure 6: Estimated prediction error power for speech simulation.

It can be seen that the accuracy of the RIR estimate is indeed improved by adding a dual regularization to the RPE algorithm. The impact of the different choices for the regularization matrices and methods on the RIR estimate convergence seems to be negligible. The norm $20\log_{10}\|\hat{\mathbf{a}}(t)\|_2$ of the estimated TVAR coefficients and the estimated prediction error power $10\log_{10}\hat{\sigma}_t^2$ are plotted in Figs. 5 and 6, respectively. It is clear that these auxiliary variables do not diverge in the DR-RPE algorithms, as they do in the unregularized RPE algorithm. Moreover, it can be seen from Fig. 5 that the norm of the estimated TVAR coefficients is somewhat smaller in case $\mathbf{R}_\mathbf{a} = \hat{\mathbf{R}}_{\mathbf{a},s}$, especially using the Tikhonov regularization method.

In a final simulation, the accuracy of the estimated TVAR coefficients is compared for the different DR-RPE regularization matrices and methods. To this end, the near-end signal is a 60 s synthetic TVAR sequence, generated by passing a Gaussian white noise signal through a time-varying all-pole filter of order $n_A = 24$. The coefficients of this filter change every 20 ms and were computed by linear prediction of 20 ms true speech frames. The quality of the estimated TVAR coefficients can be compared by evaluating the

Table 3: Time-averaged TVAR misadjustment for synthetic speech simulation of DR-RPE algorithms

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

time-averaged TVAR misadjustment, defined as

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

with $M = 960\cdot 10^3$ and $\mathbf{a}(k)$ the corresponding all-pole filter coefficients used to generate the synthetic TVAR sequence. The time-averaged TVAR misadjustment is compared for the four different DR-RPE algorithms in Table 3. It can be seen that it is advantageous to use the Tikhonov regularization instead of the Levenberg-Marquardt regularization, and to use a regularization matrix incorporating prior knowledge, such as the proposed matrix $\hat{\mathbf{R}}_{\mathbf{a},s}$.

5. CONCLUSION

In this paper, we have highlighted a numerical problem in a recently proposed RPE identification algorithm, which seems to be due to an inherent scaling ambiguity. We have proposed to solve the problem using a so-called "dual regularization" approach, which may be combined with a primal regularization method to obtain a class of Dually Regularized Recursive Prediction Error (DR-RPE) identification algorithms. User's choices within the DR-RPE class include the regularization method used (Tikhonov or Levenberg-Marquardt) and the type of regularization matrix used. A first observation from computer simulations is that using the dual regularization, the aforementioned numerical problem does not occur anymore. As a consequence, a more accurate RIR estimate may be obtained. A second observation is that using a regularization matrix that incorporates prior knowlegde on the TVAR coefficients, results in a more accurate TVAR coefficient estimate. Moreover, the Tikhonov regularization method is preferred over the Levenberg-Marquardt method.

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