Non-intrusive Regularization for Least-Squares Multichannel Equalization for Speech Dereverberation

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***Abstract*—Acoustic multichannel equalization techniques for speech dereverberation are known to be highly sensitive to estimation errors of the room impulse responses. In order to increase robustness, it has been proposed to incorporate regularization. However, the optimal regularization parameter which yields the highest perceptual speech quality has generally been determined intrusively, limiting the practical applicability.**

In this paper, we propose an automatic non-intrusive procedure for determining the regularization parameter based on the L-curve. Experimental results show that using such an automatic non-intrusive regularization parameter in a recently proposed partial multichannel equalization technique (P-MINT) leads to a very similar performance as using the intrusively determined optimal regularization parameter. Furthermore, it is shown that the automatically regularized P-MINT technique outperforms state-of-the-art multichannel equalization techniques such as channel shortening and relaxed multichannel least-squares, both in terms of reverberant tail suppression and perceptual speech quality.

I. Introduction

In many hands-free communication applications the recorded microphone signals are often corrupted by reverberation, typically leading to decreased speech intelligibility and performance deterioration in automatic speech recognition systems. In order to mitigate these detrimental effects of reverberation, several dereverberation approaches have been investigated in the past [1]. One particular class of speech dereverberation approaches is acoustic multichannel equalization [2], [5], which aims to reshape the estimated room impulse responses (RIRs) between the source and the microphone array.

A widely known multichannel equalization technique that aims at complete equalization is the multiple input/output inverse theorem (MINT) [2], which however suffers from several drawbacks in practice. Since the estimated RIRs typically differ from the true RIRs (e.g., due to the sensitivity of blind system identification methods to interfering noise [6]), MINT fails to equalize the true RIRs, possibly leading to severe distortions in the output signal. In an attempt to increase the robustness to estimation errors by relaxing the constraints on the filter design, partial multichannel equalization techniques such as channel shortening (CS) [3] and relaxed multichannel least-squares (RMCLS) [4] have been proposed. Since early reflections tend to improve speech intelligibility and late reverberation is the main cause of speech quality degradation, the objective of such techniques is to shorten the RIR by suppressing only the reverberant tail. However, by not imposing any constraints on the remaining early reflections of the shortened RIR, CS and RMCLS may lead to undesired perceptual effects.

In order to directly control the perceptual speech quality, a partial multichannel equalization technique based on MINT (P-MINT) has recently been proposed [5]. To further increase its robustness, regularization has been incorporated. However, in order to determine the optimal regularization parameter which yields the highest perceptual speech quality, an intrusive procedure requiring knowledge of the true RIRs has been typically used, limiting the practical applicability of the regularized P-MINT technique.

In this paper, we propose and extensively investigate an automatic non-intrusive procedure for determining the regularization parameter based on the L-curve [7]. Using simulations with a realistic acoustic system for several RIR estimation errors, it is shown that the non-intrusively determined regularization parameter yields a nearly optimal perceptual speech quality, making regularized P-MINT a robust, perceptually advantageous, and practically applicable multichannel equalization technique for speech dereverberation.

II. Acoustic Multichannel Equalization

Fig. 1 depicts an acoustic system with a single source and M microphones. The m-th microphone signal at time index n is given by $x_m(n) = h_m(n) * s(n),\ m = 1,\ \ldots,\ M$, where $*$ denotes convolution, $s(n)$ is the clean speech signal, and $h_m(n)$ denotes the RIR between the source and the m-th microphone, which can be described in vector notation as

$$\mathbf{h}_m = [h_m(0)\ h_m(1)\ \ldots\ h_m(L_h-1)]^T, \tag{1}$$

with L_h being the RIR length and $[\cdot]^T$ denoting the transpose operation. Given reshaping filters $g_m(n)$ of length L_g, i.e.

$$\mathbf{g}_m = [g_m(0)\ g_m(1)\ \ldots\ g_m(L_g-1)]^T, \tag{2}$$

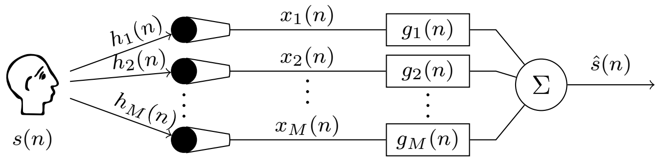


Fig. 1. Multichannel equalization system

the output signal $\hat{s}(n)$ of the multichannel equalization system is given by the sum of the filtered microphone signals, i.e.

$$\hat{s}(n) = \sum_{m=1}^{M} x_m(n) * g_m(n) = s(n) * \underbrace{\sum_{m=1}^{M} h_m(n) * g_m(n)}_{c(n)}, \quad (3)$$

where $c(n)$ is the equalized impulse response (EIR) between the source and the output of the system, which can be described in vector notation as $\mathbf{c} = [c(0)\ c(1)\ \ldots\ c(L_c-1)]^T$, with $L_c = L_h + L_g - 1$ being its length. Using the ML_g–dimensional stacked filter vector $\mathbf{g}$ and the $L_c \times ML_g$–dimensional multichannel convolution matrix $\mathbf{H}$, i.e.

$$\mathbf{g} = \left[\mathbf{g}_1^T\ \mathbf{g}_2^T\ \ldots\ \mathbf{g}_M^T\right]^T \quad (4)$$

$$\mathbf{H} = \left[\mathbf{H}_1\ \mathbf{H}_2\ \ldots\ \mathbf{H}_M\right], \quad (5)$$

with $\mathbf{H}_m$ the $L_c \times L_g$–dimensional convolution matrix of $\mathbf{h}_m$, the EIR can be expressed as

$$\boxed{\mathbf{c} = \mathbf{H}\mathbf{g}} \quad (6)$$

The reshaping filter $\mathbf{g}$ can then be constructed based on different design objectives for the EIR $\mathbf{c}$. Since the true RIRs are however typically not available in practice, acoustic multichannel equalization techniques described in the following, design the reshaping filter $\mathbf{g}$ using the estimated multichannel convolution matrix $\hat{\mathbf{H}}$ constructed from the estimated RIRs $\hat{h}_m(n)$.

MINT. The multiple-input/output inverse theorem [2] aims to exactly invert the acoustic system up to a delay τ by designing the filter $\mathbf{g}$ such that $\hat{\mathbf{H}}\mathbf{g} = \mathbf{d}$, where $\mathbf{d}$ is the desired EIR defined as a delayed impulse, i.e.

$$\mathbf{d} = [\underbrace{0\ \ldots\ 0}_{\tau}\ 1\ 0\ \ldots\ 0]^T. \quad (7)$$

The inverse filter is then computed by minimizing the least-squares cost function

$$\boxed{J_{\text{MINT}}(\mathbf{g}) = \|\hat{\mathbf{H}}\mathbf{g} - \mathbf{d}\|_2^2} \quad (8)$$

It has been shown in [2] that when the RIRs do not share any common zeros and when $L_g \geq \lceil \frac{L_h-1}{M-1} \rceil$, the filter that inverts the multichannel acoustic system can be computed as

$$\boxed{\mathbf{g}_{\text{MINT}} = \hat{\mathbf{H}}^{+}\mathbf{d}} \quad (9)$$

with $\{\cdot\}^+$ denoting the Moore-Penrose pseudo-inverse. Since the estimated convolution matrix $\hat{\mathbf{H}}$ is assumed to be a full row-rank matrix [8], its pseudo-inverse can be computed as $\hat{\mathbf{H}}^+ = \hat{\mathbf{H}}^T(\hat{\mathbf{H}}\hat{\mathbf{H}}^T)^{-1}$. When the RIRs are perfectly estimated, MINT achieves perfect equalization. However, when the estimated RIRs differ from the true RIRs, the resulting EIR $\mathbf{c} = \mathbf{H}\hat{\mathbf{H}}^+\mathbf{d}$ not only differs from the desired response $\mathbf{d}$, but usually causes large distortions in the output signal.

Whereas MINT is very sensitive to estimation errors, experimental investigations in [4], [5] have shown that techniques aiming only at partial equalization such as P-MINT, are significantly more robust.

P-MINT. The partial multichannel equalization technique based on MINT [5] aims at setting the reverberant tail of the EIR to 0, while still controlling the remaining taps corresponding to the direct path and early reflections. To accomplish this objective, the first part of one of the estimated RIRs is used as the desired EIR in (8), i.e.

$$\boxed{J_{\text{P-MINT}}(\mathbf{g}) = \|\hat{\mathbf{H}}\mathbf{g} - \hat{\mathbf{h}}_p^{\text{d}}\|_2^2} \quad (10)$$

where

$$\hat{\mathbf{h}}_p^{\text{d}} = [\underbrace{0\ldots0}_{\tau}\,\underbrace{\hat{h}_p(0)\ldots\hat{h}_p(L_d-1)}_{L_d}\,0\ldots0]^T, \quad (11)$$

with $p \in \{1, \ldots, M\}$ and L_d denoting the length in number of samples of the direct path and early reflections which is typically chosen to correspond to $L_s \in [50 \text{ ms } 80 \text{ ms}]$. The reshaping filter that partially equalizes the system can then be computed as

$$\boxed{\mathbf{g}_{\text{P-MINT}} = \hat{\mathbf{H}}^{+}\hat{\mathbf{h}}_p^{\text{d}}} \quad (12)$$

In order to further increase the robustness of P-MINT to estimation errors, a regularization term $\delta\|\mathbf{g}\|_2^2$, corresponding to the energy of the reshaping filter, is added to the P-MINT cost function in (10), i.e.

$$\boxed{J_{\text{P-MINT}}^{\text{R}}(\mathbf{g}) = \|\hat{\mathbf{H}}\mathbf{g} - \hat{\mathbf{h}}_p^{\text{d}}\|_2^2 + \delta\|\mathbf{g}\|_2^2} \quad (13)$$

with δ a regularization parameter controlling the weight given to the minimization of the filter energy. The regularized P-MINT filter minimizing (13) can be calculated as

$$\boxed{\mathbf{g}_{\text{P-MINT}}^{\text{R}} = (\hat{\mathbf{H}}^T\hat{\mathbf{H}} + \delta\mathbf{I})^{-1}\hat{\mathbf{H}}^T\hat{\mathbf{h}}_p^{\text{d}}} \quad (14)$$

where $\mathbf{I}$ is the $ML_g \times ML_g$–dimensional identity matrix.

Increasing the regularization parameter δ decreases the energy of the reshaping filter $\mathbf{g}$, increasing the robustness to RIR estimation errors. However, increasing this parameter also reduces the equalization performance with respect to the true RIRs, resulting in a trade-off between equalization performance for perfectly estimated RIRs and robustness in the presence of estimation errors.

III. Non-intrusive Selection of the Regularization Parameter

Obviously, different values of the regularization parameter δ lead to different performance. The optimal value δ_{opt} which yields the highest perceptual speech quality depends on the acoustic system to be equalized and the RIR estimation errors. While in simulations δ_{opt} can be intrusively determined exploiting the known true RIRs (cf. Section IV), an automatic non-intrusive procedure is required in practice.

Incorporating regularization in P-MINT introduces a trade-off between minimizing the residual energy $\|\hat{\mathbf{H}}\mathbf{g} - \hat{\mathbf{h}}_p^{\text{d}}\|_2^2$ and minimizing the filter energy $\|\mathbf{g}\|_2^2$ (cf. (13)). A good regularization parameter should hence incorporate knowledge about both the residual energy and the filter energy, such that both energies are kept small. In order to automatically compute a regularization parameter for regularized least-squares problems, it has been proposed in [7] to use a parametric plot of the filter norm versus the residual norm for several values of δ. This plot always has an L-shape with the corner (i.e. the point of maximum curvature) located exactly where the regularized least-squares solution changes in nature from being dominated by over-regularization to being dominated by under-regularization.

We therefore propose to non-intrusively determine the automatic regularization parameter δ_{auto} in the regularized P-MINT technique as the one corresponding to the corner of the parametric plot of the filter norm $\|\mathbf{g}^{\text{R}}_{\text{P-MINT}}\|_2$ versus the residual norm $\|\hat{\mathbf{H}}\mathbf{g}^{\text{R}}_{\text{P-MINT}} - \hat{\mathbf{h}}^{\text{d}}_p\|_2$. As will be experimentally validated in Section IV, such a regularization parameter also leads to a nearly optimal perceptual speech quality.

The L-curve can be generated by computing the reshaping filter $\mathbf{g}^{\text{R}}_{\text{P-MINT}}$ in (14) for several values of the regularization parameter δ and then calculating the required norms. However, in order to reduce the computational complexity, it is beneficial to generate the L-curve using the singular value decomposition (SVD) of the estimated convolution matrix $\hat{\mathbf{H}}$. Consider the SVD of $\hat{\mathbf{H}}$, i.e.

$$\hat{\mathbf{H}} = \hat{\mathbf{U}}\hat{\mathbf{S}}\hat{\mathbf{V}}^T, \tag{15}$$

where $\hat{\mathbf{U}}$ and $\hat{\mathbf{V}}$ are orthogonal matrices and $\hat{\mathbf{S}}$ is a diagonal matrix containing the singular values $\hat{\sigma}_n$ of $\hat{\mathbf{H}}$ in descending order, i.e. $\hat{\mathbf{S}} = \text{diag}\{[\hat{\sigma}_1 \; \hat{\sigma}_1 \; \ldots \; \hat{\sigma}_{L_c}]\}$. Using (14) and (15), the regularized P-MINT filter can be expressed as

$$\mathbf{g}^{\text{R}}_{\text{P-MINT}} = \sum_{n=1}^{L_c} \frac{\hat{\sigma}_n \hat{\mathbf{u}}_n^T \hat{\mathbf{h}}^{\text{d}}_p}{\hat{\sigma}_n^2 + \delta} \hat{\mathbf{v}}_n, \tag{16}$$

where $\hat{\mathbf{u}}_n$ and $\hat{\mathbf{v}}_n$ denote the n-th column of $\hat{\mathbf{U}}$ and $\hat{\mathbf{V}}$ respectively. Hence, for a given δ, the filter norm and the residual norm can be expressed in terms of the singular values/vectors as

$$\boxed{\|\mathbf{g}^{\text{R}}_{\text{P-MINT}}\|_2 = \sqrt{\sum_{n=1}^{L_c} \frac{\hat{\sigma}_n^2 (\hat{\mathbf{u}}_n^T \hat{\mathbf{h}}^{\text{d}}_p)^2}{(\hat{\sigma}_n^2 + \delta)^2}}} \tag{17}$$

$$\boxed{\|\hat{\mathbf{H}}\mathbf{g}^{\text{R}}_{\text{P-MINT}} - \hat{\mathbf{h}}^{\text{d}}_p\|_2 = \sqrt{\sum_{n=1}^{L_c} \frac{\delta^2 (\hat{\mathbf{u}}_n^T \hat{\mathbf{h}}^{\text{d}}_p)^2}{(\hat{\sigma}_n^2 + \delta)^2}}} \tag{18}$$

Therefore, once the SVD is computed, the L-curve can be readily generated using (17) and (18).

Fig. 2 depicts a typical L-curve obtained using regularized P-MINT for equalizing an estimated acoustic system (cf. Section IV). As illustrated in this figure, increasing the value of δ decreases the filter norm but at the same time increases the residual norm. Although from such a curve it seems easy to determine the regularization parameter that corresponds to the maximum curvature, numerical problems due to small singular values may occur and hence, a numerically stable algorithm is required. In this work, the triangle method [9] is used for locating the point of maximum curvature of the L-curve.

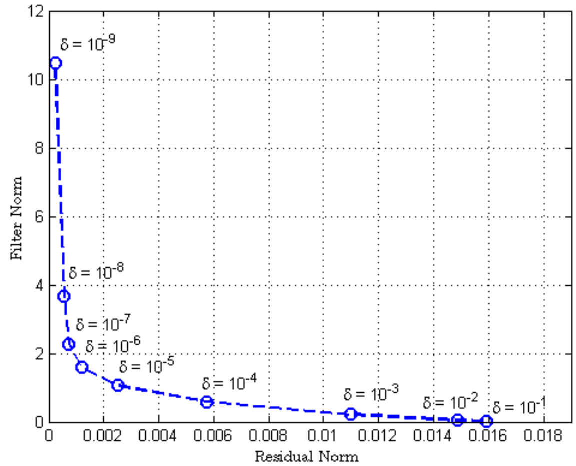


Fig. 2. Typical L-curve obtained using regularized P-MINT for an erroneously estimated acoustic system

IV. Experimental Results

We have considered an acoustic scenario with a single speech source and $M = 2$ microphones in a room with reverberation time $T_{60} \approx 600$ ms. The RIRs have been measured using the swept-sine technique with $L_h = 2000$ at a sampling frequency $f_s = 16$ kHz. In order to simulate estimation errors, the measured RIRs have been perturbed by adding scaled white noise as proposed in [10], i.e.

$$\hat{h}_m(n) = h_m(n)[1 + e(n)], \tag{19}$$

with $e(n)$ an uncorrelated Gaussian noise sequence with zero mean and an appropriate variance, such that a normalized channel mismatch E_m, defined as

$$E_m = 10 \log_{10} \frac{\|\mathbf{h}_m - \hat{\mathbf{h}}_m\|_2^2}{\|\mathbf{h}_m\|_2^2}, \tag{20}$$

is generated. The considered normalized channel mismatch values are

$$E_m \in \{-33 \text{ dB}, \; -30 \text{ dB}, \; -25 \text{ dB}, \; -20 \text{ dB}, \; -15 \text{ dB}\}. \tag{21}$$

The used simulation parameters are $L_g = 1999$, $\tau = 0$, and the desired EIR in regularized P-MINT is chosen as the direct path and early reflections of the estimated first RIR, i.e. $\hat{\mathbf{h}}^{\text{d}}_1$. Furthermore, 5 desired window lengths are investigated, i.e. $L_s \in \{10 \text{ ms}, \; 20 \text{ ms}, \; 30 \text{ ms}, \; 40 \text{ ms}, \; 50 \text{ ms}\}$.

The reverberant tail suppression is evaluated using the energy decay curve (EDC) of the true EIR $\mathbf{c} = \mathbf{Hg}$, which is defined as

$$\text{EDC}(n) = 10 \log_{10} \frac{1}{\|\mathbf{c}\|_2^2} \sum_{i=n}^{L_c - 1} c^2(i), \; n = 0, \ldots, L_c - 1. \tag{22}$$

The perceptual speech quality of the output signal $\hat{s}(n)$ is evaluated using the objective speech quality measure PESQ [11], where the reference signal employed in PESQ is $s(n) * h^{\text{d}}_1(n)$, i.e. the clean speech signal convolved with the

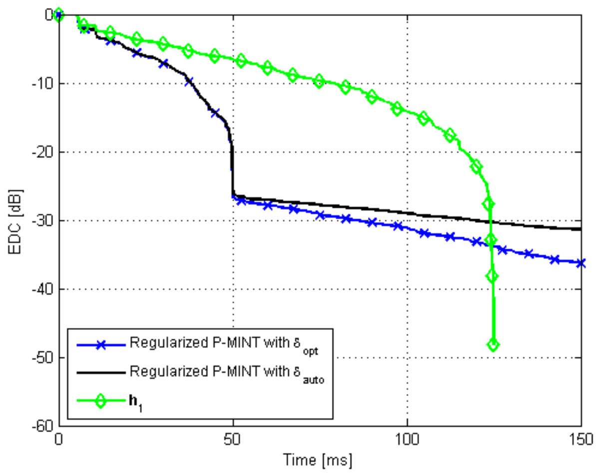


Fig. 3. EDC of the true RIR $\mathbf{h}_1$ and EDC of the EIR using regularized P-MINT with δ_{opt} and δ_{auto} ($E_m = -33$ dB, $L_s = 50$ ms)

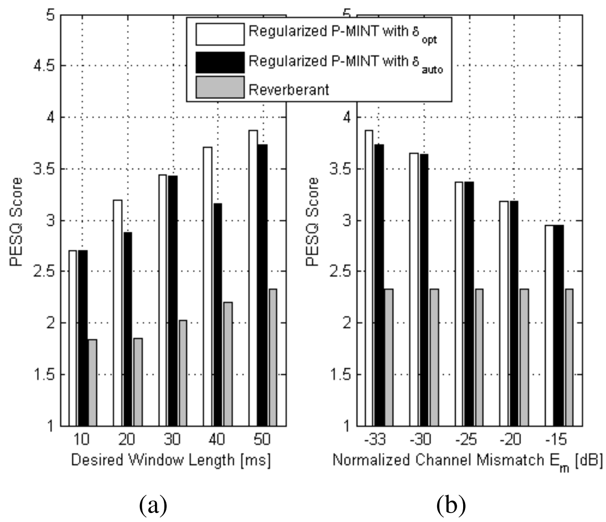


Fig. 4. PESQ score of the first microphone signal $x_1(n)$ and PESQ score of the system's output $\hat{s}(n)$ obtained using regularized P-MINT with δ_{opt} and δ_{auto} for (a) several desired window lengths ($E_m = -33$ dB) and (b) several normalized channel mismatches ($L_s = 50$ ms)

first part of the true first RIR. It has been shown in [12] that measures relying on auditory models such as PESQ exhibit the highest correlation with subjective listening tests when evaluating the quality of dereverberated speech.

For the regularized P-MINT technique, we have considered several regularization parameters, i.e.

$$\delta \in \{10^{-9},\ 10^{-8},\ \ldots,\ 10^{-1}\}. \tag{23}$$

The optimal regularization parameter δ_{opt} is selected as the one leading to the highest PESQ score. It should be noted that the computation of the PESQ score for selecting the optimal regularization parameter is an intrusive procedure that is not applicable in practice, since knowledge of the true RIRs is required in order to compute the reference signal $s(n) * h_1^{\text{d}}(n)$ and the true EIR $c(n) = \sum_{m=1}^{M} h_m(n) * g_m(n)$. Furthermore, the automatic regularization parameter δ_{auto} is determined as the one corresponding to the corner of the L-curve generated with the regularization parameters in (23).

The experiments presented in the following are structured into two parts. In the first experiment, the performance of the regularized P-MINT technique when using the automatic regularization parameter δ_{auto} is compared to the performance when using the optimal regularization parameter δ_{opt}. In the second experiment, the performance of the regularized P-MINT technique using the automatic regularization parameter δ_{auto} is compared to the performance of state-of-the-art multichannel equalization techniques such as CS and RMCLS.

Experiment 1. Fig. 3 depicts the obtained EDCs for $E_m = -33$ dB and $L_s = 50$ ms using regularized P-MINT with the optimal intrusive regularization parameter δ_{opt} and with the automatic non-intrusive regularization parameter δ_{auto}. As can be observed in this figure, the automatic regularization parameter δ_{auto} yields a very similar reverberant tail suppression as the optimal regularization parameter δ_{opt}. In order to compare the perceptual speech quality, Fig. 4 (a) depicts the PESQ score of the output signal $\hat{s}(n)$ obtained using regularized P-MINT with δ_{opt} and regularized P-MINT with δ_{auto} for $E_m = -33$ dB and several desired window lengths. As illustrated in this figure, the perceptual speech quality when using δ_{auto} is generally similar to the one obtained when using δ_{opt}, except for the desired window length $L_s = 40$ ms where the PESQ score is reduced by 0.5. However, the average PESQ score reduction over all desired window lengths is only 0.2, implying that as L_s changes as a design parameter, the automatic selection procedure for the regularization parameter still yields a good perceptual speech quality.

Since the optimal regularization parameter typically changes as the channel mismatch changes (larger estimation errors in the RIRs require larger regularization), it is important to evaluate the perceptual speech quality when the automatic regularization procedure is used for larger normalized channel mismatches. Fig. 4 (b) depicts the PESQ scores obtained using regularized P-MINT with δ_{opt} and regularized P-MINT with δ_{auto} for $L_s = 50$ ms and several normalized channel mismatches. It can be seen that using δ_{auto} yields a very similar perceptual speech quality as using δ_{opt}, with an insignificant average performance reduction over all considered E_m of 0.03.

Experiment 2. Fig. 5 depicts the EDCs obtained for $E_m = -33$ dB and $L_s = 50$ ms using MINT, CS, RMCLS, and regularized P-MINT with the automatic regularization parameter δ_{auto}. As illustrated in this figure, MINT fails to invert the acoustic system, leading to an EDC that is even higher than the one of the true RIR. Furthermore, also CS fails to reshape the channel, yielding an audible reverberant tail. On the other hand, the RMCLS and the automatically regularized P-MINT techniques are significantly more robust, with RMCLS yielding the highest reverberant tail suppression. However, since the EDC does not fully describe the quality of the processed speech, it is important to evaluate the perceptual quality that these techniques yield. Fig. 6 (a)

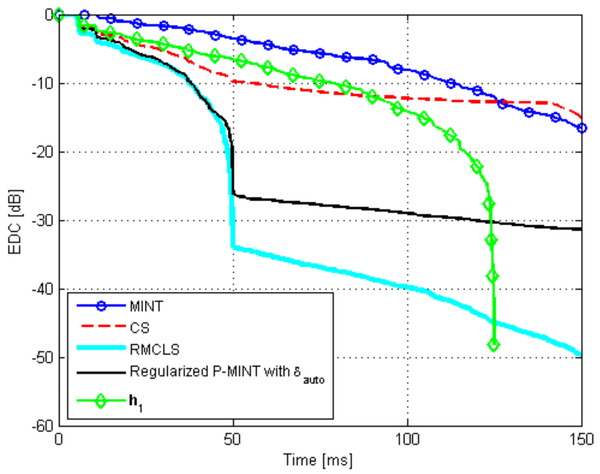
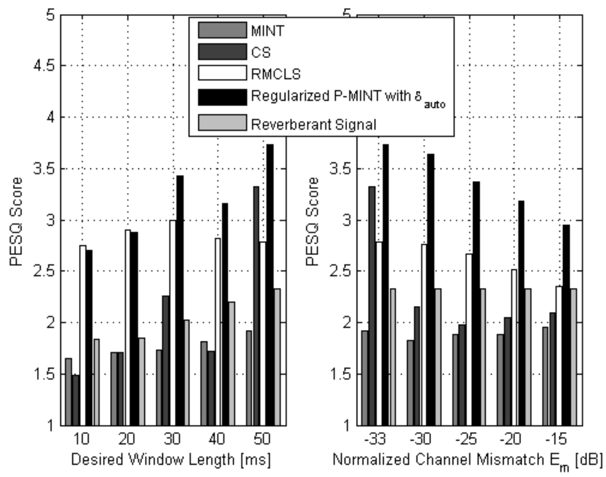


Fig. 5. EDC of the true RIR $\mathbf{h}_1$ and EDC of the EIR using MINT, CS, RMCLS, and regularized P-MINT with δ_{auto} ($E_m = -33$ dB, $L_d = 50$ ms)



(a) (b)

Fig. 6. PESQ score of the first microphone signal $x_1(n)$ and PESQ score of the system's output $\hat{s}(n)$ obtained using MINT, CS, RMCLS, and regularized P-MINT with δ_{auto} for (a) several desired window lengths ($E_m = -33$ dB) and (b) several normalized channel mismatches ($L_d = 50$ ms)

depicts the obtained PESQ scores for several desired window lengths and $E_m = -33$ dB. As illustrated in this figure, the regularized P-MINT approach using δ_{auto} outperforms MINT, CS, as well as RMCLS for $L_s \in \{30 \text{ ms}, 40 \text{ ms}, 50 \text{ ms}\}$, while a very similar performance as RMCLS is achieved for $L_s \in \{10 \text{ ms}, 20 \text{ ms}\}$. Furthermore, Fig. 6 (b) illustrates the obtained PESQ scores for $L_s = 50$ ms and several normalized channel mismatch values. It can be seen that the automatically regularized P-MINT technique yields a significantly higher perceptual speech quality than all other state-of-the-art techniques for all considered normalized channel mismatch values.

The results presented in these experiments show that the automatic non-intrusive procedure for determining the regularization parameter yields a nearly optimal perceptual speech quality in the regularized P-MINT technique. Furthermore, it is shown that the automatically regularized P-MINT technique always yields a similar or higher performance than other state-of-the-art multichannel equalization techniques.

V. Conclusion

In this paper we have presented an automatic non-intrusive procedure based on the L-curve for selecting the regularization parameter in regularized least-squares multichannel equalization techniques. The performance of this procedure has been extensively investigated and compared to the performance when the intrusively determined optimal regularization parameter is used for the regularized P-MINT technique. Simulation results show that using the non-intrusively determined regularization parameter yields a very similar performance as the optimal intrusive regularization parameter. Furthermore, it has been shown that the regularized P-MINT technique using the non-intrusively determined regularization parameter outperforms state-of-the-art techniques such as CS and RMCLS.

References

[1] P. A. Naylor and N. D. Gaubich, Eds., *Speech Dereverberation*. Springer, 2010.

[2] M. Miyoshi and Y. Kaneda, "Inverse Filtering of Room Acoustics," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 36, no. 2, pp. 145–152, Feb. 1988.

[3] M. Kallinger and A. Mertins, "Multi-channel Room Impulse Response Shaping - a Study," in *Proc. International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Toulouse, France, May 2006, pp. 101–104.

[4] W. Zhang, E. A. P. Habets, and P. A. Naylor, "On the Use of Channel Shortening in Multichannel Acoustic System Equalization," in *Proc. International Workshop on Acoustic Echo and Noise Control (IWAENC)*, Tel Aviv, Israel, Sep. 2010.

[5] I. Kodrasi and S. Doclo, "Robust Partial Multichannel Equalization Techniques for Speech Dereverberation," in *Proc. International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Kyoto, Japan, Mar. 2012, pp. 537–540.

[6] K. Hasan and P. A. Naylor, "Analyzing Effect of Noise on LMS-type Approaches to Blind Estimation of SIMO Channels: Robustness Issue," in *Proc. European Signal Processing Conference (EUSIPCO)*, Florence, Italy, Sep. 2006.

[7] P. C. Hansen and D. P. O'Leary, "The use of the L-curve in the regularization of discrete ill-posed problems," *SIAM Journal on Scientific Computing*, vol. 14, no. 6, pp. 1487–1503, Nov. 1993.

[8] G. Harikumar and Y. Bresler, "FIR Perfect Signal Reconstruction from Multiple Convolutions: Minimum Deconvolver Orders," *IEEE Transactions on Signal Processing*, vol. 46, no. 1, pp. 215–218, Jan. 1998.

[9] J. L. Castellanos, S. Gómez, and V. Guerra, "The triangle method for finding the corner of the L-curve," *Applied Numerical Mathematics*, vol. 43, no. 4, pp. 359–373, Dec. 2002.

[10] J. Cho, D. Morgan, and J. Benesty, "An Objective Technique for Evaluating Doubletalk Detectors in Acoustic Echo Cancelers," *IEEE Transactions on Speech and Audio Processing*, vol. 7, no. 6, pp. 718–724, Nov. 1999.

[11] ITU-T, *Perceptual Evaluation of Speech Quality (PESQ), an Objective Method for End-to-end Speech Quality Assessment of Narrowband Telephone Networks and Speech Codecs P.862*, Feb. 2001.

[12] S. Goetze, E. Albertin, J. Rennies, E. A. P. Habets, and K.-D. Kammeyer, "Speech quality assessment for listening-room compensation," in *AES 38th International Conference*, Pitea, Sweden, Jun 2010, pp. 11–20.