SINGLE-CHANNEL MAXIMUM-LIKELIHOOD T60 ESTIMATION EXPLOITING SUBBAND INFORMATION

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ABSTRACT
This contribution presents four algorithms developed by the authors for single-channel fullband and subband T60 estimation within the ACE challenge. The blind estimation of the fullband reverberation time (RT) by maximum-likelihood (ML) estimation based on [15] is considered as baseline approach. An improvement of this algorithm is devised where an energy-weighted averaging of the upper subband RT estimates is performed using either a DCT or 1/3-octave filter-bank. The evaluation results show that this approach leads to a lower variance for the estimation error in comparison to the baseline approach at the price of an increased computational complexity. Moreover, a new algorithm to estimate the subband RT is devised, where the RT estimates for the lower octave subbands are extrapolated from the RT estimates of the upper subbands by means of a simple model for the frequency-dependency of the subband RT. The evaluation results of the ACE challenge reveal that this approach allows to estimate the subband RT with an estimation error which is in a similar range as for the presented fullband RT estimators.

Index Terms— blind estimation, fullband reverberation time, subband reverberation time, ACE challenge, ML estimation

1. INTRODUCTION
The reverberation time (RT) $T_{60}$ is an important quantity to characterize the acoustical properties of an enclosure [1]. Furthermore, knowledge about the RT can be exploited for enhanced automatic speech recognition (ASR), e.g., [2][3], as well as speech dereverberation, e.g., [4][5][6][7]. For such applications, the RT can usually not be determined from a known room impulse response (RIR) [8], but has to be estimated blindly from a reverberant speech signal, which is frequently also distorted by noise. Especially the abovementioned applications have fueled the research interest in blind reverberation time estimation (RTE) and numerous methods were proposed in recent years [9][10][11][12][13][14][15][16][17][18][19][20]. The variety of concepts raises the desire for an objective comparison of different algorithms for $T_{60}$ estimation as published in [21]. A more comprehensive comparison of algorithms for RTE as well as direct-to-reverberant energy ratio (DRR) estimation is facilitated by the Acoustic Characterisation of Environments (ACE) challenge [22]. The participants had access to a development (Dev) database and an evaluation (Eval) database. The single-channel Dev database comprises 288 noisy and reverberant speech files for which the ground-truth of the fullband and subband RT, the signal-to-noise-ratio (SNR), as well as the DRR is provided to allow the participants to develop and tune their algorithms. The single-channel Eval database comprises 4500 speech files without ground-truth data for generating the submission results for the challenge.

This contribution provides a description of the four algorithms developed by the authors for the submission of their results for single-channel fullband and subband $T_{60}$ estimation.

All the presented algorithms for RTE employ a maximum-likelihood (ML) estimation. The use of an ML estimator for blind single-channel RTE was first presented in [9][10]. In [13], this concept is extended to estimate the RT from a noisy RIR and to estimate the RT blindly from a noisy and reverberant speech signal. A further development of this algorithm is presented in [15] to allow for a fast tracking of time-varying RTs with low complexity from noisy and reverberant speech signals. A slightly modified version of this algorithm for single-channel fullband $T_{60}$ estimation has been employed as baseline algorithm for the ACE challenge and is described in Sec.2. An improvement of this algorithm by averaging subband RT estimates has been developed, which is described in Sec.3. Moreover, results for the blind estimation of the subband RT have been submitted, and the algorithm devised for this is presented in Sec.4. The evaluation results of the ACE challenge are discussed in Sec.5 and the paper concludes with Sec.6.

2. BASELINE ALGORITHM
The baseline algorithm employed for fullband RTE is a slightly modified version of the algorithm presented in [15]. It is referred to as baseline algorithm since the Matlab code has been published on Matlab Central [23]. In contrast to [15], the fast tracking of time-varying RTs is omitted here to obtain more robust estimates.

2.1. Model for ML Estimation
It is assumed that the reverberant speech signal is obtained by a speech signal $s(k)$ convolved with a time-varying RIR $h(\eta, k)$ of length $L_h$:

$$z(k) = \sum_{\eta=0}^{L_h-1} s(k - \eta) \cdot h(\eta, k), \quad (1)$$

with $k$ denoting the discrete time index. If a speech pause begins

$$s(k - \eta) \begin{cases} \approx 0 & \text{for } \eta = 0, 1, \ldots, L_o - 1 \\ \ne 0 & \text{for } \eta = L_o, \ldots, L_h - 1 \end{cases}, \quad (2)$$
and the room reverberation causes a decaying signal \( d(k) \) since

\[
z(k) = \sum_{\eta=0}^{L_o-1} s(k - \eta) \cdot h(\eta, k) + \sum_{\eta=L_o}^{L_h-1} s(k - \eta) \cdot h(\eta, k),
\]

(3)

\[
\approx 0 = d(k)
\]

assuming that \( h(\eta, k) \neq 0 \) for at least one value \( L_o \leq \eta < L_h \).

The sound decay \( d(k) \) is modeled by a discrete random process

\[
d_m(k) = A_t v(k) e^{-\rho k T_e} \epsilon(k)
\]

(4)

with real amplitude \( A_t > 0 \), decay rate \( \rho \) and unit step sequence \( \epsilon(k) \). \( T_e = 1/f_s \) denotes the sampling period and \( v(k) \) is a sequence of i.i.d. random variables with normal distribution \( \mathcal{N}(0, 1) \). Eq. (4) can also be seen as a simple statistical model for the RIR, which considers only the effects of late reflections and models it as diffuse noise.

The energy decay curve for the corresponding continuous-time sound decay model is given by the expectation

\[
E_d(t) = E \left\{ \hat{d}_m(t) \right\} = A_t^2 e^{-2\rho t} \tilde{\epsilon}(t)
\]

(5)

where the tilde indicates the continuous-time counterparts to the discrete-time quantities of Eq. (4). A relation between decay rate \( \rho \) and reverberation time \( T_{60} \) can be established by the requirement

\[
10 \log_{10} \left( \frac{E_d(0)}{E_d(T_{60})} \right) = 60
\]

(6)

such that

\[
T_{60} = \frac{3}{\rho \log_{10}(\epsilon)} \approx \frac{6.908}{\rho}.
\]

(7)

Due to this relation, the terms decay rate and RT will be used interchangeably in the following.

According to the model given by Eq. (4), the signal value \( d(k) \) of Eq. (3) is represented by a random variable with Gaussian probability density function (PDF)

\[
p_d(x, k) = \frac{1}{\sqrt{2\pi\xi(k)}} \exp \left\{ -\frac{x^2}{2\xi(k)} \right\}
\]

(8)

\[
\xi(k) = A_t \alpha^k \epsilon(k)
\]

with \( \alpha = e^{-T_e \rho} \).

(9)

The sequence \( d(k) \) for \( k \in \{0, \ldots, N-1\} \) is then given by \( N \) independent, normally distributed random variables with zero mean and non-identical PDFs. This allows to derive an ML estimator for the unknown decay rate or RT, respectively, \( \rho^{(ML)} \), where the decay rate \( \rho \) is estimated from a given sound decay \( d(k) \) by finding the maximum

\[
\rho^{(ML)} = \arg \max_{\rho} \{ \mathcal{L}(\rho) \}
\]

(10a)

of the log-likelihood function

\[
\mathcal{L}(\rho) = \frac{N}{2} \left( (N-1) \ln(a) + \ln \left( \frac{2\pi}{N} \sum_{i=0}^{N-1} a^{-2i} d^2(i) \right) + 1 \right).
\]

(10b)

The corresponding estimate for the RT \( \tilde{T}_{60}^{(ML)} \) is given by Eq. (7).

### 2.2. Implementation

In a first step, a speech denoising is performed by spectral weighting. For this, the overlap-add scheme for the discrete Fourier transform (DFT) is employed with half-overlapping frames of 512 samples weighted with a von Hann window. The spectral weights are calculated by the spectral minimum mean-square error (MMSE) estimator for the magnitude of the speech DFT coefficients \( \hat{E}_s(d) \) where the noise power spectral density (PSD) is calculated by the MMSE-based estimator presented in [23]. A crucial parameter is the minimum value for the spectral weights \( W_{min} \), the so-called noise floor, since it controls the reduction of noise and diffuse reverberation alike. For the baseline algorithm, a frequency-independent value of \( W_{min} = 0.2 \) was found suitable.

The denoised signal \( \hat{z}(k) \) is processed in signal frames of \( M \) samples shifted by \( M \Delta \) sample instants

\[
x_l(\lambda, m) = \hat{z}(\lambda M \Delta + m) \quad \text{with} \quad m = 0, 1, \ldots, M - 1
\]

(11)

and frame index \( \lambda \), in \( N \), where no downsampling is employed here in contrast to [13].

In a first step, a pre-selection is conducted to detect potential frames with sound decays, cf., Eq. (3). For this, the current frame \( x_l(\lambda, m) \) is divided into \( L = M/P \in \mathbb{N} \) sub-frames of length \( P \)

\[
y_l(\lambda, l, \kappa) = x_l(\lambda, l P + \kappa)
\]

(12)

with \( \kappa \in \{0, 1, \ldots, P - 1\} \) and \( l \in \{0, 1, \ldots, L - 1\} \). It is then checked for frame \( \lambda \) whether the energy, maximum and minimum value of a sub-frame \( l \) deviates from the successive sub-frame \( l + 1 \) according to

\[
\sum_{\kappa=0}^{P-1} y_l^2(\lambda, l, \kappa) > w \cdot \sum_{\kappa=0}^{P-1} y_l^2(\lambda, l + 1, \kappa)
\]

(13a)

\[
\max \{y_l(\lambda, l, \kappa)\} > w \cdot \max \{y_l(\lambda, l + 1, \kappa)\}
\]

(13b)

\[
\min \{y_l(\lambda, l, \kappa)\} < w \cdot \min \{y_l(\lambda, l + 1, \kappa)\}
\]

(13c)

with sub-frame counter \( l = 0, 1, \ldots, L - 2 \) and weighting factor \( 0 < w \leq 1 \). If the conditions of Eq. (13) are fulfilled for \( l \geq l_{min} - 1 \) consecutive sub-frames, a possible sound decay is detected. In this case, the RT is calculated from the signal segment of these \( l \) consecutive sub-frames by means of Eq. (10) for a finite set of RT values (decay rates), which is here given by \( \hat{T}_{60}^{(ML)} / s \in \{0.2, 0.3, \ldots, 1.1\} \). Otherwise, no sound decay is detected and the next signal frame \( y_l(\lambda + 1, l, \kappa) \) is processed.

A new ML estimate is used to update a histogram calculated for the last \( K_t \) ML estimates of the RT. The RT value associated with the maximum of the histogram is taken as preliminary estimate \( \hat{T}_{60}^{(1)}(\lambda) \). The variance for the estimated RT is reduced by recursive smoothing

\[
\hat{T}_{60}(\lambda) = \beta \cdot \hat{T}_{60}(\lambda - 1) + (1 - \beta) \cdot \hat{T}_{60}^{(1)}(\lambda)
\]

(14)

with \( 0 < \beta < 1 \). For the ACE challenge, time-invariant RTs are considered such that the final estimate is obtained by the average

\[
\hat{T}_{60}^{(base)}(\lambda) = \frac{1}{n_2 - n_1 + 1} \sum_{\lambda=n_1}^{n_2} \hat{T}_{60}(\lambda)
\]

(15)

with \( n_1 \) and \( n_2 \) denoting the first and last frame for which an RT has been calculated. Table I lists the algorithmic parameters of the described baseline algorithm used for the ACE challenge submission.
Table 1: Algorithmic parameters of the baseline algorithm.

| \( f_s \) | \( M \) | \( M_d \) | \( P \) | \( L_{\text{min}} \) | \( L \) | \( w \) | \( K_f \) | \( \beta \) |
|---|---|---|---|---|---|---|---|---|
| 16 kHz | 4923 | 137 | 547 | 3 | 9 | 1 | 800 | 0.95 |

Table 2: Algorithmic parameters for fullband RTE with subband RT averaging by means of a DCT-IV filter-bank.

| \( N_{\text{det}} \) | \( n_{\text{det}} \) | \( L_{\text{det}} \) | \( W_{\text{min}} \) |
|---|---|---|---|
| 12 | 3 | 174 | 0.35 |

3. SUBBAND RT AVERAGING

The baseline algorithm has been extended to improve the estimation accuracy by averaging subband RT estimates. The concept of averaging subband RT estimates has already been proposed in [16], but a very different realization of this concept is suggested here.

The denoised signal \( z(k) \) is split into \( N_{\text{det}} \) subband signals \( x_\mu(k) \) with subband index \( \mu \in \{1, \ldots, N_{\text{det}}\} \) by a uniform discrete cosine transform (DCT)-IV filter-bank without downsampling as described in [28], where the FIR prototype filter of length \( L_{\text{det}} \) is designed according to [27] for a stopband attenuation of 100 dB.

The estimate for the subband RT \( \hat{T}_{60}(\mu) \) is calculated by the previously described baseline algorithm for the upper subbands \( n_{\text{det}}, \ldots, N_{\text{det}} \). The fullband estimate is obtained by the weighted average

\[
\hat{T}_{60}^{\text{(dct)}} = \frac{1}{N_{\text{det}} - n_{\text{det}} + 1} \sum_{\mu = n_{\text{det}}}^{N_{\text{det}}} w_\mu \hat{T}_{60}(\mu). \tag{16}
\]

The weighting factors are given by the ratio of the subband signal energy to the sum of all considered subband energies

\[
w_\mu = \frac{1}{E_0} \sum_k x_\mu^2(k) \text{ for } \mu \in \{n_{\text{det}}, \ldots, N_{\text{det}}\} \tag{17}
\]

\[
E_0 = \sum_{\mu = n_{\text{det}}}^{N_{\text{det}}} \sum_k x_\mu^2(k). \tag{18}
\]

This weighting is motivated by the rationale that subband signals with a higher energy provide on average more reliable RT estimates than subband signals with a low energy. This concept was confirmed by experiments with the Dev database where the weighting has led to superior results in comparison to a non-weighted averaging (as well as the baseline approach). Table 2 lists the algorithmic parameters used for the submission to the ACE challenge.

The described concept for fullband RTE by subband RT averaging has also been implemented with a 1/3-octave filter-bank with \( N_{\text{oct}} = 30 \) subbands. Thereby, the fullband RT estimate \( \hat{T}_{60}^{\text{(oct)}} \) is determined by the weighted average of the subband estimates \( \hat{T}_{60}(\mu) \) for \( \mu = n_{\text{oct}}, \ldots, N_{\text{oct}} \) with \( n_{\text{oct}} = 20 \). The octave filter-bank design employed for this equals that considered in the ACE challenge for the evaluation of the subband RT, cf. [22].

Results obtained with the DCT filter-bank as well as the octave filter-bank were submitted to the ACE challenge (see Sec. 5).

4. FREQUENCY-DEPENDENT RT ESTIMATION

The estimation of the subband RT with an octave filter-bank is especially difficult for the lower subbands, even if the RIR is given (see, e.g., [25] and the references cited within). This problem becomes even more pronounced w.r.t. a blind estimation, and calculating the subband RT by means of the baseline algorithm has led to a high estimation error especially for the lower subbands \( (1, \ldots, n_{\text{oct}} - 1) \). To alleviate this problem, the following approach has been developed: The subband estimates for the lower subbands are extrapolated from the more reliable estimates of the upper subbands \( n_{\text{oct}}, \ldots, N_{\text{oct}} \) by means of a model function for the subband RT. For this purpose, the following simple model for the frequency-dependent RT is devised. Inspection of the ground-truth data for the subband RT \( \hat{T}_{60}(\mu) \) of the Dev database has shown that the frequency-dependency of the subband RT can be often roughly approximated by a function similar to that of a scaled Rayleigh distribution with an offset \( m_0 \). This led to the following model function

\[
f_{\text{mod}}(\mu, b) = \frac{\mu}{\alpha b^2} \exp \left\{ -\frac{\mu^2}{2 \alpha^2 b^2 \mu} \right\} + m_0 \tag{19}
\]

\[
m_0 = \frac{1}{N_{\text{oct}} - n_{\text{oct}} + 1} \sum_{\mu = n_{\text{oct}}}^{N_{\text{oct}}} \hat{T}_{60}(\mu) \tag{20}
\]

with subband index \( \mu \) and \( \alpha = 7.5 \). The optimal scaling factor is calculated by minimizing the least-square error between the model function and the RT estimates for the upper subbands

\[
b_{\text{opt}} = \arg \min_b \left\{ \sum_{\mu = n_{\text{oct}}}^{N_{\text{oct}}} \left| f_{\text{mod}}(\mu, b) - \hat{T}_{60}(\mu) \right|^2 \right\} \tag{21}
\]

which is calculated here for \( n_{\text{oct}} = 20 \) and the discrete values \( b \in \{0.5, 1, 1.5, \ldots, 5\} \). The subband RT estimates are finally given by

\[
\hat{T}_{60}(\mu) = f_{\text{mod}}(\mu, b_{\text{opt}}) \forall \mu \in \{1, \ldots, N_{\text{oct}}\} \tag{22}
\]

The developed algorithm is exemplified in Fig. 1 which shows the RTs obtained for the speech file ‘Single_Red_B_Phi_Live_Ambient_6dB.wav’ of the Dev database. The mean-square error over all subband estimates for this example equals 0.1218 for the direct approach and 0.071 for the model-based RTE. Evaluation for the Dev database has on average shown a superior performance for the model-based approach in comparison to the direct approach so that only results for the model-based approach were submitted. It is important to notice that the model-based subband RTE also possesses a significantly lower computational complexity than the direct approach.
5. EVALUATION RESULTS

The evaluation figures provided by the ACE challenge are shown in Figs. 2-4. They display the minimum, first quartile, median, third quartile, and maximum of the relative estimation error \((T_{\text{est}} - T_{\text{true}})/T_{\text{true}}\) in percent for different noise types and SNRs of -1 dB, 12 dB, and 18 dB for the 4500 speech files of the Eval database. It can be observed that averaging the subband RT estimates generally leads to a lower variance for the estimation error and a different bias for the mean value than the baseline approach. Thereby, the DCT-based averaging shows mostly a slightly better performance than averaging over octave subband estimates. The superior performance of the DCT-based approach over the other two fullband estimators becomes most pronounced for low SNRs. The priorities assigned to the three algorithms for fullband RT in the submission phase are given in brackets in Fig. 2 and show that the evaluation results comply with the expected performance ranking.

The model-based subband RT estimator achieves, with the exception for low and medium fan noise, a similar performance for the estimation error than the fullband RT estimators, even though the blind estimation of the subband RT can be considered to be more challenging than the estimation of the fullband RT.

6. CONCLUSIONS

The presented baseline algorithm allows to estimate the fullband RT with low complexity (cf., [15]). The proposed weighted averaging of the subband RT estimates reduces the estimation variance at the price of an increased computational complexity. The devised model-based subband RTE achieves an estimation error, which is for most scenarios in a similar range as for the presented fullband algorithms.

For all treated algorithms, the estimation errors are mainly caused by the fact that the underlying statistical model for the RIR with an exponential decay according to Eq. (4) is often not valid, especially at high DRRs. Therefore, the search for blind estimation algorithms with an improved, more appropriate model for the reverberant sound decay remains a promising direction for further work.
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