Blind Estimation of Room Acoustic Parameters and Speech Transmission Index using MTF-based CNNs

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Abstract-Room acoustic parameters, such as reverberation time (T_{60}) and clarity (C_{80}) , as well as the speech transmission index (STI), are essential in acoustics. However, such parameters and STI are difficult to obtain in everyday places where people exist. Blind estimation for those parameters without measuring room impulse response (RIR) is necessary and challenging. This paper proposes a method based on the modulation transfer function (MTF) and Schroeder's RIR model for estimating T_{60} s in seven-octave bands. The estimated T_{60} s are used to approximate the MTF and RIR. Consequently, the STI and five room-acoustic parameters, including T_{60} , early decay time (EDT), C_{80} , Deutlichkeit (D_{50}), and center time (T_s), can be estimated. We deploy convolutional neural networks for mapping temporal amplitude envelopes of a reverberated speech signal to $T_{60}s$ for the sub-bands. Simulations were carried out by estimating the five parameters and STI from unseen reverberated speech signals. The root-mean-square errors between ground-truths and estimated parameters suggest that the accuracy of the estimated T_{60} and STIs can be improved by about 40% and 25% compared with previous methods, respectively. The other parameters were also correctly estimated, and they are comparable with those obtained from standard measurements.

Index Terms—reverberation time, speech transmission index, room acoustic parameter, room impulse response, modulation transfer function

I. INTRODUCTION

Subjective aspects in speech and music assessments, such as speech intelligibility and music clarity in enclosures, can be objectively described through room acoustic parameters and objective indices [1]. Room acoustic parameters are also crucial for architectures or acousticians who are involved in an auditorium [2]. Most of the parameters in ISO 3381, such as reverberation time (T_{60}), early decay time (EDT), clarity (C_{80}), Deutlichkeit (D_{50}), and center time (T_s), are derived from room impulse response (RIR) [3]. Similarly, a speech transmission index (STI), which is an objective index in IEC 60268, can be calculated by measuring the modulation transfer function (MTF) or can be derived from the RIR [4], [5]. Therefore, the RIR or MTF needs to be measured in general.

However, it is difficult to measure RIR or MTF in daily places where people cannot be excluded (e.g., stations, airports, and schools). As a result, many methods have been proposed to estimate such a parameter without measuring the RIR as so-called blind estimation. Unoki et al. proposed methods based on the concept of the MTF to estimate T_{60} and STI [6]-[8]. Kendrick et al. proposed the maximum likelihood estimation to approximate energy decay curves from reverberated speech and music [9]. The energy decay curve is used for calculating T_{60} and EDT, as described in ISO 3381. Techniques based on deep neural networks (DNNs) were also successful, such as a deep convolutional neural network (CNN) for estimating STI [10]. For T_{60} estimation, many approaches have been evaluated in the Acoustic Characterization of Environments (ACE) Challenge [11], for example, the CNN with spectra-temporal features in the time-frequency domain [12]. Also, a recent combination of a CNN and long short-term memory (LSTM) network has been proposed [13].

In addition to STI and T_{60} , Parada *et al.* proposed an estimator for the clarity index at 50 ms (C_{50}) by using a spectral envelope in the modulation-domain with a bidirectional LSTM [14]. We previously proposed a robust method to estimate STI by using the full-band temporal amplitude envelope (TAE) of a noisy reverberated speech signal with a CNN [15]. This method could overcome a mismatch problem between the model and real acoustic conditions.

However, current blind estimation methods, as the aforementioned ones, can estimate only a single parameter. It is limited to a specific aspect and is inadequate to describe the characteristics of room acoustics completely. To this end, in this paper, we propose a scheme to simultaneously estimate multiple parameters based on the basis of the MTF, Schroeder's RIR model, and CNNs for sub-bands. Therefore, T_{60} , EDT, C_{80} , D_{50} , T_s , and STI can be simultaneously estimated from a speech signal in reverberant environments.

II. PROPOSED METHOD

We propose a scheme for estimating five room-acoustic parameters and an STI, namely MTF-based CNNs, as shown in Fig. 1. The scheme incorporates the MTF concept into a nonlinear regression using CNNs. The T_{60} s for sub-bands are mapped in accordance with the characteristics of the TAEs

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Fig. 1. Block diagram of proposed method.

under reverberant conditions. RIR is approximated from the estimated T_{60} s to derive the five parameters and STI.

A. Definitions

In a reverberant environment, we assume that an observed signal, y(t), is the result of the convolution between an original speech, x(t), and RIR, h(t). The RIR is used to represent acoustic characteristics of a given room in the time domain. In the modulation-frequency domain, the MTF is used to quantify the effect of reverberation [5]. The MTF is defined as

$$m(f_m) = \frac{\int_0^\infty h^2(t)e^{-j2\pi f_m t}dt}{\int_0^\infty h^2(t)dt},$$
 (1)

where $m(f_m)$ is the MTF at a modulation frequency, f_m . In this study, h(t) is the RIR model proposed by M. R. Schroeder [16], and it is defined as

$$h(t) = e_h(t) c_h(t) = a \exp\left(-\frac{6.9t}{T_{60}}\right) c_h(t), \qquad (2)$$

where $e_h(t)$ is an exponential decay, $c_h(t)$ is a carrier of white Gaussian noise (WGN), and *a* is a gain factor. The MTF according to Schroeder's RIR can be expressed as

$$m(f_m, T_{60}) = \left[1 + \left(2\pi f_m \frac{T_{60}}{13.8}\right)^2\right]^{-\frac{1}{2}}.$$
 (3)

According to ISO 3381 and IEC 60268, the definitions of the interested room acoustic parameters and STI are as follows. T_{60} is the period in seconds unit from the energy decay curve of the RIR when the curve decreases by 60 dB. The period of the energy decay curve by 10 dB is the EDT.

 C_{80} and D_{50} are the energy ratio between the reflection components and total energy of the RIR. C_{80} is used to characterize the transparency of music halls in dB unit and is defined as

$$C_{80} = 10 \log_{10} \frac{\int_0^{80 \text{ms}} h^2(t) dt}{\int_{80 \text{ms}}^\infty h^2(t) dt}.$$
 (4)

 D_{50} is used to evaluate the speech intelligibility of lecture halls and classrooms in percent and is defined as

$$D_{50} = \frac{\int_0^{50 \text{ms}} h^2(t) dt}{\int_0^\infty h^2(t) dt} \times 100.$$
 (5)

Center time, T_s , is the period at the center of gravity of the RIR. T_s shows the balance between clarity and reverberation related to speech intelligibility and is defined as

$$T_{s} = \frac{\int_{0}^{\infty} h^{2}(t) \cdot t \, dt}{\int_{0}^{\infty} h^{2}(t) dt}.$$
 (6)

Finally, the STI, an objective index, is used to assess the speech transmission quality from a talker to a listener of a given room [4], [5]. Hence, speech intelligibility can be predicted by calculating STI in a scale from 0 to 1. The STI algorithm is based on the measurement of the MTF in subbands. 98 modulated stimuli are used to calculate the distortion ratios between the inputs and observed signals. The stimuli are amplitude-modulated signals from seven-octave-band carriers and 14 modulation frequencies. The STI is calculated by weighting the modulation transmission indices of the sevenoctave bands. See [4] for more details. However, since the MTF can be derived from RIR, as shown in (1) and known as the indirect method, the STI can be calculated from the RIR.

B. Sub-band analysis

The sub-band analysis for estimating room acoustic parameters is derived from the STI algorithm, which is from the basis of the MTFs in seven-octave bands. Thus, we exploit the relation between the MTF and RIR, as shown in (1), within the same bands as the STI. The bands have center frequencies ranging from 125 Hz to 8 kHz. The normalized reverberantspeech signal is the input. The signal is then decomposed to each sub-band using octave-band filters.

Based on the MTF concept, a temporal envelope of any signal is a smoothed version of the original signal when it is passed through a reverberant space [5]. We then utilize the seven TAEs to represent the modulation distortion characteristics caused by reverberation in the bands. The reverberation, in terms of the T_{60} s, attenuates the observed TAEs. The seven TAEs account for the accuracy enhancement of the estimating T_{60} and STI as well as the other parameters.

The TAE in each band is extracted according to (7). The observed signal is decomposed by using the Hilbert transform and a lowpass filter (LPF). The LPF is a sixth-order Butterworth filter with a cut-off frequency of 20 Hz. We downsample the signal to 40 Hz to reduce the computation complexity. Then, the TAEs are mapped to their associated T_{60} s for the seven-octave bands by using CNNs.

$$e_{y}(t) = \text{LPF}\left[|y(t) + j\text{Hilbert}(y(t))|\right].$$
(7)

C. MTF-based CNN models

We deploy one-dimensional CNNs for mapping the characteristics of the TAEs with their associated T_{60} s in each octave band. Each model consists of four convolutional layers. The input layer takes a TAE to be convoluted with the filters. The regulated linear unit (ReLU), $f(x) = \max(x, 0)$, performs nonlinear activation in all convolutional layer. Batch normalization is applied after the first convolution. Max pooling is also used for reducing the dimensions before the next layer. The dropout rate before the last layer is set to 20%. The fully connected layer is the output layer. The seven CNNs are trained from the TAEs/ T_{60} s pairs. The trained models are supervised by the T_{60} s ground-truths. The ground-truths are calculated from simulated RIRs. The output of each CNN for each sub-band is the estimated T_{60} . The details of the MTF-based CNN model is shown in Table. I.

D. RIR approximation

The estimated T_{60} s are used to approximate RIR, $\hat{h}(t)$ according to Schroeder's RIR model. As Schroder's RIR depends on only the reverberation time, the estimated T_{60} for each octave-band is used to construct the temporal envelope of the RIR, $\hat{e}_{h}(t)$. The temporal envelope of each band is modulated with a band-limited Gaussian noise with a bandwidth of 1/3 of

TABLE I Network architecture of the MTF-based CNN model.

No.	Layer Type	Parameters			
1	Input	TAE shape = 1×200			
2	Conv1D ^{1st}	32 filters, filter size = 10×1 , ReLU			
3	Pooling	max pooling, size $= 2$, stride $= 1$			
4	Conv1D ^{2nd}	16 filters, filter size $= 5 \times 1$, ReLU			
5	Pooling	max pooling, size $= 2$, stride $= 1$			
6	Dropout	0.2			
7	Conv1D ^{3rd}	8 filters, filter size $=$ 5 \times 1, ReLU			
8	Pooling	max pooling, size $= 2$,			
9	Conv1D ^{4th}	4 filters, filter size $= 5 \times 1$, ReLU			
10	Fully Connected	1 output (i.e., T_{60}), ReLU			
11	Regression Output	mean-square-error (MSE)			



Fig. 2. Example of the approximated MTFs from the estimated T_{60} s, where dashed lines are the estimated MTFs, and the solid line is the ground-truths.

an octave. Then, the sub-band RIRs are then summed together. The approximated RIR can be expressed as

$$\hat{h}(t) = \sum_{k=1}^{K} \exp\left(-\frac{6.9t}{T_{60,k}}\right) c_{h,k}(t),$$
(8)

where $T_{60,k}$ is the estimated T_{60} in the k-th band and K = 7, and $c_{h,k}(t)$ is band-limited Gaussian noise. The STI can then be calculated from the estimated T_{60} s based on the basis of the MTF, in (3). Also, the T_{60} , EDT, C_{80} , D_{50} , and T_s can be calculated according to the definitions, in (4), (5), and (6).

III. EXPERIMENTAL SETUP

A total of 29,000 reverberanted speech signals with a sampling rate of 16 kHz were generated from the simulated RIRs convoluted with speech signals. The simulated RIRs are based on Schroeder's RIR model. The reverberation time of the RIRs varies from 0.2 to 3.0 s with a step size of 0.1 s. Each envelope with a different T_{60} was modulated with a different random seed WGN carrier. There are a hundred different WGN carrier seeds. The speech signals were ten short (five-second) Japanese sentences uttered by five men and five women in 17. These reverberant signals were separated into 70% for training, and the rest for testing the model (simulated RIR).



Fig. 3. Estimated results of room acoustic parameters and STI from observed speech signals in reverberant environments: (a) T_{60} , (b) EDT, (c) C_{80} , (d) D_{50} , (e) T_s , and (f) STI. The symbol "o" corresponds to the estimated value from the simulated RIR, "square" indicates the estimated value from the measured RIR, "*" indicates the estimated result using the previous method [6], [15], and the dashed line represents the ground-truth calculated from the RIRs.

TABLE II CORRELATION COEFFICIENTS BETWEEN THE ESTIMATED AND CALCULATED PARAMETERS.

	T_{60}	EDT	C_{80}	D_{50}	T_s	STI
Simulated rooms	0.996	0.996	0.992	0.994	0.996	0.997
Real rooms	0.915	0.870	0.918	0.818	0.822	0.902

We determine whether the proposed method can estimate the parameters and STI even though the acoustic characteristics might not follow Schroeder's RIR model by using reverberated speech signals in an unknown realistic environment. We utilized 43 measured RIRs from the SMILEdataset [18]. Rootmean-square error (RMSE) and correlation coefficient were the metrics for indicating the accuracy of the estimation.

IV. RESULTS AND DISCUSSION

Fig 2 shows an example of the approximated MTFs from a speech signal in a simulated room ("o") and real room ("*") where $T_{60} = 0.7$ s. The dashed lines indicate the estimated MTFs, and the solid line is the ground-truth. The averaged 14 MTFs are derived from the estimated T_{60} s in the seven bands. It was found that the shapes of the approximated MTFs were similar to the ground-truths within an RMSE of 0.15 dB.

Fig 3 shows the estimated results of the estimated roomacoustic parameters and STI from speech signals in reverberant environments. The symbols "o" and "square" correspond to the estimated parameters in the simulated room and realistic room, respectively, where '*" is the value estimated using the previous methods. The horizontal axis indicates the parameter directly calculated from the RIRs, and the vertical axis indicates estimated values. It was found that the results from the simulated rooms were excellent in all parameters. On the other hand, in the real rooms, the results suggested that the proposed method can be used to estimate the five roomacoustic parameters and STI. However, none of the current methods can estimate these parameters simultaneously. We then directly compared only T_{60} and STI with our previous methods [6], [15]. The others were discussed from the results compared with their ground-truths.

The results of the estimated T_{60} and STI show that the proposed method outperforms the previous methods since it provided significantly lower RMSEs. The estimated T_{60} was improved about 40%, and 25% for the STI compared with the previous methods, respectively. For C_{80} , D_{50} , and T_s , the RMSE were 1.66 dB, 11.85%, and 0.06, respectively. The estimated C_{80} was close to the accuracy from the standard measurement [3]. However, the estimated D_{50} and T_s have remaining outliers. Those errors might be caused by a mismatch between the RIR model we used and the real RIRs.

Table II shows the correlation coefficients between the estimated parameters and ground-truths. The results show that the proposed method was successful in unseen simulated rooms since the correlation coefficients were close to 1. For the real rooms, the proposed method has high correlations in all parameters, but the estimated D_{50} and T_s were slightly low.

V. CONCLUSION

We proposed a blind method for estimating five roomacoustic parameters (i.e., T_{60} , EDT, C_{80} , D_{50} , and T_s) and the STI. We leveraged the relationship between a stochastic RIR model and its MTF to estimate T_{60} for seven-octave bands. The proposed scheme estimated T_{60} from the temporal amplitude envelope of an observed signal in each band. The estimated T_{60} s were used to approximate the MTF and RIR for deriving of the room acoustic parameters and STI. Simulations were carried out to determine whether the proposed method could estimate the room acoustic parameters and STI from reverberated speech signals even if the RIRs were not the same as Schroeder's RIR model. The experimental results in terms of RMSEs and correlation coefficients showed that the proposed method yielded a better accuracy, compared with the baselines for the STI and T_{60} . Also, the estimated EDT, C_{80} , D_{50} , and T_s were also close to the standard methods.

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