

# BLIND REVERBERATION TIME ESTIMATION BASED ON LAPLACE DISTRIBUTION

Tariqullah Jan<sup>†</sup> and Wenwu Wang<sup>‡</sup>

<sup>†</sup> Department of Electrical Engineering,  
University of Engineering & Technology Peshawar, Pakistan  
Email: tariqullahjan@yahoo.com

<sup>‡</sup> Centre for Vision, Speech, and Signal Processing,  
University of Surrey, UK  
Email: w.wang@surrey.ac.uk

## ABSTRACT

We propose an algorithm for the estimation of reverberation time (RT) from the reverberant speech signal by using a maximum likelihood (ML) estimator. Based on the analysis of an existing RT estimation method, which models the reverberation decay as a Gaussian random process modulated by a deterministic envelope, a Laplacian distribution based decay model is proposed in which an efficient procedure for locating free decay from reverberant speech is also incorporated. Then the RT is estimated from the free decays by the ML estimator. The method was motivated by our observation that the distribution pattern for temporal decay of the reverberant hand clap is much closer to the Laplace distribution. The estimation accuracy of the proposed method is evaluated using the experimental results and is in good agreement with the RT values measured from room impulse responses.

## 1. INTRODUCTION

*Reverberation time* (RT) is an important parameter for characterising the enclosed auditory environments. It is commonly used to determine the level of reverberations of a room. The RT of an enclosed environment is defined as the time for which a sound prevails after it has been turned off, due to its multiple reflections from the different surfaces within the environment. The RT is usually referred to as the time for the sound level to drop to 60 dB below its original value [4], [10]. Reverberation leads to speech distortion both in terms of its envelop and fine structure, therefore RT is an important parameter that measures the listening quality of the enclosed environment, i.e., room.

Different methods have been employed to measure the RT. In the early days of the 20th century, Sabine [12] implemented an empirical formula for the calculation of RT based entirely on the geometry of the environment (i.e., volume and surface area) and the absorption attributes of its surfaces. Later on, Sabine's RT equation has been modified and its accuracy has been improved (refer to [4] for the details of the modifications). However, such methods require that the room geometry and absorptive characteristics of the room be determined first. When these can not be determined easily, it is important then to find some method which is based on the test sound signal radiated in the enclosed environment.

Such methods are based on sound decay curves, e.g., the interrupted noise method [16], in which a burst of noise having broad or narrow band is radiated into the test room. In the time instant where the sound field attains the steady state, the noise source is switched off and the decay curve is obtained.

The slope of the decay curve is used to estimate the RT. As the noise source signal has fluctuations, the decay curve obtained will differ from trial to trial. Hence to estimate the reliable RT, averaging must be applied to the large number of obtained decay curves. In order to overcome this issue, Schroeder developed an integrated impulse response method in 1965 [13] in which the excitation signal is a pulse either broad band or narrow band. Schroeder proved that there is a certain integral relation between the impulse response of the room and the overall average of the decay curves obtained via the interrupted noise method, and hence the repeated trials were inessential. Both the methods require controlling environment for the experiment, particularly a *prior* suitable excitation signal must be accessible.

Although Schroeder's method has been used immensely over the past few decades for the estimation of RT, there is a need of some *blind* method that can estimate room RT from the available microphone signals, i.e., without any information about the room geometry and absorption attributes, or when the test sound signal is not available. Such blind method which works with speech sound directly will be very useful for incorporating in hands free telephony devices or hearing aids. Several methods have been developed recently that can estimate RT *blindly*, i.e., directly from the recorded reverberant signals [5, 6, 11, 10, 15]. These methods are based on the statistical modelling of the sound decay such that the maximum likelihood (ML) estimator can be used to determine the RT. Some partially blind methods have also been developed where the room characteristics are 'learned' using neural network approaches [14, 7, 1].

Ratnam *et al.* [10] developed an algorithm for the blind estimation of RT based entirely on the available recorded sound, by modelling the reverberation characteristics of the enclosure using a noise decay curve model. A running estimate of RT is achieved by continuously processing the sounds in the test environment employing the ML parameter estimation procedure. A decision making step is then applied to obtain the estimates of RT over a period of time and the most probable RT is attained using an order statistics filter. However correctly detecting the sound decay from a reverberant speech signal is a challenging problem and the method in [10] used an iterative approach for that purpose, which makes the algorithm computationally expensive. Later on Ratnam *et al.* presented another algorithm in [11] based on their original model in [10] in order to improve the computational efficiency of their method. Very recently Lollmann *et al.* [5] presented an algorithm for the blind estimation of

RT from reverberant speech signals. The method is using a statistical model for the sound decay developed in [10], followed by the ML estimation approach to estimate the decay rate presented in [11]. However, the method of Lollmann *et al.* is employing a pre-selection mechanism to detect the possible sound decay which makes the estimation robust and computationally efficient. The method we presented in this work for the blind estimation of RT is based on Lollmann *et al.* method and using the Laplace distribution for modelling the decay rate along with a pre-selection mechanism to detect the possible sound decays.

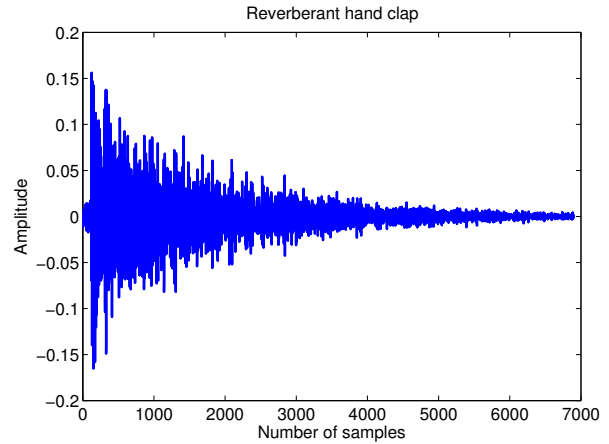
The rest of the paper is organized as follows. Section 2 presents the sound decay model and ML estimation procedure used by the proposed method followed by the efficient RT estimation procedure in Section 3. Section 4 evaluates the performance of the proposed method and reports the experimental results followed by a conclusion in Section 5.

## 2. PROPOSED SOUND DECAY MODEL AND ML ESTIMATION

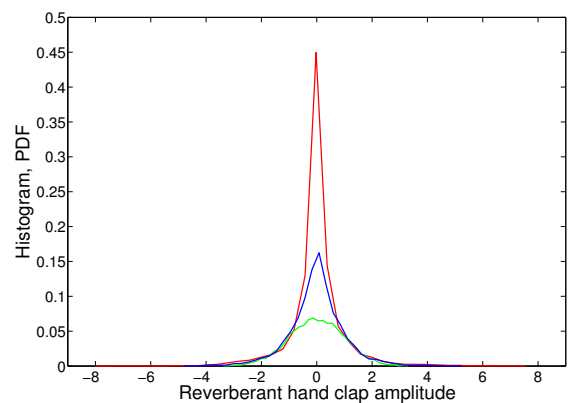
Before describing the proposed method, an example is provided here to motivate the work. A hand clap sound signal is convolved with the RIR from the AIR database [2] recorded in a lecture room with a source-microphone distance of 7.1 m. The resulting reverberant hand clap sound is shown in Figure 1(a). Then the histogram of this sound is shown in Figure 1(b). Theoretical probability density functions (PDFs) histograms are also plotted in Figure 1(b) for Gaussian and Laplacian distribution with mean and variance equal to that of the reverberant hand clap sound signal. The distribution pattern for temporal decay of the hand clap shows that it is much closer to the Laplace distribution, and hence different from the state of the art methods, in this work the statistical model used for modelling the energy decay of the reverberant signal is based on the Laplace distribution. Also the findings in [8] show that the amplitude distribution of the reverberant speech is better modeled by Laplace distribution when the level of reverberations falls in a certain range.

Therefore, the reverberant tail of a decaying sound is modeled using a sequence of random variables with Laplace distribution  $\mathcal{L}(\theta, \beta)$ , where  $\theta$  is the mean considered as zero here and  $\beta$  is the variance of the Laplace distribution. The model is based on the assumption that the reverberation tail of a decaying sound denoted here as  $y$  is the product of a fine structure denoted as  $x$  that is a random process, and an envelop  $a$  that is deterministic. Suppose  $x(n)$  is a random sequence for  $n \geq 0$ , of independent and identically distributed (i.i.d.) random variables having Laplace distribution with zero mean and variance  $\beta$ ,  $\mathcal{L}(0, \beta)$ . Similarly for each  $n$  a deterministic sequence is defined as  $a(n) > 0$ . As a result, the model for the room decay  $y$  is represented as  $y(n) = a(n)x(n)$  [10]. As  $a(n)$  is a time varying term,  $y(n)$  are independent but not identically distributed, with probability density function  $\mathcal{L}(0, \beta a(n))$ .

In order to estimate the decay rate, consider a finite sequence of observations,  $n = 0, \dots, N-1$ . For notational convenience,  $N$ -dimensional vectors of  $y$  and  $a$  are denoted as  $\mathbf{y}$  and  $\mathbf{a}$  respectively. Hence the likelihood function of  $\mathbf{y}$  (the



(a)



(b)

Figure 1: (a) Temporal decay of a reverberant hand clap generated from the room impulse response of the AIR database recorded in a lecture room. (b) Distribution of the decay of a reverberant hand clap shown in (a) (red line), and two theoretical distributions (green line for Gaussian and blue for Laplace) with the same mean and variance.

joint probability density), parameterized by  $\mathbf{a}$  and  $\beta$ , is [3]

$$L(\mathbf{y}; \mathbf{a}, \beta) = \frac{1}{a(0) \cdots a(N-1)} \left( \frac{1}{2\beta} \right)^N \times \exp \left( - \frac{\sum_{n=0}^{N-1} |y(n)/a(n)|}{\beta} \right) \quad (1)$$

where  $\mathbf{a}$  and  $\beta$  are the  $(N+1)$  unknown parameters that are required to be estimated from the observation  $\mathbf{y}$ . As the main goal here is to model the sound decay in a room and the likelihood function obtained in Equation (1) can be further simplified. Suppose that a single decay rate  $\rho$  defines the damping of the sound envelop during the regions of free decay (i.e., the period following the sharp offset of a speech sound) instead of those regions where the sound is actually ongoing, onset, or gradually declining speech offsets. As a result the sequence  $a(n)$  is determined by [10]

$$a(n) = \exp(-n/\rho) \quad (2)$$

Hence, the  $N$ -dimensional parameter  $a(n)$  can be replaced by a single scalar parameter  $a$  which is denoted by  $\rho$  as

$$a = \exp(-1/\rho) \quad (3)$$

As a result Equation (2) can be written as

$$a(n) = a^n \quad (4)$$

Now Equation (1), after incorporating Equation (4) becomes

$$L(\mathbf{y}; a, \beta) = \left( \frac{1}{2a^{(N-1)/2}\beta} \right)^N \times \exp\left( -\frac{\sum_{n=0}^{N-1} |a^{-n}y(n)|}{\beta} \right) \quad (5)$$

ML approach is then used to estimate the parameters  $a$  and  $\beta$ . Firstly, the logarithm of Equation (5) is taken to obtain the log-likelihood function

$$\ln L(\mathbf{y}; a, \beta) = -N \ln(2) - \sum_{n=0}^{N-1} \ln(a^n \cdot \beta) - \frac{1}{\beta} \sum_{n=0}^{N-1} a^{-n} |y(n)| \quad (6)$$

To get the maximum of  $\ln(L)$ , we differentiate the log-likelihood function in Equation (6) with respect to  $a$  to obtain the score function  $SF_a$  [9]

$$SF_a(a; \mathbf{y}, \beta) = \frac{\partial \ln L(\mathbf{y}; a, \beta)}{\partial a} = -\frac{1}{a} \sum_{n=0}^{N-1} n + \frac{1}{\beta} \sum_{n=0}^{N-1} n |y(n)| a^{-n-1} \quad (7)$$

Let  $\partial \ln L(\mathbf{y}; a, \beta) / \partial a = 0$ , then the log-likelihood function attains the extremum, given as

$$-\frac{1}{a} \sum_{n=0}^{N-1} n + \frac{1}{\beta} \sum_{n=0}^{N-1} n |y(n)| a^{-n-1} = 0 \quad (8)$$

Denote the estimate of  $a$  by  $\hat{a}^{(ML)}$  which should satisfy Equation (8). It can be verified that the second derivative  $\partial^2 \ln L(\mathbf{y}; a, \beta) / \partial a^2 |_{a=\hat{a}^{(ML)}} < 0$ , i.e., the estimate  $\hat{a}^{(ML)}$  maximizes the log-likelihood function.

Similarly differentiate the log-likelihood function in Equation (6) with respect to  $\beta$ ,

$$SF_\beta(\beta; \mathbf{y}, a) = \frac{\partial \ln L(\mathbf{y}; a, \beta)}{\partial \beta} = -\frac{N}{\beta} + \frac{1}{\beta^2} \sum_{n=0}^{N-1} a^{-n} |y(n)| \quad (9)$$

When  $\partial \ln L(\mathbf{y}; a, \beta) / \partial \beta = 0$ , the log-likelihood function achieves the extremum, which results in

$$\beta = \frac{1}{N} \sum_{n=0}^{N-1} a^{-n} |y(n)| \quad (10)$$

Using the score function  $SF_\beta$ , the log-likelihood function can be maximized for  $\beta$  also in the same way as done above by taking the second derivative.

It can be observed that Equation (8) is an implicit expression and  $a$  can not be solved explicitly, while Equation (10) provides the explicit estimate of  $\beta$  if  $a$  is known. As defined in Equation (3) already,  $\rho$  is a time constant to be estimated.

It is noted that  $a \in [0, 1)$  maps one-to-one onto  $\rho \in [0, \infty)$ . Here, we use a similar method to that in [10] and [11] for the estimation of  $a$  based on quantisation. First the given range of  $a$  is quantized such that the bins of the histogram of  $a$  are formed. Then the likelihood values are calculated, and the highest likelihood is assigned to that bin in the histogram.

Let the range of  $a \in [0, 1)$  be quantized into  $Q$  values, so that  $a_j$  is obtained with  $j = 1, \dots, Q$ . Then, for each  $a_j$ , the log-likelihood given by Equation (6) can be calculated as

$$\ln L(a_j; \mathbf{y}) = -N \ln(2) - \sum_{n=0}^{N-1} \ln(a_j^n \cdot \beta) - \frac{1}{\beta} \sum_{n=0}^{N-1} a_j^{-n} |y(n)| \quad (11)$$

And  $\hat{a}^{(ML)}$  can be selected as

$$\hat{a}^{(ML)} = \max_a \{ \ln L(a_j; \mathbf{y}) \} \quad (12)$$

Finally the estimate of the decay rate  $\hat{\rho}^{ML}$  is obtained using Equation (3), followed by the calculation of the RT value, i.e.,  $\hat{\tau}_{60}^{(ML)}$  using the following formula [10]

$$\hat{\tau}_{60}^{(ML)} = 6.908 \times \hat{\rho}^{ML} \quad (13)$$

### 3. EFFECTIVE RT ESTIMATION

As the original method presented in [10] used an iterative approach to estimate the sound decay rate which makes the algorithm computationally very demanding. The method presented in [11] improves the computational efficiency of the original method, however it uses the whole recorded reverberant speech signal for the ML estimation of the sound decay rate instead of using only the free sound decay regions. To further improve the computational efficiency it would be helpful to first capture the free sound decay regions in the reverberant speech signal so that only the detected sound decay regions are used for the ML estimation of the decay rate. Lollmann *et al.* [5] devised an estimation procedure which can be used for this purpose. Such a procedure also has the advantage in reducing the effects of the outliers on the estimated RT value. We have used this efficient procedure in our proposed method to improve the ML estimation of the Laplacian parameters.

The reverberant speech signal  $z(n)$ , where  $n$  is the discrete time index, is processed on a frame by frame basis. The sequence is divided into the frames of  $B$  samples shifted by instants of  $\Delta B$  samples [5], given as

$$Z(\lambda, b) = z(\lambda \Delta B + b) \quad \text{with } b = 0, 1, \dots, B-1 \quad (14)$$

where  $\lambda \in \mathbb{N}$ . In the first step, pre-selection is carried out to detect the possible sound decays. In order to achieve this, the current frame  $Z(\lambda, b)$  is divided into  $L = B/P \in \mathbb{N}$  sub frames

$$V(\lambda, l_{sub}, k_{sub}) = Z(\lambda, l_{sub}P + k_{sub}) \quad (15)$$

where  $k_{sub} = 0, 1, \dots, P-1$  and  $l_{sub} = 0, 1, \dots, L-1$  are sub-frame indices. Now it is examined whether the maximum energy and minimum energy values of a sub-frame deviates from the succeeding sub-frames according to [5]

$$\sum_{k_{sub}=0}^{P-1} V^2(\lambda, l_{sub}, k_{sub}) > \tau_{l_{sub}} \cdot \sum_{k_{sub}=0}^{P-1} V^2(\lambda, l_{sub} + 1, k_{sub}) \quad (16a)$$

$$\max_{k_{sub}}\{V(\lambda, l_{sub}, k_{sub})\} > \tau_{l_{sub}} \cdot \max_{k_{sub}}\{V(\lambda, l_{sub} + 1, k_{sub})\} \quad (16b)$$

$$\min_{k_{sub}}\{V(\lambda, l_{sub}, k_{sub})\} < \tau_{l_{sub}} \cdot \min_{k_{sub}}\{V(\lambda, l_{sub} + 1, k_{sub})\} \quad (16c)$$

where  $0 \leq \tau_{l_{sub}} \leq 1$  is a weighting factor. If one of these conditions is violated, it is examined whether the counter  $l_{sub}$  has reached a minimum value  $1 < l_{submin} < L - 2$ . If this is not the case, the comparison is terminated and the next signal frame  $Y(\lambda + 1, b)$  is processed. Otherwise, the sequence of sub-frames for which Equation (16) applies is detected as a possible sound decay. For this detected frame, the RT, i.e.,  $\hat{T}_{60}^{(ML)}$  is calculated using Equations (11), (12), (3), and (13) for a finite set of RT values (decay rates).

To improve the estimation accuracy with low complexity, a histogram with a bin size 10 containing the estimated RT values obtained above (i.e.,  $\hat{T}_{60}^{(ML)}$ ) is generated, and updated each time when another RT value (i.e.,  $\hat{T}_{60}^{(ML)}$ ) is obtained. The current RT estimate  $\hat{T}_{60}^{(ML)}$  is associated with the maximum of this histogram (The maximum instead of the first peak can be taken as this histogram contains no significant number of outliers as for the Ratnam *et al.* method [10], due to the pre-selection). The variance for the estimated RT is reduced by a recursive smoothing such that the final estimate is given by

$$\hat{T}_{60}^{(ML)}(\lambda) = \alpha \cdot \hat{T}_{60}^{(ML)}(\lambda - 1) + (1 - \alpha) \cdot \hat{T}_{60}^{(ML)}(\lambda) \quad (17)$$

where  $0.9 < \alpha < 1$ . The final RT value is estimated by

$$\hat{T}_{60} = \text{mean}(\hat{T}_{60}^{(ML)}(\lambda)) \quad (18)$$

The proposed blind RT estimation algorithm using the Laplacian distribution based energy decay model is summarized in Table 1.

#### 4. EXPERIMENTAL RESULTS AND DISCUSSIONS

The performance of the proposed method for blind estimation of RT shall be illustrated by some simulation examples. Ten different anechoic speech signals randomly selected from the TIMIT database, uttered by 5 males and 5 females all sampled at 16 KHz, are convolved with the real RIRs from the AIR database [2] to generate the different reverberant speech files. The RIRs were recorded in four different room environments, namely booth, office, meeting, and lecture (Note that the stairway case from the AIR database is not considered here, as the mean RT values for the stairway are not reported in the original paper that describes the AIR database [2]). For each room environment, a pair of source-microphone distances  $\{D_1, D_2\}$  m respectively, are selected, i.e.,  $\{0.5, 1.5\}$ ,  $\{1, 3\}$ ,  $\{1.45, 2.8\}$ , and  $\{2.25, 7.1\}$ . Other parameters used are given as :  $Q = 10$ ,  $L = 7$ ,  $l_{submin} = 3$ ,  $\alpha = 0.995$ ,  $B = 1631$  (corresponds approximately to a time span of 0.10 s),  $P = 233$ ,  $\Delta B = 67$  (corresponds approximately to a frame shift of 0.0042 s), and  $\tau_{l_{sub}} = 1$ .

For each room environment and each source-microphone distance, ten different reverberant speech signals have been generated and then tested for the RT estimation. For each room type and source-microphone distance, the average results of the estimated RT over the ten different signals, are given in Figures 2 and 3 respectively, where the RT estimated

directly from RIRs based on Schroeder's method [13] and the mean RT reported in [2] are also plotted for comparison purpose. For estimated RT based on Schroeder's method, the recorded RIRs in four different rooms for distances  $D_1$  and  $D_2$  have been used to estimate the RT value. On the other hand, the mean RT values are obtained from the results reported in [2], which are calculated for each room by taking the average of the RT values obtained over all positions of source-microphone in the room (further details can be found in [2]).

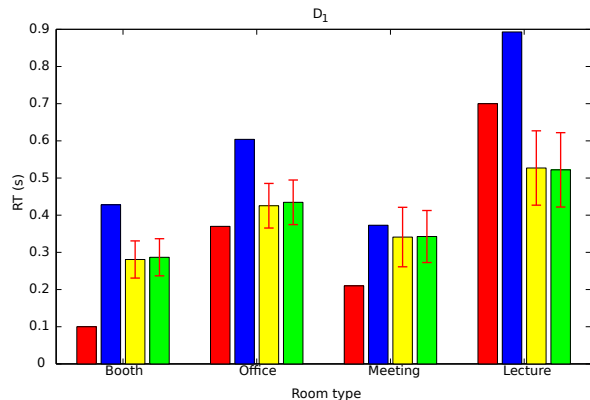


Figure 2: Performance measurement of different RT estimation methods in terms of accuracy obtained for different room environments from the AIR database. The mean RT is shown by red bars, the RT estimated from the RIRs by Schroeder's method [13] is shown by blue bars, the RT estimated by the Lollmann *et al.* method [5] is shown by yellow bars, and the RT estimated by our proposed method is shown by green bars. The distances between source and microphone for all of the four rooms are  $D_1 = \{0.5, 1.0, 1.45, 2.25\}$  m respectively. The standard deviations are also plotted as short lines on top of the yellow and green bars.

Note that the results shown in Figure 2 are obtained for the shorter source-microphone distances from the above used pairs, i.e.,  $D_1$ , while the results in Figure 3 are obtained for the longer source-microphone distances from the pairs, i.e.,  $D_2$ . It can be observed that the difference between the RT estimated using our proposed method and the mean RT (shown by red bars) is small in different room environments. For example, for the office room at  $D_1$ , the RT value obtained by our proposed method is 0.43 seconds and the measured RT value is 0.37 seconds, and similarly for the office room at  $D_2$ , the RT value estimated by our proposed method is 0.46 seconds and the measured RT value is 0.48 seconds. Overall, the proposed method achieves comparable performance to the baseline method by Lollmann *et al.*

#### 5. CONCLUSION

A new approach has been presented for the blind estimation of RT. The method is built on a Laplacian distribution based statistical model for the sound decay and a maximum likelihood approach for parameter estimation. As shown in our experiments, the results obtained using our proposed method with the real data using speech signals are in good agreement with the measured reverberation times. The proposed method achieves comparable results to the state-of-the-art method.

Table 1: The proposed blind RT estimation method

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**Task:** Use Laplacian distribution based energy decay model for the estimation of RT.

**Input:** Reverberant speech, i.e.,  $z(n)$ .

**Output:** Estimated RT, i.e.,  $\hat{T}_{60}$ .

**Initialization:** 1) In (14),  $B = 1631$  and  $\Delta B = 67$  are used.  
 2) In (15),  $P = 233$  is used.  
 3) In (17),  $\alpha = 0.995$  is used.  
 4) In (11) and (12),  $j = 1, \dots, Q$  while  $Q = 10$  is used.

**Case:** The goal is to estimate the RT from reverberant speech signal. The steps are:  
 1) Use (14)-(16) to detect the free decay regions indexed by frame number  $\lambda$ .  
 2) For the detected regions, use (11), (12), (3), and (13) to obtain  $\hat{T}_{60}^{(ML)}(\lambda)$ .  
 3) Apply recursive smoothing via (17) to the estimated RT values, i.e.,  $\hat{T}_{60}^{(ML)}(\lambda)$ .

**Output:** Compute  $\hat{T}_{60}$  according to (18).

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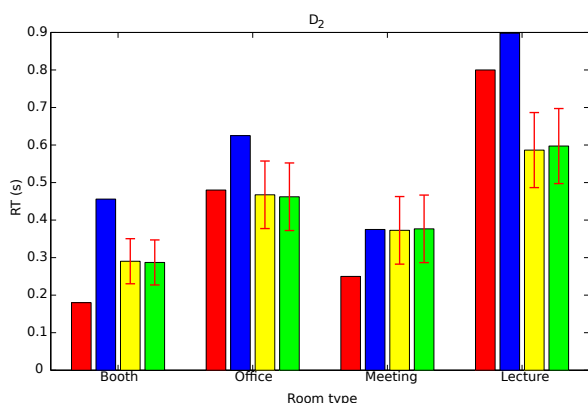


Figure 3: Performance measurement of different RT estimation methods in terms of accuracy obtained for different room environments from the AIR database. The mean RT is shown by red bars, the RT estimated from the RIRs by Schroeder's method [13] is shown by blue bars, the RT estimated by the Lollmann *et al.* method [5] is shown by yellow bars, and the RT estimated by our proposed method is shown by green bars. The distances between source and microphone for all of the four rooms are  $D_2 = \{1.5, 3.0, 2.8, 7.1\}$  m respectively. The standard deviations are also plotted as short lines on top of the yellow and green bars.

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