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A New and Effective Technique for Blind RT Estimation Via Laplacian Decay Model

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Abstract: In this research a statistical model based on Laplacian distribution is adopted for modeling the reverberant signal energy decay, and then the maximum likelihood (ML) estimator is used to estimate its reverberation time (RT). Based on the study of existing technique for RT estimation, which uses Gaussian random process for modeling the reverberation decay; a decay model based on Laplacian distribution is presented in this work which includes an efficient method for detecting free decays from the reverberant signal and then using these decays RT is estimated with the help of ML estimator. Our observation about the closeness of temporal decay distribution pattern of the reverberant hand clap signal to the Laplacian distribution was the motivation behind this research. Experimental results show that the proposed algorithm is more efficient and provides accuracy in RT estimation.

Keyword: Blind RT Estimation, Maximum Likelihood, Decay Model, Effective RT Estimation, Laplace Distribution.

1. INTRODUCTION

When a sound signal is generated in an enclosed space, it follows multiple routes from the generating source to the receiver, this phenomenon results in reverberations. The reverberation time of an enclosure refers to the time duration required during which the level of sound signal in a closed space reduces/decreases by 60dB of its original value after ceasing the signal generating source (Kuttruff *et al.* 1999, Ratnam *et al*, 2003.). Factors that affect the reverberation time are the enclosed space geometry and the absorptive or reflective surfaces present within the enclosed area. Reverberation distorts fine structure of the signal and it's envelop therefore RT is used to quantify the acoustic characteristics of an enclosure. The RT can be estimated in two possible ways, (i) with known acoustics characteristics of a room, (ii) without knowing the room acoustics. Large value of reverberation time results in signal with decreased intelligibility and quality.

Various methods have been adopted for RT measurement. In 20th century, an empirical formula was implemented by Sabine (Sabine, 1922) for RT measurement. This formula is based on the known absorption attributes and geometry (i.e., surface area and volume) of the environment. Later on Kuttruff (Kuttruff *et al.* 1999) modified this Sabine's RT formula with improved accuracy. However these methods require the knowledge of absorptive characteristics and geometry of the room. In situation where one cannot determine these room acoustics easily, then it is required to use some methods based on radiating test signal in the enclosed space. Such techniques use sound decay curves for RT estimation, e.g., interrupted noise technique (ISO, 1999). In this method a noise burst having narrow or broad band is generated in an enclosure (test room). When the field of the sound achieves its steady state, the noise generating source is turned off, and then the decay curve for the noise signal is recorded. The slop information of this curve is used for RT estimation. Due to fluctuations or variations in the source noise signal, there will be different decay curves obtained for different/ various trials. Thus one must apply averaging to these decay curves for ***reliable*** RT estimation. To address this problem Schroeder (Schroeder, 1965) presented an integrated impulse response technique, in which a pulse either narrow or broad band is used as an excitation signal. This method proved that the impulse response of an enclosed space has a certain integral relationship with the average of the obtained decay curves; hence repeated trials were unessential. Under the condition of controlled environment and availability of suitable exciting signal, both the methods give reliable RT estimation.

Although Schroeder's technique for RT estimation has been extensively used and modified over the years, there is a requirement of some blind technique that can provide room RT estimation from the microphone signals, without knowing ***absorption*** attributes and room geometry, or when a test signal cannot be used. Such blind technique will be important and effective for use in hands-free equipments or hearing aids/devices. Recently various methods (Ratnam *et al.* 2003, Lollmann *et al.* 2010, Lollmann *et al.* 2008, Ratnam *et al.* 2004, Wen *et al.* 2008) have

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been employed for the blind estimation of RT, using the reverberant signals. These techniques involve statistical modeling of reverberant speech decay and then with the help of ML estimator one can measure the RT. In partially blind techniques of RT estimation, the room acoustics are 'learned' adopting various neural network techniques (Tahara *et al.* 1998, Nannareillo *et al.* 1999, Cox *et al.* 2001).

For blind estimation of reverberation time, an algorithm is developed by Ratnam et al. in 2003. In this algorithm a decay curve model is used to model the enclosure (test room) reverberation parameters. Using ML procedure a running estimate of reverberation time is obtained by continuously processing the signals in the enclosure. Then in the decision making step estimates of RT are obtained for a given time period, and then with the help of an order statistics filter the most likely RT is achieved. However it is a challenging issue to detect decay from the signal (reverberant speech) correctly, and for this reason an iterative approach is used in (Ratnam *et al.* 2003); which increases the computational complexities of the algorithm. Later on, based on same model in (Ratnam *et al.* 2003), another algorithm to decrease computational complexities is developed by Ratnam et al. in 2004. In 2010, Lollmann proposed a method inspired by the technique in (Ratnam *et al.* 2003) to blindly estimate RT. It statistically model the sound decay obtained in the method mentioned in (Ratnam *et al.* 2003). Then ML estimation technique is used for the estimation of decay rate mentioned in (Ratnam *et al.* 2004). A pre-selection strategy is used for the detection of plausible sound decays which increases the computational efficiency of the estimate and also makes it robust. In our research, we presented a method based on the technique proposed in (Lollmann *et al.* 2010). Our method uses Laplacian distribution to model the decay rate also a pre-selection strategy is used for the detection of sound decays.

The remaining of the paper is arranged as follows: Section 2 is related to the proposed work including the model for the sound decay and process of ML estimation. Section 3 describes the efficient and effective procedure for RT estimation. Section 4 gives the performance evaluation of our research work and also provides the experimental results. Section 5 concludes the paper.

2. MATERIAL AND METHODS

Proposed Sound Decay Modeland Ml Estimation

An example to motivate our work is considered before presenting the description of our proposed technique. The lecture room response (RIR), is recorded in the situation in which the microphone-source distance is kept at 7.1m as mentioned in AIR database (Jeub *et al.* 2009). This RIR is convolved with the hand clap signal. **(Fig.1)** shows the resultant reverberant sound and Figure 2 shows the histogram of this sound signal. The theoretical distributions (histograms) for Laplace and Gaussian with the same variance and mean as that of the reverberant signal are also presented in **(Fig. 2).**

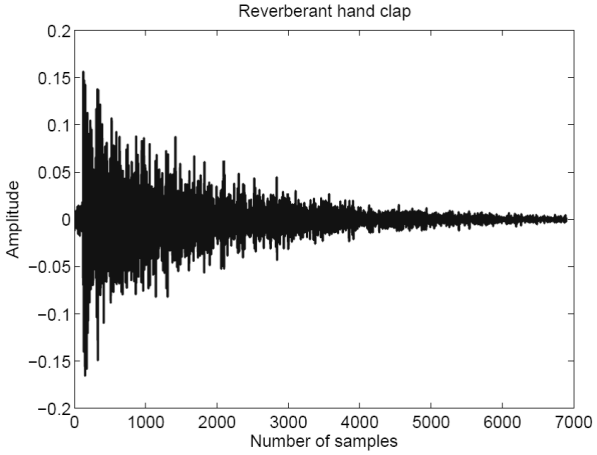


Fig. 1: Reverberant hand clap temporal decay

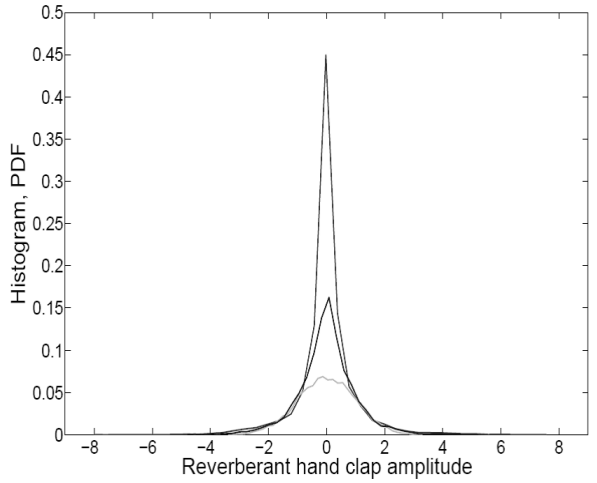


Fig.2: Line with circle shows decay distribution of reverberant hand clap, line with ellipse and line with rectangle show theoretical distributions (histograms) for Laplace and Gaussian respectively, with the same variance and mean.

The temporal decay distribution pattern of a handclap demonstrates its closeness to the Laplacian distribution, hence in our work; we have used a Laplace distribution based statistical model to model the reverberant signal energy decay. Also the results obtained in (Petsatodis *et al.* 2011) demonstrate that when the reverberations level exists in certain limits then the reverberant speech amplitude distribution is better modeled by using Laplacian distribution.

Therefore the tail of the reverberant signal is modeled adopting Laplacian distribution $\mathcal{L}(\theta, \beta)$, here β represents the variance and θ represents the mean of the Laplacian distribution and its value is taken to zero. Let *y* denotes the tail of decaying reverberant signal, and *a* denotes the envelop which is ***deterministic***, and *x* a random process denotes the fine structure. In our model we assume that *y* is the product of *a* and *x*. Suppose a random sequence of identically distributed and independent random variables with Laplacian distribution $\mathcal{L}(\theta, \beta)$ be denoted by $x(n)$ for $n \geq 0$. Similarly $a(n) > 0$ denotes the deterministic sequence for each value of *n*. Thus $y(n) = a(n)x(n)$ represents room decay model [10]. The sequence $y(n)$ is independent but because of the time dependant parameter/ quantity $a(n)$, $y(n)$ are not distributed identically with $\mathcal{L}(\theta, \beta\ a(n))$, as probability density function.

A sequence $n = 0, 1, \ldots, N\text{-}1$ of finite observations is considered for the estimation of the decay rate. For notational ease, the terms **a** and **y** are used to denote N-dimensional vectors of *a* and *y* respectively. Therefore likelihood function for **y**, characterized by β and **a** is (Kotz *et al.* 2001)

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

Here β and **a** are the unknown (N+1) parameters and it is required to estimate these parameters from observation **y**. Our aim is to develop a sound decay model and to further simplify the general likelihood function represented by equation (1). Suppose the decay rate ρ represents the damping of envelop of the reverberant sound in the areas of free decay, consequently the sequence $a(n)$ given in (Ratnam *et al.* 2002) becomes,

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

A scalar parameter *a* defined by equation (3) in terms of ρ can be used to replace $a(n)$,

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

Hence equation (2) becomes,

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

Putting equation (4) in equation (1),

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

Now ML scheme is adopted for estimating the parameters β and *a*. First a log- likelihood function in equation (6) is obtained by taking logarithm of equation (5)

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

To obtain the maximum of $ln(L)$, equation (6) is differentiated with respect to *a* to get SF_a; the score function defined in (Poor, 1994).

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

An extremum is achieved by log-likelihood function when $SF_a(a; \mathbf{y}, \beta) = 0$ in equation (7).

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

Let $\hat{a}^{(ML)}$ represents estimate of *a* and it satisfies equation (8). Also it is proved that the second derivative, $\partial^2 lnL(\mathbf{y}; a, \beta) / \partial a^2|_{a=\hat{a}^{(ML)}} < 0$, i.e., for $\hat{a}^{(ML)}$ the log-likelihood function is maximized.

Similarly equation (6) is now differentiated with respect to β to get SF_β.

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

An extremum is achieved by the likelihood function when $SF_\beta(a; \mathbf{y}, a) = 0$ in equation (9) hence,

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

Considering the second derivative of SF_β in equation (9), it is proved that log-likelihood function also maximizes for β. Note that the implicit expression in equation (8) cannot be used to give explicit estimation of *a*, whereas equation (10) with known *a* gives the explicit β estimation. Now the decay rate ρ in equation (3) represents a time constant and it is required

to estimate its value. It is observed that the expression in equation (3) maps the decay rate ρϵ[0, ∞) one-to-one onto aϵ[0, 1). In this work, we used a technique based on quantization to estimate a. This technique is similar to the one adopted in (Ratnam *et al.*2003) and (Ratnam *et al.* 2004). After quantizing the range of a bins are formed for the histogram of a. The values of likelihood are then calculated and the likelihood with the highest value is allocated to that bin in the histogram.

Here we quantized the range of a into Q values a_j for j=1, 2,…, Q. The we calculated the likelihood represented in equation (6) for each value of a_j as,

$$lnL(a_j;\ \mathbf{y}) = -Nln(2) - \sum_{n=0}^{N-1} ln(a_j^{\,n}\,.\beta) - \frac{1}{\beta}\sum_{n=0}^{N-1} a_j^{\,-n}\,|y(n)| \tag{11}$$

The following equation is used to select $\hat{a}^{(ML)}$ as,

$$\hat{a}^{(ML)} = \max_{a}\{lnL(a_j;\ \mathbf{y})\} \tag{12}$$

And then using equation (3) we obtained the estimated value of decay rate, i.e., $\hat{\rho}^{(ML)}$. Finally the formula mentioned in is the used to calculate the value of RT i.e. ,$\hat{T}_{60}^{(ML)}$,

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

3. EFFECTIVE RT ESTIMATION

The original technique used in (Ratnam *et al.* 2003) for the estimation of decay rate of speech signal adopted an iterative approach which makes the presented technique computationally complex. The technique used in (Ratnam *et al.* 2004) decreases the computational complexity of the original technique, but in this technique the whole recorded reverberant sound is considered for estimating the decay rate of the sound instead of considering only the free decay areas. The computational efficiency can be further improved by first capturing the free decay regions in the sound signal and then using only these detected regions in ML estimation of the decay rate. For this purpose, an estimation strategy is devised in (Lollmann *et al.* 2010) by Lollmann et al. The advantage of this procedure is that it reduces the outlier effects on RT estimate. In our research this efficient and effective procedure is adopted for improving the ML estimation of the parameters of Laplacian distribution.

Let $z(n)$ is a reverberant sound signal for which frame by frame processing strategy is used. The sequence divides into various frames of C samples with a shift of ΔC sample instants (Lollmann *et al.* 2010) represented as,

$$Z(\lambda, c) = z(\lambda\,\Delta C + c) \quad with\ c = 0, 1, \ldots C-1 \tag{14}$$

Here λ ϵ N. First a pre-selection process is performed for the detection of possible sound decays. For this reason, the given current frame $Z(\lambda, c)$ is split into L sub-frames, where L=C/P ϵ N.

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

where l_{sub}=0, 1, 2,…L-1 and k_{sub}=0, 1, …P-1 are indices for sub-frame. Now according to (Lollmann *et al.* 2010), the sub-frame minimum and maximum energy values are then checked whether they deviate from the energy values of the succeeding sub-frame.

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

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

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

with weighting factor $0 \le \tau_{l_{sub}} \le 1$ and a counter l_{sub} =0, 1, 2, …, L-2. If one of the conditions presented by equation (16) is violated then the counter l_{sub} is examined whether it has attained a minimum value 1< $l_{sub\,min}$ < L-2. If this is not the situation then after terminating the comparison, the processing of the next signal Y (λ+1, c) starts. Otherwise sub-frame sequence is noted as possible sound decay provided equation (16) applies to this sequence (frame). Then $\hat{T}_{60}^{(ML)}$ is calculated for the noted frame utilizing equations (11), (12), (3) and (13) for the finite group of decay rates.

For making the estimation more accurate with reduced complexity, a histogram is generated having bin size 10 that contains RT estimated values i.e., $\hat{T}_{60}^{(ML)}$ obtained above, and it is constantly updated when another $\hat{T}_{60}^{(ML)}$ is observed. The present or current estimated RT value $\hat{T}_{60}^{(ML)}$ is related to the histogram maximum (here the

maximum value is taken rather than considering the first peak, as this histogram does not contain large quantity of outliers as in (Tahara *et al.* 1998), because of the pre-selection process). Using recursive smoothing, variance is reduced for RT estimate and equation (17) gives final estimate

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

with limits for α as $0.9 < \alpha < 1$. Equation (18) gives final estimated RT value, as

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

Table 1 summarizes the proposed technique for blind RT estimation adopting energy decay model based on Laplacian distribution.

Table 1: Summary of the proposed blind RT Estimation technique

Task: Develop an energy decay model based on Laplacian distribution for estimating the value of RT.
Input: Reverberating sound *z*(*n*)
Output: Final RT estimate i.e., $\hat{T}_{60}$.
Initialization:

- Set Q=10 in equations (11) and (12).
- In equation (14) ΔC = 67 and C = 1631 are used.
- Set α = 0.995 in equation (17).
- Set P = 233 in equation (15).

Case: The following steps are used to get RT estimate from reverberant sound

(i) Using equations (14)-(16), free decay areas indexed by λ are detected. Here λ represents the frame number.

(ii) Obtain $\hat{T}_{60}^{(ML)}(\lambda)$ by applying equations (11), (12), (3) and equation (13) for these detected areas or regions.

(iii) In equation (17) apply recursive smoothing to these RT estimates $\hat{T}_{60}^{(ML)}(\lambda)$

Output: Finally using equation (18) to compute $\hat{T}_{60}$.

4. RESULTS AND DISCUSSION

The following simulation examples illustrate the performance and effectiveness of the proposed technique for estimating RT blindly. We randomly selected 10 anechoic sound signals from a TIMIT database. These signals sampled at 16 KHz are voiced by 5 females and 5 males. Then we created reverberant speech files by convolving these sound signals with RIRs in AIR database (Jeub *et al.* 2009). The room environments in which these RIRs were recorded include office, booth, lecture and meeting (here the stairway case is not considered, because in the original paper mean RT values are not mentioned for this case). A pair of distances between microphone and source (D_1, D_2) is selected for the mentioned room environments as, (1, 3) for office, (0.5, 1.5) for booth, (2.25, 7.1) for lecture and (1.48, 2.8) for meeting room.

For each distance between microphone and source we have generated 10 different reverberant sounds in the above mentioned room environments and then they are tested to get RT estimate. Figure 3 illustrates the average simulation results for RT estimate over the reverberant sounds for different room types with microphone-source distance D_1. Also Figure 4 illustrates the average simulation results for RT estimate over the reverberant sounds for different room types with microphone-source distance D_2. For comparison purpose we have plotted the reported mean value of RT in (Jeub *et al.* 2009) and the estimated value of RT from RIRs using Schroeder's technique (Schroeder, 1965). For RT estimation using Schroeder's technique the recorded RIRs for different room types and microphone-source distances D_1 and D_2 were utilized to estimate RT. Also the mean values of RT are calculated using the reported experimental results in (Jeub *et al.* 2009) measured for different rooms by taking average of the obtained values of RT, with different microphone-source positions.

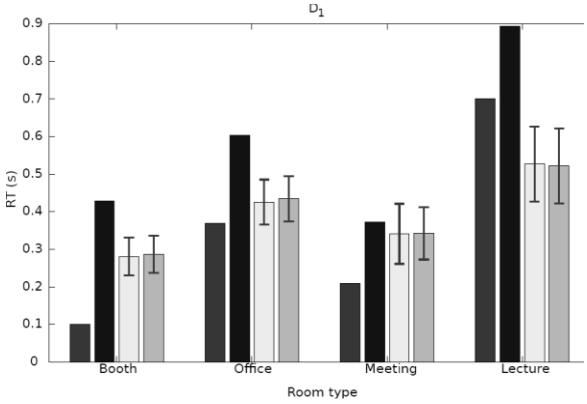


Figure 3: Performance accuracy measured for various techniques of RT estimation in different rooms. Bar with circles show the mean RT, bars with ellipse show the RT estimate calculated using Schroeder's technique, bars with rectangle represent the estimated RT in the method presented by Lollmann et al in (Lollmann et al. 2010) and the bars with star represent the estimated RT calculated in our proposed technique. Also we have plotted short lines representing standard deviation on top of the bars with rectangle and star. The microphone-source distance D_1 for different rooms are selected as 0.5 for booth, 1.0 for office environment, 1.45 for meeting room and 2.25 for lecture room.

The estimated RT in the method presented by Lollmann *et al* in (Lollmann *et al.* 2010) and the green bars represent the estimated RT calculated in our proposed technique. Also we have plotted short lines representing standard deviation on top of green and yellow bars. The microphone-source distance D_1 for different rooms are selected as 0.5 for booth, 1.0 for office environment, 1.45 for meeting room and 2.25 for lecture room.

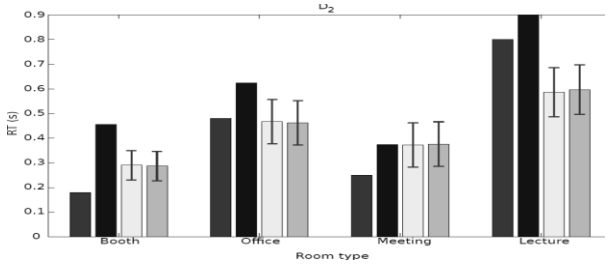


Figure 4: Performance accuracy measured for various techniques of RT estimation in different rooms. Bar with circles show the mean RT, bars with ellipse show the RT estimate calculated using Schroeder's technique, bars with rectangle represent the estimated RT in the method presented by Lollmann et al in (Lollmann et al. 2010) and the bars with star represent the estimated RT calculated in our proposed technique. Also we have plotted short lines representing standard deviation on top of the bars with rectangle and star.. The microphone-source distance D_2 for different rooms are selected as 1.5 for booth, 3.0 for office environment, 2.8 for meeting room and 7.1 for lecture room.

Note that in **Figure 3-4** the simulation results are obtained for smaller distances between microphone and source i.e., D_1 selected from the above mentioned pairs, and in Figure 4 the simulation results are obtained for larger distances between microphone and source i.e., D_2. Also note that there is small difference between the mean value of RT (represented by red bars) and the estimated RT calculated in our proposed technique. For example, considering distance D_1 for the office environment, the measured RT is 0.37 seconds and the value of RT calculated in the proposed technique is 0.43 seconds. Similarly, considering distance D_2 for the office the measured value of RT is 0.48 seconds and the estimated RT in the proposed technique is 0.46 seconds. The overall performance of the proposed technique is comparable to Lollmann *et al.,* technique.

5. CONCLUSION

A new and effective technique for blind RT estimation has been presented in this paper. In this technique a statistical model based on Laplacian distribution is developed to model the signal energy decay and a maximum likelihood strategy is adopted for parameter estimation. **The results achieved in our work are based on real scenarios and the error is small in our results in terms of its difference with the measured values. The performance of our proposed work is good and shows accuracy and also comparable with state of the art technique.**

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