Statistical Analysis of Datasets of Spatial Room Impulse Responses

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***Abstract*—Understanding room acoustics is crucial for a wide range of applications, from architectural design to immersive audio systems. This study investigates spatial room impulse responses (SRIRs) using statistical methods to analyze and compare the acoustic characteristics of different environments. SRIR datasets, recorded using spherical microphone arrays, provide detailed information about how sound propagates and reflects in various rooms [1]. Different acoustic parameters are extracted and used to characterize each space.Principal Component Analysis (PCA) was already employed on the data set by the supervision team to reduce dimensionality and highlight key patterns, our objective is to apply additional statistical techniques—specifically Linear Discriminant Analysis (LDA) and Exploratory Factor Analysis (EFA)—and compare their outcomes with those of PCA to evaluate their relative performance and effectiveness.**

***Index Terms*—Spatial room impulse responses (SRIRs), room acoustics, linear discriminant analysis (LDA), exploratory factor analysis (EFA), principal component analysis (PCA).**

I. Introduction

Sound plays a fundamental role in how we experience indoor environments, whether through speech communication, music performance, or immersive audio systems. The acoustic properties of a room—such as how sound reflects, decays, and spreads—can greatly affect how that space is perceived and used. Comprehending these properties is instrumental in fields like architectural acoustics, audio engineering, and virtual reality design.

Room Impulse Responses (RIRs) are widely used to capture how sound behaves in enclosed spaces. A more advanced form,SRIRs, also includes directional (spatial) information, providing a comprehensive three-dimensional characterization of room acoustics[2]. SRIRs are typically measured using microphone arrays, and datasets[3] offer extensive SRIR recordings gathered with robotic platforms in complex environments, enabling detailed analysis of room coupling and sound propagation.

In this project, the datasets from multiple room environments are analyzed using a combination of statistical methods, including PCA[4], LDA[5], and EFA[6]. Various acoustic parameters are extracted to quantify each room's acoustic characteristics which will be cover in later section. hese methods are used to lower data dimensionality, classify rooms based on their acoustic profiles, and reveal hidden patterns in the parameter space.

II. Objective

The main goal of this study is to investigate and assess the use of statistical methods for describing and categorizing acoustic environments based on SRIR data. While PCA has already been applied to the dataset to uncover major axes of variance, this project investigates alternative methods—namely, LDA and EFA to assess their effectiveness in identifying acoustically distinct room groupings. LDA is employed to maximize class separability among predefined room categories, whereas EFA seeks to uncover latent factors that explain correlations between acoustic parameters. By comparing the outcomes of LDA and EFA with those of PCA, the study aims to determine which approach yields better interpretability and classification accuracy in the context of room acoustics. This multi-method analysis contributes to the broader goal of developing robust data-driven tools for room characterization, spatial audio optimization, and intelligent acoustic system design.

III. Dataset Description

This research uses a high-resolution SRIR dataset published by Stolz, Spors, and Werner (2024) and made publicly available on Zenodo.[1] The dataset was collected within the Helmholtz building at Technische Universität Ilmenau using the TORY mobile robot platform, which was equipped with a seven-channel spherical microphone array. Measurements were conducted in a variety of acoustic environments, with selected rooms for this study including H1539b, H2505, H3522-HW, HL-WV, and ML2-102—each offering distinct characteristics in terms of geometry, surface materials, and volume. Information regarding the measurement setup, room configurations, and recording methodology can be found in the referenced dataset publication[1]

To ensure spatial fidelity, receiver positions were spaced at 25 cm or 50 cm intervals along pre-defined measurement paths, allowing for dense three-dimensional acoustic mapping[1]. The excitation signals used were exponential sine sweeps, enabling the capture of high signal-to-noise ratio impulse responses. All recorded data were stored in the SOFA (Spatially Oriented Format for Acoustics) in compliance with the AES69-2022 standard, facilitating compatibility with spatial audio processing tools.

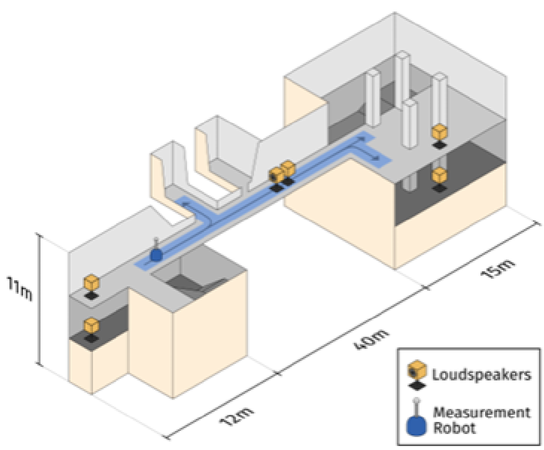

Fig. 1: General overview of the measurement setup in isometric and not to scale view showing the location of the speakers and the area covered by the robot[1]

IV. Acoustic Parameters

In this study, a comprehensive set of room acoustic parameters was analyzed to characterize the temporal and spatial sound behavior in enclosed environments. The parameters included **T60** (reverberation time), **EDT** (Early Decay Time), **C50** and **C80** (clarity indices for speech and music, respectively), **D50** (Definition), **DRR** (Direct-to-Reverberant Ratio), **Ts** (Centre Time), and **Grel** (Relative Strength). These parameters were derived from SRIRs using the Spatial Decomposition Method (SDM) and processed according to the guidelines outlined in ISO 3382-1. The calculation of decay-related parameters such as T60 and EDT relied on backward integration of the energy decay curve, while clarity and definition metrics like C50, C80, and D50 involved comparing early and late arriving energy portions within defined temporal thresholds (50 ms and 80 ms). DRR was calculated as the logarithmic ratio between direct sound energy and the reverberant tail, providing a critical cue for spatial perception and localization. Ts was computed as the energy-weighted mean arrival time of the impulse response, reflecting the balance of early and late reflections. Grel quantified the overall received sound energy relative to a free-field reference. These parameters, extracted across octave bands from 62 Hz to 8 kHz, offer a multidimensional view of each room's acoustic characteristics and form the basis for the statistical analyses in this research. These features are essential for distinguishing perceptual attributes of spaces and understanding acoustic variability, as also highlighted by Meyer-Kahlen et al. [7].

V. Background and Related Work

PCA is an unsupervised statistical method used to reduce the dimensionality of high-dimensional datasets while preserving as much of the original variance as possible. It does this by transforming correlated variables into a smaller set of uncorrelated variables called principal components, derived from the eigenvectors of the data's covariance matrix[4]. It is particularly useful for simplifying complex data structures before visualization, clustering, or further analysis. In the context of room acoustics, PCA has been successfully used to identify dominant acoustic parameters and reveal patterns in datasets such as SRIRs, which contain rich temporal, spectral, and directional information.

In this project, a PCA study was conducted in advance by the supervising professor to serve as a foundation for further analysis[1]. The PCA was applied to SRIR data collected from five rooms: H1539b, H2505, H3522-HW, HL-WV, and ML2-102. The aim was to determine the most influential acoustic features and observe how different rooms cluster based on their sound behavior. The results include a heatmap of parameter loadings and 2D/3D scatter plots of room groupings in the reduced PCA space. The heatmap indicated that features such as C50, C80, DRR, and Grel significantly influenced the principal components. The scatter plots revealed clear clustering of rooms, particularly distinguishing acoustically unique environments such as H1539b and H2505. These findings demonstrate PCA's effectiveness in capturing essential acoustic distinctions and its value as a preprocessing step for supervised classification methods such as Linear Discriminant Analysis.

LDA is a supervised learning algorithm that reduces high-dimensional data to a lower-dimensional space while maximizing class separation[8]. Unlike PCA, which emphasizes variance, LDA leverages class labels to enhance separation between predefined groups by increasing between-class variance and decreasing within-class variance. In this study, LDA was applied to the PCA-reduced dataset to classify rooms based on their acoustic signatures, allowing us to investigate how well different room types can be linearly separated using acoustic features derived from SRIRs.

Exploratory Factor Analysis (EFA), on the other hand, is a data-driven technique used to uncover latent structures (factors) within observed variables, especially when the underlying relationships are unknown[6].It assumes that correlations between measured variables are driven by fewer unobserved variables (factors). It is particularly useful in grouping variables that measure similar underlying constructs—such as clarity or reverberation—within acoustic analysis. In this work, EFA was employed to investigate the latent dimensions of the acoustic parameter space, offering deeper insight into covarying features and their potential perceptual interpretations.

The SRIR datasets analyzed in this project, along with the PCA results, offer a compact representation of acoustic parameters such as T60, D50, C50, DRR, and others, extracted from various rooms. These methods—PCA, LDA, and EFA—together form the statistical backbone of this study, enabling classification, grouping, and interpretation of acoustic environments based on multidimensional feature spaces.

Previous research has explored the use of RIRs and SRIRs for applications in room classification and audio enhancement. For example, McKenzie et al. [6] used deep embeddings of RIRs for environment classification and speaker diarization. Werner and Liebetrau [7] examined perceptual thresholds in DRR, emphasizing its role as a key descriptor, while MeshRIR [8] demonstrated the value of high-resolution SRIRs in spatial sound field modeling and directional parameter analysis.

VI. Methodology

To ensure a consistent basis for analysis, this study adopts the same eight acoustic parameters previously used in the PCA performed by the supervising team. The data were standardized using z-score normalization to align feature scales and facilitate meaningful comparisons.

Building on this foundation, we applied Linear Discriminant Analysis (LDA) and Exploratory Factor Analysis (EFA) to the standardized dataset[1]. LDA was used to explore class separability among rooms, while EFA aimed to uncover latent structures within the acoustic parameters. This unified approach allows us to evaluate and compare the performance and insights provided by each statistical method.

To extract meaningful insights from the dataset, our analysis is structured into the following steps:

A. Data Acquisition and Preprocessing

The SRIR files were imported using MATLAB. Each file contains directional, temporal, and spectral information for all five loudspeaker positions across different room configurations. The selected acoustic parameters were computed for each SRIR using standard algorithms. Parameters were standardized to ensure comparability across measurements. Initial outliers or incomplete data points were excluded.

B. Linear Discriminant Analysis (LDA)

Our primary contribution involves applying LDA to the PCA-reduced dataset to classify rooms based on their acoustic signatures. This supervised method, implemented using MATLAB's classification toolbox, evaluates how well different room types can be distinguished using features derived from SRIR recordings across multiple octave bands. The dataset was normalized using z-score standardization and labeled by room identifiers to support supervised learning. The LDA was implemented in two stages. First, a band-wise analysis was performed by applying LDA separately to each octave band. For each band, a subset of features was extracted, and a linear discriminant model was trained using MATLAB's `fitcdiscr` function[9]. This process facilitated the computation of discriminant coefficients for each acoustic parameter within individual bands.

In the second stage, a full-spectrum LDA was performed using the entire set of standardized features across all bands. A comprehensive discriminant model was trained to assess the classification structure of the full feature space. All computational steps, including data preparation, parameter selection, standardization, model training, and coefficient extraction, were executed in MATLAB R2023a using custom-developed scripts. In this study, each measurement instance was labeled with its corresponding room identifier, enabling the use of supervised learning techniques. These room labels served as class targets for the LDA, allowing the model to learn how to distinguish between different acoustic environments based on their parameter profiles. This classification framework supports the evaluation of room-specific acoustic signatures within the dataset. This procedure forms the foundation for evaluating the acoustic distinctiveness of different rooms, as discussed in the results section.

C. Exploratory Factor Analysis (EFA)

To further uncover latent structures in the data, we applied EFA on the full dataset. This helped us identify underlying constructs influencing the acoustic profiles of rooms. Factors were extracted using principal axis factoring with varimax rotation. The analysis revealed clusters of parameters that covary, potentially representing perceptual dimensions such as clarity or reverberance. To investigate the underlying structure among the selected room acoustic parameters (RAPs), EFA was conducted on the standardized dataset[1]. The RAPs were extracted from SRIR measurements collected across multiple rooms and octave bands. In this part of the study, the same eight parameters were considered.

Before applying EFA, the dataset was normalized using z-score standardization to ensure uniform scale across all features[10]. The number of latent factors to retain was determined using the Kaiser criterion, which preserves factors with eigenvalues greater than one, computed from the correlation matrix of the standardized RAP dataset.

EFA was performed using MATLAB's `factoran` function with varimax orthogonal rotation to enhance interpretability of the factor loadings[11]. The process generated factor loadings, unique variances for each variable, and the factor scores for all instances in the dataset.

This analysis framework was implemented entirely in MATLAB using custom scripts, allowing flexibility in parameter selection and reproducibility of the workflow.

D. Parameter Sensitivity Analysis

A critical step involved sequentially excluding individual acoustic parameters from the LDA and EFA analyses to observe the impact on classification accuracy and factor structure. This sensitivity analysis identified key parameters—such as DRR and C80—as the most influential for discriminating between rooms.

All analyses were performed using MATLAB, leveraging both built-in functions and custom scripts. Visualizations were generated to interpret clustering, discriminant directions, and factor loadings. These insights provide a comprehensive understanding of the acoustic similarity and diversity among room configurations captured in the SRIR datasets.

The dataset was partitioned using a stratified 70/30 hold-out validation strategy to ensure balanced representation across classes. Classification performance was assessed through confusion matrices and overall accuracy, enabling a direct comparison of the discriminative capabilities of PCA, LDA, and EFA-based feature sets.

VII. RESULTS AND ANALYSIS

A. Results from Linear Discriminant Analysis

To support the interpretation of the LDA results, two key visualizations were employed. Firstly, a coefficient heatmap was used to depict the magnitude and direction of linear discriminant coefficients for each acoustic parameter across the octave bands. This visualization highlights the relative importance of specific frequency-parameter combinations in driving class discrimination. Secondly, a one-dimensional (1D) scatter plot was constructed based on the first linear discriminant component (LD1), where each data point represents a room recording and is color-coded according to its corresponding class label. This projection enables a direct visual assessment of how well the LDA transformation separates the room classes in the reduced feature space.

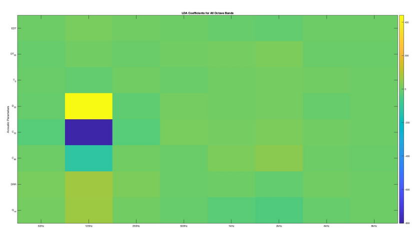

Fig. 2: LDA Coefficient Heatmap Across Acoustic Parameters and Octave Bands

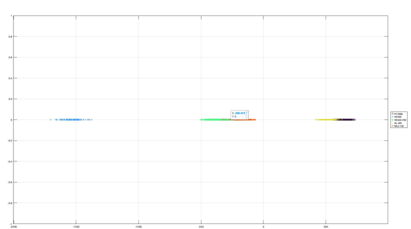

Fig. 3: LDA-Based Clustering of Room Samples Across Classes in Reduced Discriminant Space.

The coefficient heatmap revealed that acoustic parameters D50 and C50 at 125 Hz exhibited the highest discriminative power, with strong positive and negative coefficients, respectively. This suggests that low-frequency reverberation and clarity measures are particularly influential in distinguishing between different room types. In the LD1 scatter plot, room classes appear as relatively compact clusters along the horizontal axis, with minimal overlap between categories. This spatial separation confirms that the LDA projection successfully preserved class discriminability, providing strong evidence that the selected acoustic parameters contain sufficient information to differentiate room environments based on their sound field characteristics.

A targeted parameter sensitivity analysis was conducted to evaluate the contribution of individual acoustic parameters to the overall classification performance. In this context, DT20m emerged as the most influential variable. Its removal from the feature set led to a substantial collapse in the discriminative power of the LDA model, as evidenced by the resulting scatter plot in which previously distinct room classes became highly entangled. This disruption in the spatial organization of the data strongly suggests that DT20m encapsulates critical temporal characteristics of the acoustic environment that are essential for effective room type differentiation. The finding reinforces the necessity of including DT20m in the feature space for robust and interpretable acoustic classification using LDA.

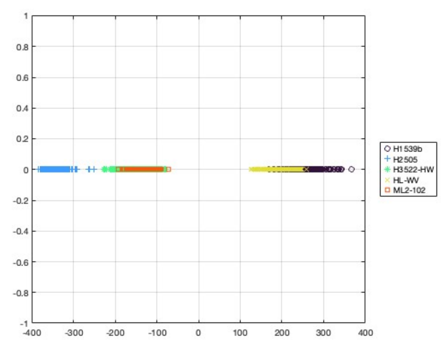

Fig. 4: LDA-Based Clustering of Room Samples Excluding Parameter DT20m

B. Results from Exploratory Factor Analysis

EFA provided three key visualizations to support the interpretation of latent structures within the acoustic parameter space. First, a factor loading matrix heatmap was generated to illustrate the strength and direction of the relationship between each acoustic parameter and the extracted latent factors. Higher loading values (approaching ±1) indicated a stronger association between a parameter and a specific factor, revealing how parameters clustered according to shared underlying dimensions. Second, 2D scatter plots of factor scores were used to show how individual observations (i.e., room recordings) were distributed within the reduced-dimensional space defined by the factors. These plots revealed clear clustering patterns among different room types. Third, 3D scatter plots of factor scores provided an extended view of the distribution by incorporating an additional factor dimension, allowing for deeper exploration of class separability. Together, these visual tools facilitated the identification of underlying patterns in the data and demonstrated the effectiveness of EFA in distinguishing between room types based on shared acoustic characteristics.

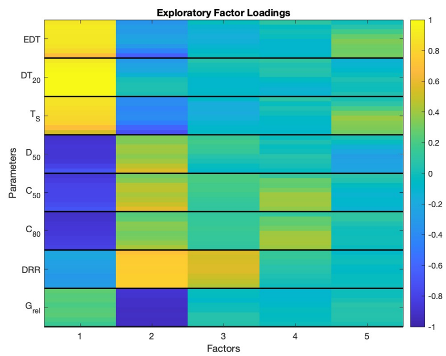

Fig. 5: EFA Factor Loading Matrix for Acoustic Parameters

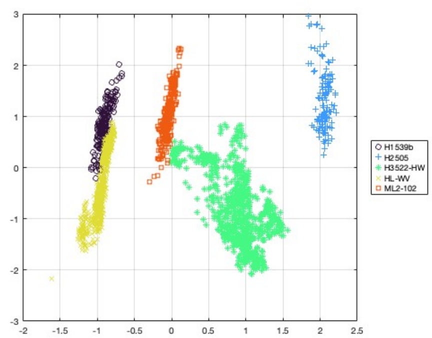

Fig. 6: EFA 2D Factor Score Plot of Room Classes

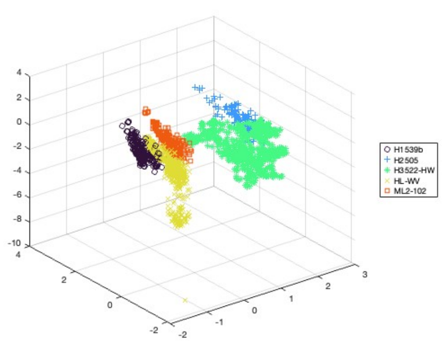

Fig. 7: EFA 3D Factor Score Plot of Room Classes

The results reveal meaningful structure within the multivariate acoustic dataset. The factor loading heatmap demonstrates that specific acoustic parameters exhibit strong associations with distinct latent factors, suggesting that these parameters are not independent but instead reflect underlying dimensions of room acoustics. For instance, parameters such as EDT, DT20, and TS loaded highly onto a common factor, indicating a shared temporal decay characteristic, while DRR loaded prominently onto a separate factor, potentially reflecting early-to-late energy ratios. This dimensional reduction enabled the transformation of complex acoustic profiles into a smaller set of interpretable components. The 2D and 3D scatter plots of factor scores further support this interpretation by illustrating clear groupings among recordings from different room classes. These distinct clusters in reduced-dimensional space indicate that the extracted factors successfully capture systematic variation in acoustic characteristics across room types. Collectively, the results affirm the utility of EFA in uncovering latent structures within acoustic data and highlight its potential for classifying or characterizing diverse acoustic environments based on underlying perceptual or physical features.

A complementary parameter sensitivity analysis was conducted for the EFA model to identify which acoustic parameters contributed most significantly to the latent structure underpinning the observed room classification. Among the evaluated features, DRR and Grel emerged as the most critical variables. Exclusion of DRR from the analysis resulted in a noticeable degradation of cluster compactness and separability; however, the overall spatial orientation of the room classes in the factor score plot remained largely intact. In contrast, the removal of Grel not only disrupted the integrity of the clusters—causing room classes to overlap significantly—but also altered the alignment and orientation of the factor axes themselves. This dual impact of Grel underscores its pivotal role in both defining the internal structure of the latent factors and preserving the geometric relationships among room types in the reduced-dimensional space.

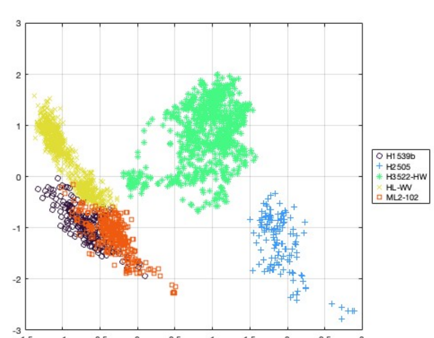

Fig. 8: EFA 2D Factor Score Plot of Room Classes Excluding Parameter DRR

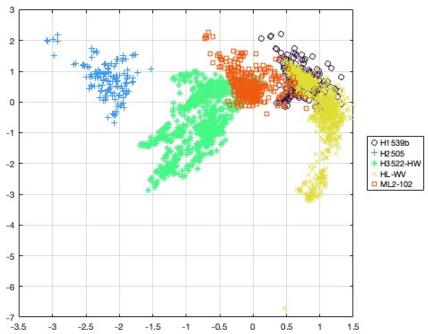

Fig. 9: EFA 2D Factor Score Plot of Room Classes Excluding Parameter Grel

VIII. Confusion Matrix Analyses

A. EFA

The confusion matrix resulting from the this analysis demonstrates high overall classification accuracy across the five room classes. Specifically, Class 1 achieved 81.9% accuracy, with the remaining 18.1% misclassified primarily into Class 4. Classes 2 and 5 exhibited perfect classification with 100% accuracy. Class 3 achieved 94.4% accuracy, and Class 4 yielded 94.9%, with minor misclassifications of 5.6% and 5.1%, respectively. These findings indicate that EFA effectively captures the underlying structure of the acoustic feature space, although some overlap persists between acoustically similar rooms, most notably between Class 1 and Class 4.

TABLE I: EFA Classification Accuracy per Class

Class	Correctly Classified (%)	Misclassified (%)
1	81.9	18.1
2	100.0	0.0
3	94.4	5.6
4	94.9	5.1
5	100.0	0.0

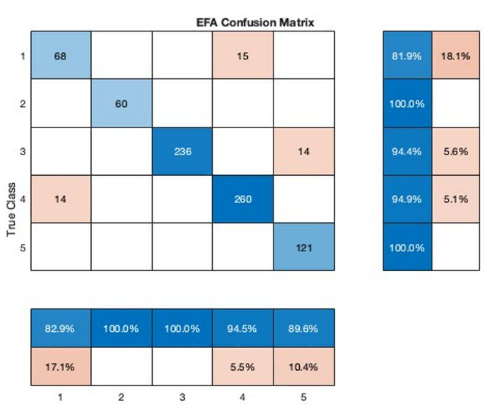

Fig. 10: EFA Confusion Matrix for Room Classification

B. LDA

The confusion matrix obtained from the Linear Discriminant Analysis (LDA) classifier demonstrates strong overall classification performance across the five room classes. Class 2 and Class 4 achieved perfect classification accuracy (100%), indicating that these rooms possess distinct acoustic signatures well-separated in the LDA-transformed feature space. Class 1 and Class 5 exhibited minor misclassifications, with accuracies of 86.7% and 94.2%, respectively. The most notable confusion occurred between Class 3 and Class 5, where 11.6% of Class 3 instances and 5.8% of Class 5 instances were misclassified. These results highlight LDA's effectiveness in capturing discriminative acoustic features while also revealing overlap in the feature distributions of acoustically similar rooms.

TABLE II: LDA Classification Accuracy per Room Class

Class	Classification Accuracy
Class 1	86.7%
Class 2	100.0%
Class 3	88.4%
Class 4	100.0%
Class 5	94.2%

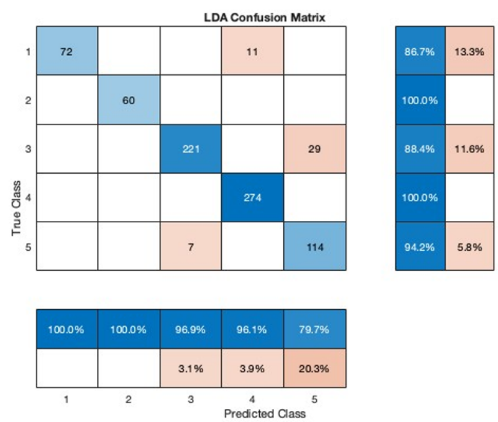

Fig. 11: EFA Confusion Matrix for Room Classification

IX. Classification Accuracy Comparison

To quantify the performance of each dimensionality reduction technique in distinguishing between acoustic environments, confusion matrices were generated and analyzed for PCA, LDA, and EFA. The overall classification accuracy was computed as the ratio of correctly identified room samples to the total number of samples. The resulting accuracies are as follows:

TABLE III: Classification Accuracy of Dimensionality Reduction Techniques

Method	Accuracy (%)
PCA	99.11
LDA	94.04
EFA	94.54

These results highlight the superior classification capability of PCA in this context, while also demonstrating that both

LDA and EFA achieve comparably high performance. Notably, EFA slightly outperformed LDA despite being an unsupervised technique, indicating its potential in revealing meaningful latent structures relevant to room classification.

X. Conclusion

This study presented a comprehensive statistical analysis of Spatial Room Impulse Response (SRIR) datasets, with the goal of characterizing and classifying diverse acoustic environments. Building upon prior work involving Principal Component Analysis (PCA), we introduced and evaluated two additional techniques—Linear Discriminant Analysis (LDA) and Exploratory Factor Analysis (EFA)—to assess their effectiveness in uncovering structure and separability within the acoustic parameter space.

Our findings demonstrate that each method offers unique advantages. PCA provided the highest classification accuracy, effectively reducing dimensionality while preserving key discriminative information. LDA, by leveraging supervised class labels, enabled robust separation of room classes and highlighted the importance of parameters such as DT20m and C50 in acoustic differentiation. EFA, on the other hand, uncovered latent dimensions underlying the acoustic feature space, offering interpretability in terms of perceptual constructs such as clarity and reverberance. The factor structure revealed by EFA emphasized the pivotal role of DRR and Grel in shaping acoustic identity.

Moreover, parameter sensitivity analyses underscored the necessity of carefully selecting acoustic descriptors for effective classification and interpretation. The integration of these statistical approaches enabled both quantitative classification and qualitative insight into the nature of spatial acoustics.

In conclusion, this multi-method analysis provides a robust framework for data-driven room characterization. The outcomes support future applications in spatial audio rendering, architectural acoustics design, and intelligent auditory scene analysis. Further research could explore combining these techniques with machine learning models or perceptual evaluations to enhance the granularity and practical impact of room acoustic analysis.

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