AUDIO DATASET ANALYSIS FOR LAPLACIAN NOISE ESTIMATION

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Abstract:

This study explores the analysis of audio datasets for Laplacian noise estimation. With noise being a significant concern in audio applications, we propose techniques to estimate Laplacian noise parameters directly from audio data. Our framework includes parameter estimation, correlation analysis, alongside statistical modeling and joint probability density evaluation methodologies used to estimate the Laplacian noise of audio dataset are all thoroughly investigated in this research. The Gaussian distribution was shown to be the most appropriate model for most datasets after a variety of distribution models, including Rayleigh, Gamma, Inverse Gamma, Exponential, and Gaussian, were evaluated for their fit to the dataset using the Kullback-Leibler (KL) divergence score. The advantage of Maximum Likelihood Estimation (MLE) in estimating both mean and variance parameters was then demonstrated by a comparison of MLE's and Method of Moments (MOM) efficacy for parameter estimation. Additionally, using the proper correlation coefficients, the connection between the two components of skewness and kurtosis was found. To clarify the joint distribution of the data, the two-dimensional probability density function (PDF) of the audio dataset was also compared to the product of the individual PDFs of each component. This thorough examination advances our knowledge of Laplacian noise characteristics and statistical techniques, providing insightful information that can be used to evaluate underlying physical events and guide decision-making across a range of scientific and technical fields. This study establishes a basis for future research in related disciplines and advances the state-of-the-art in estimating Laplacian noise of audio datasets by integrating different analytical methodologies.

Keywords: *MOM (Method of moments), MLE (Maximum Likelihood Estimation), Laplacian noise, KL Divergence Score, Skewness, Kurtosis.*

I. INTRODUCTION

In the realm of audio signal processing, the accurate estimation and management of noise are critical for optimizing the quality of audio recordings and facilitating a wide array of applications ranging from speech recognition to music production. Among various types of noise, Laplacian noise poses a unique challenge due to its specific statistical characteristics. Laplacian noise exhibits heavy-tailed distributions, making its estimation and removal particularly challenging yet essential for preserving signal fidelity.

The analysis of audio datasets to estimate Laplacian noise involves a multifaceted approach that integrates statistical modeling, parameter estimation, correlation analysis, and joint probability density assessment techniques. By employing sophisticated methodologies tailored to Laplacian noise, researchers aim to extract meaningful insights from audio data, identify noise patterns, and develop effective noise reduction strategies.

This endeavor begins with the evaluation of different distribution models, including Gaussian, Rayleigh, Gamma, Inverse Gamma, and Exponential distributions, to determine the most suitable model for describing the statistical properties of the audio dataset. Subsequently, parameter estimation techniques such as Maximum Likelihood Estimation (MLE) and Method of Moments (MOM) are employed to accurately estimate key parameters such as mean and variance, crucial for characterizing Laplacian noise.

Correlation analysis provides further understanding of the relationship between various components of the audio dataset, shedding light on the intricate interplay between different sources of noise. Moreover, the joint probability density assessment helps in visualizing the overall distribution of the data, enabling researchers to discern patterns and anomalies indicative of Laplacian noise.

In order to achieve these goals, we have taken the direct audio dataset from kaggle and examined the **"pcm_intensity_sma_skewness"** and **"pcm_intensity_sma_kurtosis"** columns which are basically **skewness** and **kurtosis** values in order to estimate Laplacian noise. Using the SMA **(Simple Moving Average)** approach, the feature "pcm_intensity_sma_skewness" quantifies the asymmetry of the intensity distribution in a PCM (**Pulse Code Modulation)** audio signal. This statistic provides information about the shape of the noise distribution while estimating Laplacian noise. Laplacian noise usually has a heavy-tailed, symmetric distribution; deviations from symmetry are indicated by skewness. A symmetric distribution is suggested by a skewness value near zero, which may also indicate Gaussian noise or very little noise. On the other hand, large departures from zero suggest asymmetric distributions, which could be a hint of the presence of Laplacian noise.

The feature "pcm_intensity_sma_kurtosis" measures the kurtosis of intensity distribution in a PCM audio signal, computed using the SMA method. Kurtosis quantifies the peakedness or flatness of a distribution compared to a normal distribution.

II. METHODS

1. Distribution Models

We employed various distribution models to characterize the probability distribution of Laplacian noise. These models include:

Gaussian Distribution: Also known as the normal distribution, this model assumes a symmetric, bell-shaped curve.

Gamma Distribution: Used for continuous, positive-valued variables, the Gamma distribution is characterized by its shape and scale parameters.

Inverse Gamma Distribution: This distribution, the reciprocal of the Gamma distribution, is suitable for modelling positive-valued variables with a right-skewed distribution.

Exponential Distribution: Describing the time between events in a Poisson process, the Exponential distribution is commonly used for modelling waiting times.

Rayleigh Distribution: Frequently used to model the magnitude of vectors, such as wind speeds or wave heights, the Rayleigh distribution is characterized by a right-skewed shape.

2. Parameter Estimation

We compared two estimation techniques to determine the parameters of the selected distribution models:

Maximum Likelihood Estimation (MLE): This method estimates the parameters that maximize the likelihood of observing the given data, assuming a particular distribution model.

Method of Moments (MOM): MOM estimates the parameters of a distribution by equating sample moments (e.g., mean and variance) to theoretical moments.

3. Correlation Analysis

To understand the relationship between the two components of audio data namely skewness and kurtosis, we conducted correlation analysis using appropriate correlation coefficients:

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4. Joint Probability Density Assessment

We evaluated the joint probability density function (PDF) of magnetometer data by comparing it with the product of the individual PDFs of each component. This assessment provides insights into the joint distribution of the data, highlighting any deviations from the product of individual PDFs.

III. RESULTS

KL SCORES	**Gaussian**	**Gamma**	**Exponential**	**Rayleigh**	**Inverse Gamma**
Skewness	**0.62682608**	0.63670794	1.593142824	1.0937041384	0.64572163
Kurtosis	0.693931583	0.52891656	1.006058821	0.6399014218	**0.48517800**

The best fitting distribution for skewness is the **Gaussian distribution.**
The best fitting distribution for Kurtosis is **Inverse Gamma distribution.**

MLE for skewness using gaussian distribution:

	MLE estimation
Mean	1.457213618
Variance	0.573737136

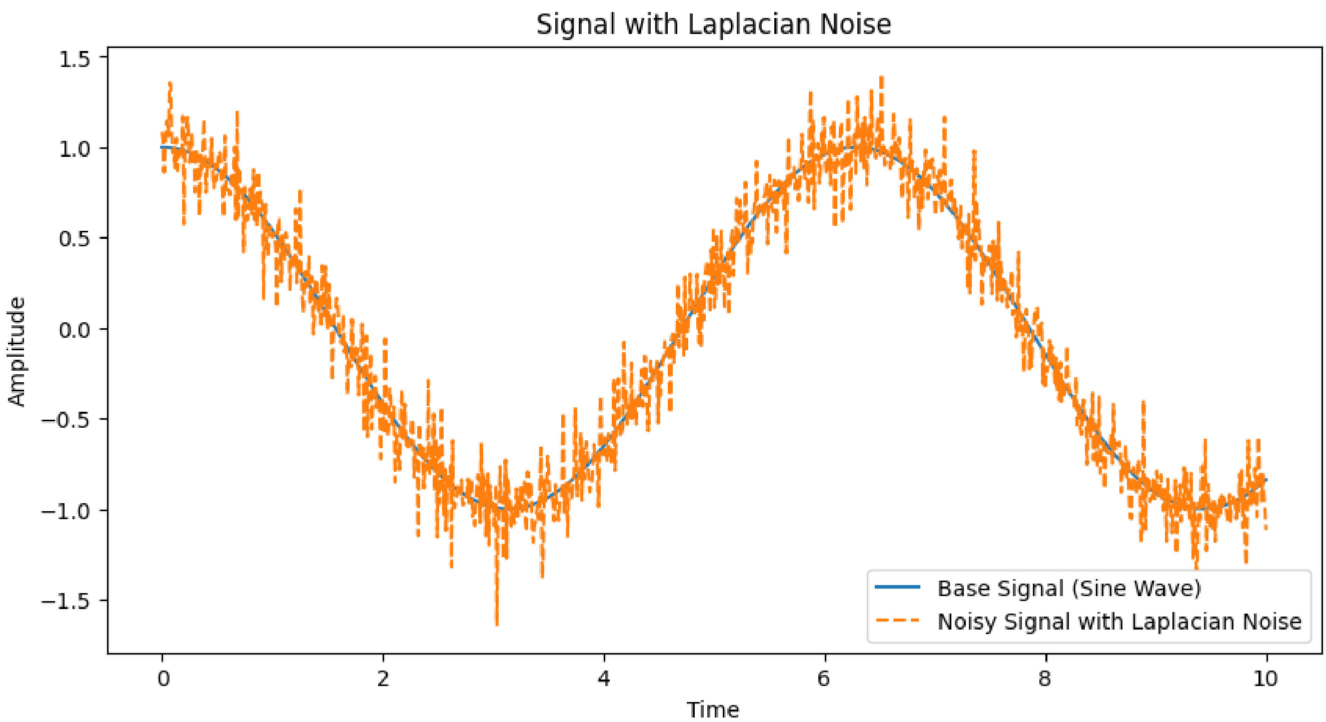
MLE for kurtosis using inverse gamma distribution:

	MLE estimation
Alpha	17.751997744
Beta	133.841992393

Covariance Matrix:

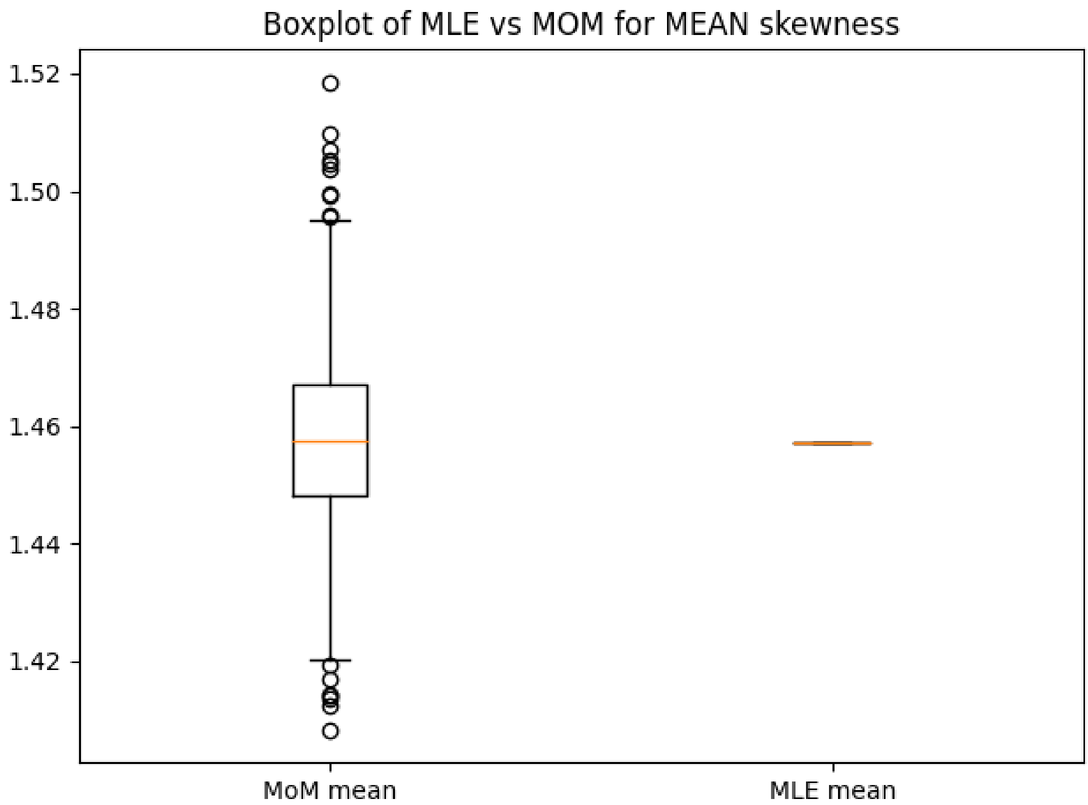
0.00984101	**0.00890377**
0.00890377	**0.01034497**

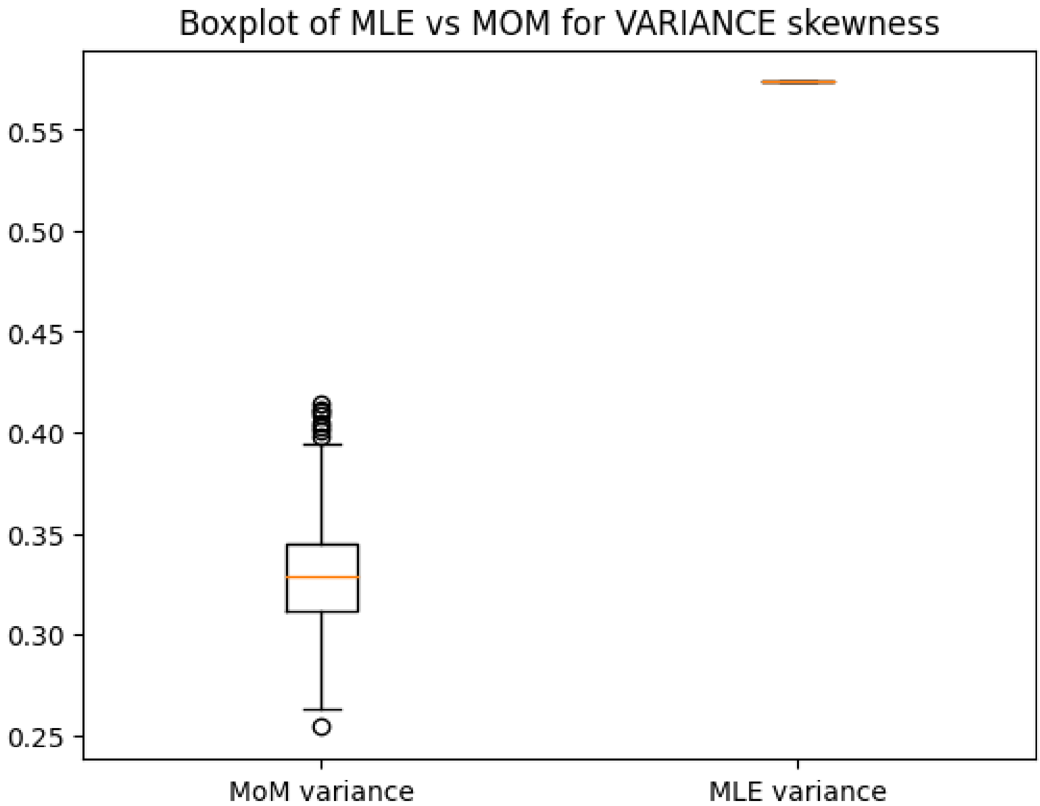
Correlation for skewness and kurtosis: 0.8824491796435042

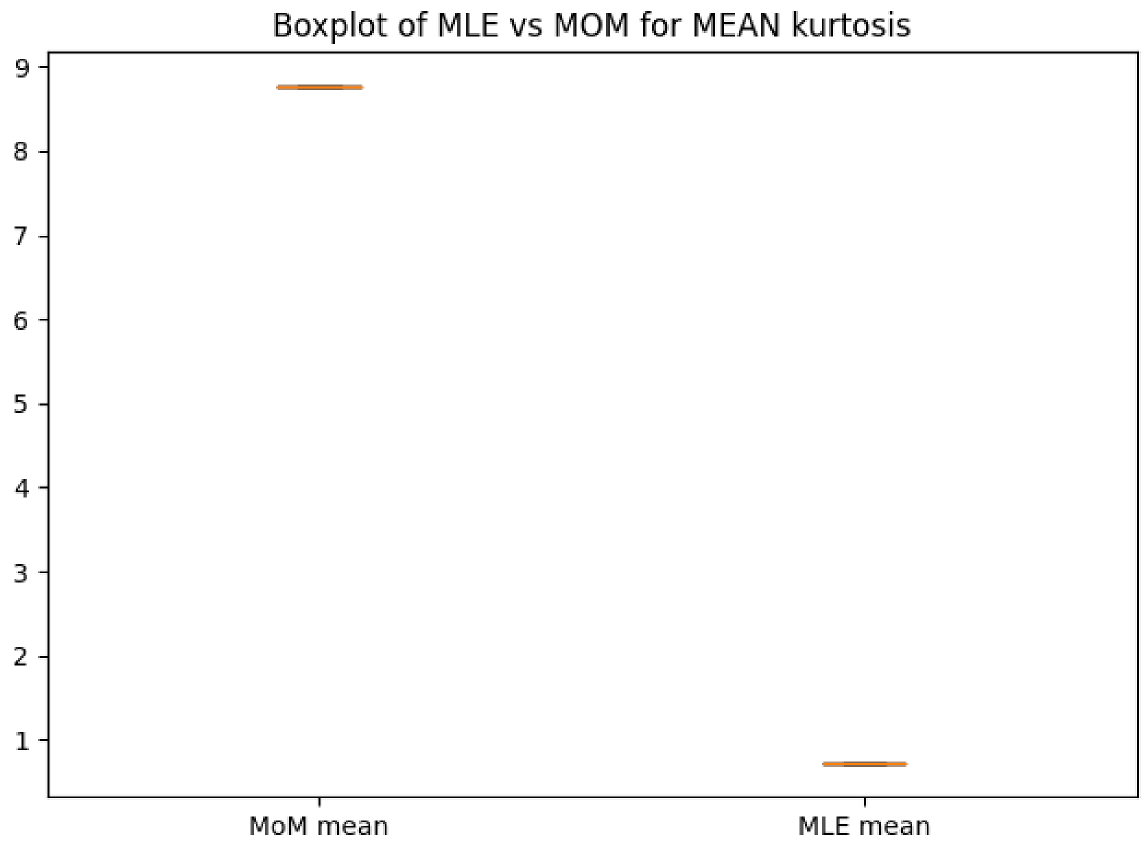


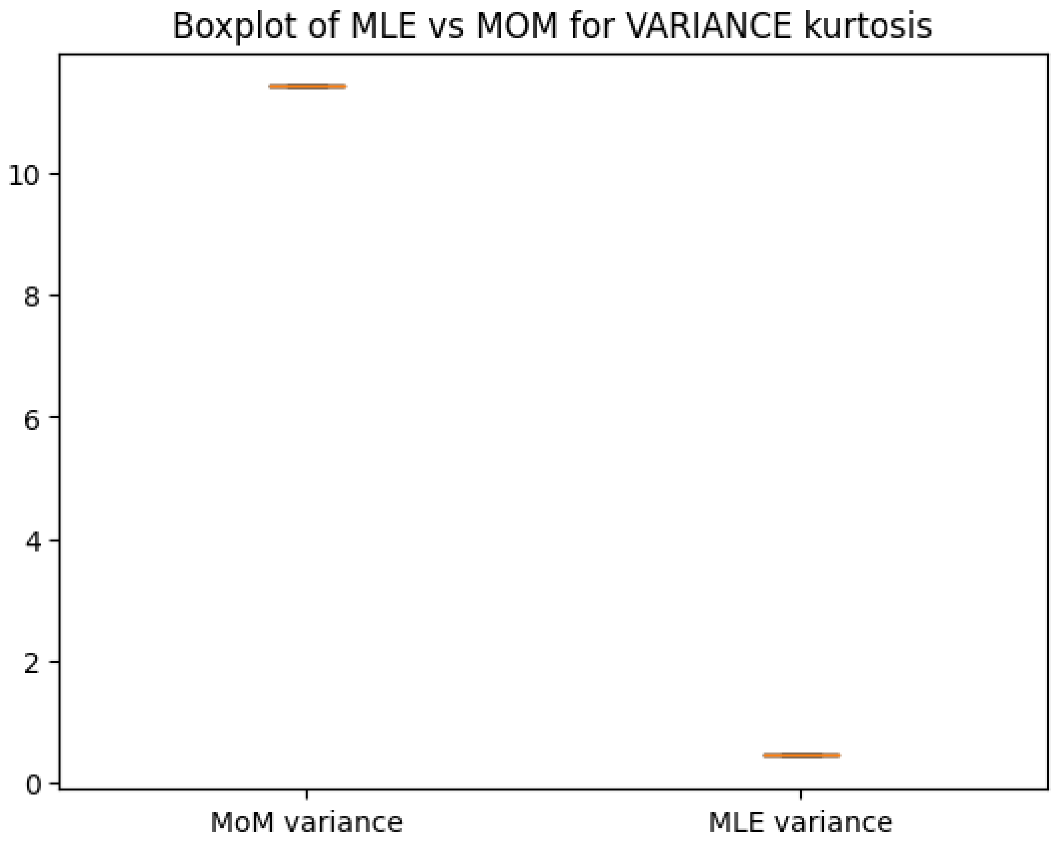
MOM and MLE for Laplacian noise:

	MLE estimates	MOM estimates
Mean	**1.457213618**	**-0.056514992**
Variance	**0.573737136**	**0.6544466732**


Boxplot of MLE vs MOM for MEAN skewness
1.52
1.50
1.48
1.46
1.44
1.42
MoM mean
MLE mean


Boxplot of MLE vs MOM for VARIANCE skewness
0.55
0.50
0.45
0.40
0.35
0.30
0.25
MoM variance
MLE variance


Boxplot of MLE vs MOM for MEAN kurtosis
9
8
7
6
5
4
3
2
1
MoM mean
MLE mean


Boxplot of MLE vs MOM for VARIANCE kurtosis
10
8
6
4
2
0
MoM variance
MLE variance

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