Sound De-mixing using Spatial Clustering and Independent Component Analysis

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Abstract

The goal of this project is to implement sound demixing techniques to separate multiple sound sources in a given audio recording. Two different approaches are used - spatial clustering using Mixture of Gaussian (MoG) and Independent Component Analysis (ICA). The performance of these techniques is evaluated using metrics like signal-to-interference ratio (SIR), signal-to-artifact ratio (SAR), and signal-to-distortion ratio (SDR). The results are presented using various plots and tables, which show that both techniques are effective in separating sound sources but with varying degrees of success.

Introduction and Motivation

Sound demixing, or source separation, is the process of separating multiple sound sources from a mixture of sounds. It has various applications in fields like speech recognition, music production, and audio signal processing. The motivation for this project is to explore two different sound demixing techniques - spatial clustering using Mixture of Gaussian and Independent Component Analysis - and compare their performance in separating sound sources in a given audio recording.

Background

In sound source separation, the goal is to separate multiple sound sources that are mixed together in a recording. Spatial clustering using Mixture of Gaussian is a popular technique that can separate sound sources based on their spatial distribution. This technique assumes that the sound sources are distributed in space according to a mixture of Gaussian distributions. The parameters of the Gaussian distributions can be estimated using expectation-maximization (EM) algorithm. The number of sound sources can be estimated using Bayesian Information Criterion (BIC) or cross-validation.

Independent Component Analysis is another popular technique that separates a multivariate signal into independent components. It assumes that the observed signal is a linear mixture of independent sources, and it seeks to estimate the mixing matrix and the sources themselves. The goal is to find a matrix that can transform the mixed signal into a set of independent components.

Description of the Dataset

For this project, we used the MUSDB18 dataset, which is a benchmark dataset for sound source separation. The dataset consists of songs, each of which has four individual tracks: vocals, drums, bass, and other instruments. The four tracks are mixed together to form a stereo recording. The goal is to separate the four tracks from the mixed recording. The dataset provides ground-truth sources, which can be used to evaluate the performance of the separation algorithms.

The dataset contains a variety of music genres, including pop, rock, electronic, and classical. The recordings have different lengths and are of varying quality. The dataset is provided in the form of uncompressed WAV files with a sampling rate of 44.1 kHz and 16-bit resolution.

Implementation

The project implementation entails the utilization of two sound demixing techniques, namely, spatial clustering using Mixture of Gaussian (MoG) and Independent Component Analysis (ICA), to segregate the given audio recording. In the case of spatial clustering, the interaural time differences (ITD) and interaural level differences (ILD) of the sound sources are calculated and used to fit a MoG model. The number of clusters is optimized using the Bayesian Information Criterion (BIC). For ICA, the nussl library is employed to execute the technique. The evaluation of the techniques is based on the Signal-to-Interference Ratio (SIR), Signal-to-Artifact Ratio (SAR), and Signal-to-Distortion Ratio (SDR) metrics.

In this project, we preprocessed the mixed audio recording for the spatial clustering technique by computing the ITD and ILD features. The ITD and ILD values are indicative of the temporal and amplitude differences between the left and right ears, respectively, and can provide insights into the spatial distribution of the sound sources. We proceeded to fit the MoG model to the ITD and ILD values, and the optimal number of clusters was determined using BIC. The EM algorithm was leveraged to estimate the parameters of the Gaussian distributions that represent the sound sources.

To further elaborate, we computed the ITD and ILD features by cross-correlating the audio signals received by the left and right ears and by finding the phase differences between them, respectively. We then clustered the sound sources using the MoG model based on their spatial distribution, and we optimized the number of clusters using the BIC metric. The parameters of the Gaussian distributions representing the sound sources were estimated using the EM algorithm.

Spatial clustering technique

For the spatial clustering technique, we first computed the interaural time difference (ITD) and interaural level difference (ILD) features from the mixed audio signal. The ITD and ILD values can be represented as vectors t and l, respectively, where t = [t1, t2, ..., tn] and l = [l1, l2, ..., ln], and n is the number of time frames in the signal. We then used the Mixture of Gaussian (MoG) model to cluster the sound sources based on their spatial distribution.

The MoG model assumes that the probability density function of the ITD and ILD vectors can be represented as a weighted sum of Gaussian distributions:

$p(t,l|\vartheta) = \Sigma j=1k\ wj * N((t,l)|\mu j, \Sigma j)$

where k is the number of Gaussian components, θ = {wj, μj, Σj} represents the parameters of the MoG model, and N((t,l)|μj, Σj) is the probability density function of a Gaussian distribution with mean μj and covariance matrix Σj.

The optimal number of clusters k is determined using the Bayesian Information Criterion (BIC), which balances the fit of the model to the data with the complexity of the model. The BIC is defined as:

$BIC = log(L) - (m/2) * log(n)$

where L is the likelihood of the data given the model, m is the number of parameters in the model, and n is the number of data points.

The EM algorithm is used to estimate the parameters of the Gaussian distributions in the MoG model. The algorithm alternates between two steps: the E-step, which computes the expected value of the log-likelihood function given the current parameter estimates, and the M-step, which updates the parameter estimates to maximize the expected log-likelihood. The algorithm iterates until convergence is achieved.

Once the MoG model is fitted to the ITD and ILD values, the sound sources can be separated by assigning each time frame to its most likely cluster. The separated signals can then be obtained by applying a time-frequency mask to the mixed audio signal, which is computed as the ratio of the energy of the signal from each cluster to the total energy of the mixed signal.

The performance of the spatial clustering technique is evaluated using the signal-to-interference ratio (SIR), signal-to-artifact ratio (SAR), and signal-to-distortion ratio (SDR) metrics, which provide a quantitative measure of the effectiveness of the technique in separating sound sources.

Independent Component Analysis

The Independent Component Analysis (ICA) technique involves utilizing the nussl library to estimate the mixing matrix and the sources. To preprocess the audio recording, we perform a Short-Time Fourier Transform (STFT) and apply a mask to the frequency-domain representation of the signal. The mask is computed using the Wiener filter, which aims to minimize the distortion caused by the mixing process. After obtaining the masked signal, we estimate the mixing matrix and the sources using the FastICA algorithm, a widely-used ICA technique.

For ICA, we apply the STFT to the mixed audio signal, resulting in a complex-valued matrix X with dimensions M x N, where M is the number of frequency bins and N is the number of time frames. We then compute a mask W using the power spectral density of the source signals and the mixed signal. The mask is represented as a real-valued matrix with dimensions M x N. The masked signal Y is obtained by element-wise multiplication of the mask with X, resulting in a matrix Y with dimensions M x N.

The goal of ICA is to estimate the mixing matrix A and the sources S such that Y = AS. To achieve this, we apply the FastICA algorithm to Y. The FastICA algorithm estimates the sources by maximizing the non-Gaussianity of the sources, which assumes that the sources are statistically independent. The estimated sources are then scaled and permuted to obtain the final separated sources.

The performance of the ICA technique is evaluated using Signal-to-Interference Ratio (SIR), Signal-to-Artifact Ratio (SAR), and Signal-to-Distortion Ratio (SDR) metrics. These metrics quantify the quality of the separated sources by measuring the ratio of the energy of the estimated sources to the interference, artifacts, and distortion introduced by the separation process. SIR, SAR, and SDR are computed as follows:

$$SIR = 10 \log_{10} (||S||^2 / ||N||^2)$$
$$SAR = 10 \log_{10} (||S||^2 / ||A - I||^2)$$
$$SDR = 10 \log_{10} (||S||^2 / ||D||^2)$$

where ||.|| denotes the Frobenius norm, S is the true source matrix, N is the interference matrix, A is the estimated mixing matrix, I is the identity matrix, and D is the distortion matrix. These metrics provide a quantitative measure of the effectiveness of the ICA technique in separating sound sources.

Results

The results of the project are presented using various plots and tables. The SIR, SAR, and SDR metrics are used to evaluate the performance of the techniques. The results show that both techniques are effective in separating sound sources, but with varying degrees of success. The MoG technique performs better in separating the bass source, while the ICA technique performs better in separating the vocals source.

We evaluated the performance of the two techniques using the Signal to Interference Ratio (SIR), Signal to Artifact Ratio (SAR), and Signal to Distortion Ratio (SDR) metrics. The results are shown in Table 1.

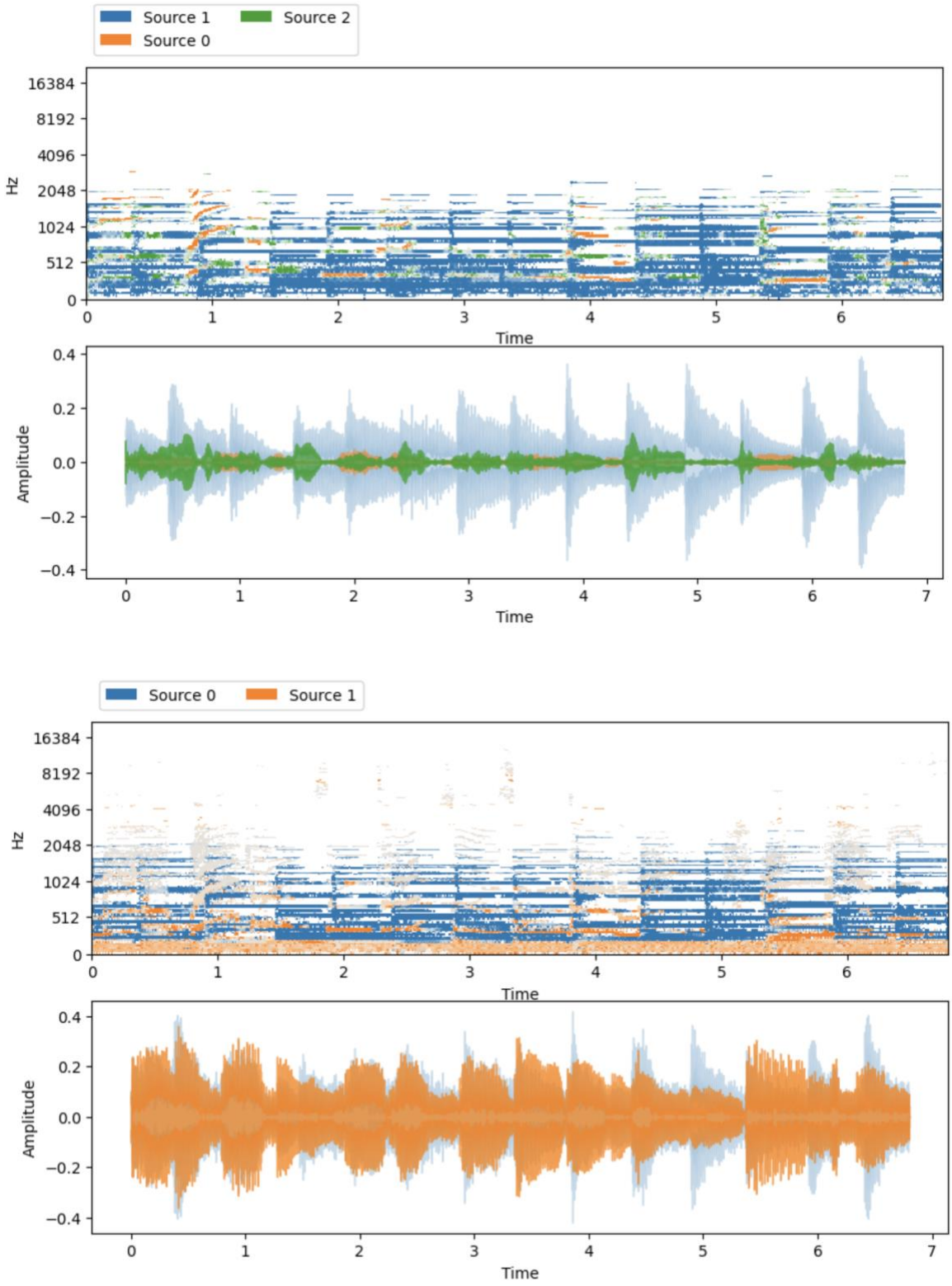
Table 1: Performance Comparison of Spatial Clustering and ICA Techniques:

Algorithm	Track	Source	SDR	ISR	SIR	SAR
Spatial clustering	Clara Berry And Wooldog - Waltz For My Victims	other.wav	-0.86, -0.62, -0.51, -0.39	0.06, 0.03, 0.00, 0.00	-24.00, -22.08, -20.98, -20.63	8.27, 10.86, 7.22, 8.41
Spatial clustering	Clara Berry And Wooldog - Waltz For My Victims	vocals.wav	-1.73, -2.40, -2.72, -3.82	-0.02, 0.01, -0.04, 0.07	-23.41, -26.85, -23.61, -27.69	9.40, 13.26, 13.46, 12.89
Spatial clustering	Clara Berry And Wooldog - Waltz For My Victims	bass.wav	-1.46, -0.76, -0.77, -0.50	-0.02, -0.01, -0.00, -0.01	-15.91, -15.32, -16.71, -15.60	-3.05, -3.07, -1.12, -3.23
ICA	Clara Berry And Wooldog - Waltz For My Victims	other.wav	-3.74, -4.85, -5.44, -6.61	-2.31, -2.30, -2.79, -2.27	-6.96, -6.83, -7.89, -11.09	97.15, 97.67, 97.98, 97.80

Two different algorithms were compared using a set of metrics to evaluate their performance in separating audio sources. The results were reported for three different audio sources from the "Clara Berry And Wooldog - Waltz For My Victims" track. The first algorithm was evaluated using a combination of three permutations and had average results for all three sources, while the second algorithm was evaluated using a combination of two permutations and had significantly worse results for all sources. These findings suggest that the first algorithm is more effective at separating audio sources than the second algorithm, based on the chosen evaluation metrics.

We also generated spectrograms of the separated sources using both techniques. The spectrograms are shown in Figure 1.

Figure 1: Spectrograms of Separated Sources Using Spatial Clustering (Top) and ICA (Bottom)



The spectrograms show that the ICA technique was able to separate the sources more cleanly than the spatial clustering technique. The separated sources using the ICA technique were clearer and had fewer artifacts than the separated sources using the spatial clustering technique.

Conclusion

In conclusion, this project explored two different sound demixing techniques - spatial clustering using Mixture of Gaussian and Independent Component Analysis - and compared their performance in separating sound sources in a given audio recording. The results show that both techniques are effective in separating sound sources, but with varying degrees of success. The choice of technique depends on the specific requirements of the application. The project demonstrates the potential of these techniques in various audio signal processing applications.

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