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Independent Component Analysis Enhancements for Source Separation in Immersive Audio Environments

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INDEPENDENT COMPONENT ANALYSIS ENHANCEMENTS FOR SOURCE SEPARATION IN IMMERSIVE AUDIO ENVIRONMENTS

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering in the College of Engineering at the University of Kentucky

By

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ABSTRACT OF THESIS

INDEPENDENT COMPONENT ANALYSIS ENHANCEMENTS FOR SOURCE SEPARATION IN IMMERSIVE AUDIO ENVIRONMENTS

In immersive audio environments with distributed microphones, Independent Component Analysis (ICA) can be applied to uncover signals from a mixture of other signals and noise, such as in a cocktail party recording. ICA algorithms have been developed for instantaneous source mixtures and convolutional source mixtures. While ICA for instantaneous mixtures works when no delays exist between the signals in each mixture, distributed microphone recordings typically result various delays of the signals over the recorded channels. The convolutive ICA algorithm should account for delays; however, it requires many parameters to be set and often has stability issues. This thesis introduces the Channel Aligned FastICA (CAICA), which requires knowledge of the source distance to each microphone, but does not require knowledge of noise sources. Furthermore, the CAICA is combined with Time Frequency Masking (TFM), yielding even better SOI extraction even in low SNR environments. Simulations were conducted for ranking experiments tested the performance of three algorithms: Weighted Beamforming (WB), CAICA, CAICA with TFM. The Closest Microphone (CM) recording is used as a reference for all three. Statistical analyses on the results demonstrated superior performance for the CAICA with TFM. The algorithms were applied to experimental recordings to support the conclusions of the simulations. These techniques can be deployed in mobile platforms, used in surveillance for capturing human speech and potentially adapted to biomedical fields.

Multimedia Elements Used: WAV (.wav)

KEYWORDS: Blind Source Separation, Independent Component Analysis, Audio Signal Processing, Convolutional Source Separation, Information Theory

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To my loving parents, dear teachers, friends and colleagues

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF FILES

Chapter 1 : Introduction and Literature Review

1.1 A Brief History for Blind Source Separation and Independent Component Analysis

In digital signal processing, one goal is to recover the original signals from the signal mixtures, and this process is referred to as Source Separation (SS). A typical scenario for source separation is the cocktail party scenario where we have multiple speakers, background music and noise, and we only know the mixtures, but we try to estimate or even reconstruct the original source of interest (SOI) from the sound mixtures recorded by microphones [1].

Blind Source Separation (BSS), also referred to as Blind Signal Separation, is a type of Source Separation (SS) where we have little or no prior knowledge of the sources and the mixing system. Many methods are used for BSS. The basic methods are Principal Component Analysis, Singular Value Decomposition, Independent Component Analysis, Dependent Component Analysis, Non-negative Matrix Factorization, Low-complexity Coding and Decoding, Stationary Subspace Analysis, and Common Spatial Pattern. Depending on the kind of source separation problem and the kind of mixing system involved, we may combine a few of these algorithms for processing mixed data in order to get optimized separation results. BSS originated with audio processing due to audio signals' spatial feature, but can also be applied to image processing, biomedical data, economic analysis, telecommunications, etc. In this thesis, the research is focused on BSS in audio environment signal processing [1, 2].

Independent Component Analysis (ICA) is a blind source separation and is one of the state-of-the-art topics in signal processing, biomedical fields, telecommunications, etc. Independent Component Analysis (ICA) is a special case of the Blind Source Separation and this algorithm's premise is the independent feature of source signals. ICA can analyze and uncover hidden factors from a set of signals. In the audio signal environment, the data signals are assumed to be linear or nonlinear mixtures of some unknown latent source signals, and the mixing system is assumed to be unknown. The latent signals are

assumed to be non-Gaussian and mutually independent, and these latent signals are referred to as the independent components of the observed signal data. Processing the observed data through BSS/ICA, we can get these independent components, referred to as sources [1].

1.2 BSS/ ICA Research and Thesis Motivation

Early acoustic source separation systems relied on fixed or adaptive beamforming, and these techniques are still in use today. Beamforming is a mature technique, and it has been deployed in commercial products such as cell phones and other electronics to separate the sources of interest [3]. These methods require prior knowledge such as the relative positions of the microphones and target source or time intervals during which the target source is inactive. In our lab, beamforming takes a very long processing time, requires the location coordinates of the sources to perform separation, and the beamforming algorithm requires a large number of microphones for good separation results.

In reality, prior knowledge is rarely available, so we need to consider BSS. Blind Source Separation (BSS) requires little to no prior knowledge of the sources and/or the mixing process, does not need nearly as many microphones to perform separation, does not take nearly as long to perform separation, and theoretically does not need the locations of the microphones to perform separation, but the layout of the microphones affect the separation results with related toolbox. Due to the convenience and advantages of the ICA and BSS, this thesis aims at exploring the feasibility of the ICA and BSS algorithms in audio environments. Later on, this thesis also explores enhancements of the ICA for source separation in immersive audio environments.

1.3 ICA in Audio Signal Processing

Two techniques that use BSS for audio separations are convolutive independent component analysis (convolutive ICA) and sparse component analysis (SCA). These two techniques characterize real-world audio mixtures and summarize the performance of existing systems for such mixtures. But these two strategies face permutation alignment problems.

Strategies for permutation alignment [4] are as follows: we can make the separation matrices W smooth in frequency domain (Window the separation filter in Time Domain, average the separation matrices among adjacent frequencies); we can relate separation results to source location, such as direction of arrival (DOA) or time difference of arrival (TDOA), but these directivity patterns are practically possible only for a two-source case; we can evaluate the dependence of already separated bin-wise signals; finally, we can also incorporate the inter-frequency dependence evaluation into an ICA/BSS criterion and algorithm. The last two strategies are less affected by severe reverberation or closely located sources. We may combine a few of these strategies with BSS to get optimized source separation. We have to consider permutation alignment in ICA because we do not know the underlying source locations, while in beamforming we have knowledge of the source location. If we know the position, permutation of ICA will not matter.

We need to process the recorded mixtures, so we need to consider microphone physical characteristics in the process. Common microphone arrangements may involve both near-field and far-field microphones and the acoustic-electric conversion performed by the microphones. The direction of the cardioid microphones accounts for up to a 3 dB improvement in the SNR over that of the omnidirectional microphones [5].

In the cocktail party scenario, noise may come from clinking glasses or footsteps. The level of the SOI is increased if within each estimated source signals, distortions remain low compared to original source signal SOI. Such distortions may include filtering of the source of interest, residual sounds from other sources of interest as interference, residual noise from undesired sources, and additional “gurgling” sounds known as artifacts.

Audio sources exhibit significant dependencies on average over short durations, which decrease with increasing signal duration in most but not all situations. Speech and music sources are similar, so we consider fairly longer signal clips in our experiment for better performance (ICA book chapter 19) [6]. Speech signals are practically zero most of the time, and this characteristic is reflected in their strong gaussianity; we assume that only two signals are nonzero at the same time, and reconstruct these signals.

Speech signals consist of a sequence of phones; and it consist of a period, noisy or transient sounds. Audio sources are generally sparse in the time-frequency domain; in the time domain, speech sources are generally sparse, but only some music sources are sparse. Convolutive ICA separates the sources by convolving the mixture signals with multichannel FIR unmixing filters by maximizing some contrast function. Interference cancellation improves when the number of notches or their spatial width increases; this means increasing the number of microphones or the length of the unmixing filters. It will result in worse performance if sources are less stationary; this happens because interference must then be canceled over a range of positions even within a short duration. Also we can only employ the Convolutive ICA method for determined audio sources.

SIRI decreases when the microphones have close locations. Room recordings and car recordings show that when microphone spacing is smaller, it has larger performance degradation. But when running experiments on the signals recorded when playing a speech source through the loudspeaker situated at the driver's head position are added to real noise recordings made in a moving car with the same microphone arrays, performance is better when microphones are closer. The best SIRI obtained for these mixtures was about 2 dB, which is low communication quality [6].

Separation performance over stereo mixtures dramatically decreases with 1) increasing reverberation time, 2) decreasing microphone distance, and 3) diffuse interfering sources.

1.4 Current Research on BSS and their Literature Review

Depending on whether the system is under-determined or over-determined, meaning or we have less microphones than speakers or we have more microphones than speakers, and also depending on the number of microphones and/ or speakers we have, we can deploy different BSS algorithms for good separation results.

In the Generative Topographic Mapping (GTM) algorithm, we have mutually similar impulse (delta) functions that are equispaced on a rectangular grid that are used to model the discrete uniform density in the space of latent variables, or the joint density of the sources in our case. GTM is based on a generative approach that starts by assuming a

model for the latent variables, in our case [7]. Bayesian learning solves trade-off between under(under-) and over(-)fitting [8]. Ensemble learning/Variational learning is a method for parametric approximation of posterior pdfs where the search takes into account the probability mass of the models [9].

There are also BSS methods using time structure. In many cases, the mix is time signals instead of random variables. If ICs are time signals, it may contain more structures than simple random variables, i.e. Autocovariances, which can help improve the estimation of the model. Autocovariances are an alternative to non-Gaussianity. This additional information can actually make the estimation of the model possible in cases where the basic ICA methods cannot estimate it, such as if the ICs are Gaussian but correlated over time. The AMUSE algorithm is used when we have one time lag in Autocovariances[10].

More literature reviews on state of art BSS algorithms are covered below.

1.4.1 Using one microphone to separate singing voice

Ozerov, Phoolippe, Gribonval, and Bimbot modified the general Gaussian Mixture Model (GMM) and came up with a probabilistic approach to study the separation of the singing voice using the short time spectra. Their goal is to use only one microphone to do the separation. To achieve this goal, authors used adapted filters via Maximum Likelihood Linear Regression (MLLR) [11]. Traditional GMM-Based Source Separation model is shown in figure 1.1.

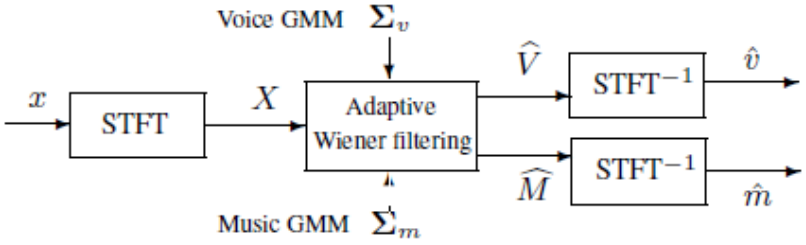


Figure 1.1 GMM- Based Separation Scheme from Ozerov, A.; Philippe, P.; Gribonval, R.; Bimbot, F., "One microphone singing voice separation using source-adapted models," [11]

x is the incoming singing voice (music and voice direct addition). After we do short term frequency transform on mixture x, it became mixture X in frequency domain. Then we tune the Adaptive Wiener filter with regard to Voice GMM and Music GMM to process the mixture. This Adaptive Weiner filter is actually a Minimum Mean Square Error (MMSE) estimator. Covariance matrix $\sum_v$ and $\sum_m$ are learned through the Expectation Maximization (EM) algorithm [12] by Vector Quantization (VQ) to optimize separation results. After we got the separated V (voice spectral) and M (music spectral) in frequency domain, we take the inverse short term frequency transform yielding the separated music and voice in time domain.

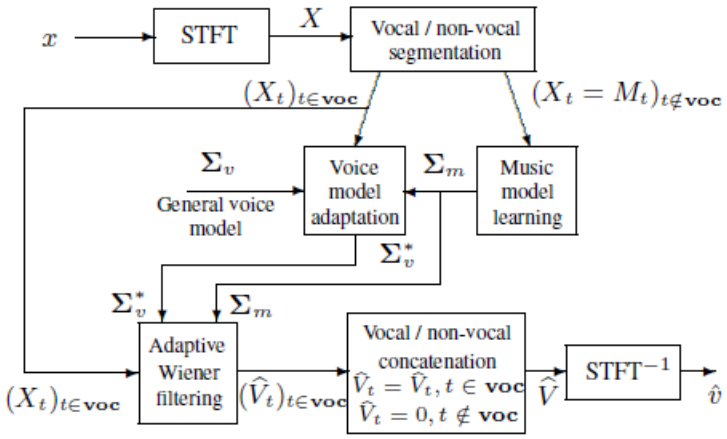


Figure 1.2 Source-adapted separation scheme from Ozerov, A.; Philippe, P.; Gribonval, R.; Bimbot, F., "One microphone singing voice separation using source-adapted models," [11]

To alleviate the work load of modeling large sound classes of music and voice, meaning to alleviate the large workload of learning process of the Covariance matrix $\sum_v$ and $\sum_m$, authors proposed the adapted model described in Figure 1.2. The adaptive model is proposed based on the existence of vocal and non-vocal parts in a music clip and different influences of vocal and non-vocal parts in the separation process. The adaptive model is optimized in three aspects: music model learning on the non-vocal parts, filter-adaptive learning of the general voice model, and filter adaptation of the voice model at the separation stage.

Advantages of this adapted model are that this model is beneficial to the cocktail party scenario where voices and music coexist. Also, this adaptive model has fairly good separation results. Drawbacks of this adaptive model include that it is not blind source separation because it requires data training. The model is also very simple and not very applicable in real-life situations due to the fact that their mixture is a direct addition of the music and voice, while in real life we need to process convolutive blind source separation instead of instantaneous two-source separation. Separation results from this approach are not as good as the results from using the FASS toolbox. We also cannot use this adaptive model to do two human voice separations due to the algorithm internal premiers. Unfortunately we cannot compare the performance of this adaptive model with the FastICA model because FastICA needs more or the same number of sensors than the speakers while here we have one sensor and two sources.

1.4.2 Blind Separation of Convolutive Mixtures using Spatio-Temporal FastICA Algorithms

FastICA algorithm that was developed by Hyvärinen and Oja is a famous and convenient method for Blind Source Separation, but its usage is limited to processing instantaneous mixtures of the sources. While in real life situations, such as in a room setting, room noise, reverberation, delays and so on coexist, these factors influence individual microphone recording, making microphone recordings complex, i.e. convolutive mixtures of sources. To process separations on convolutive microphone recordings, Douglas, Gupta, Sawada, and Makino came up with two spatio-temporal extensions of the traditional FastICA algorithm to extract individual sources from convolutive mixtures blindly [13].

Blind Source Separation (BSS) consists of instantaneous BSS and convolutive BSS. The FastICA method is typically used for instantaneous BSS where mixtures are linear combinations of sources. Convolutive BSS is more suitable for our experiment; that is, the cocktail party scenario where we separate multi-talker speech from multi-microphone audio recordings. Researchers generally construct multichannel filters to recover latent

signals. One way to solve convolutive BSS is to do the separation process in frequency domain by taking the Fourier Transform of the mixtures and applying spatial-only complex-valued ICA and BSS on each frequency bin. But these methods have to consider making permutation, amplitude, and scaling consistent across different frequency bins to perform good separation. Another way to solve convolutive BSS is using a time-domain separation criterion. A typical example is the information-theoretic natural gradient convolutive BSS separation. But this method requires knowledge of an exact number of sources, source distributions, making it not BSSin a strict sense. This method also imposes a potential problem of appropriate step sizes selection for fast convergence. A new extension of the FastICA Time Domain fast fixed algorithms for convolutive ICA algorithm has constraints of the error accumulations of the deflation separation process [14].

With all the limitations of the up-to-date convolutive BSS methods, authors proposed two new spatio-temporal extensions of the FastICA. These new approaches imposed constraints on the multichannel separation filter by combining multichannel whitening through multi-stage least-squares linear prediction within iteration. These new approaches have the advantages of easily and individually reconstructing the sources, a technique called single-input multiple-output (SIMO) BSS separation.

These approaches are based on the traditional FastICA. Systemic block diagram is shown in Figure 1.3. This new strategy has three stages: prewhitening, separation and reconstruction. The prewhitening stage decorrelates the original mixtures in both space and time. The separation stage separates prewhitened signal mixtures based on non-Gaussianity. Two algorithm spatio-temporal FastICA 1(STFICA 1) and spatio-temporal FastICA 2(STFICA 2) are used. The reconstruction stage tries to reconstruct the individual sources as they appear in the original mixtures. The separation is achieved by passing each signal through the inverse of the prewhitening and separation systems.

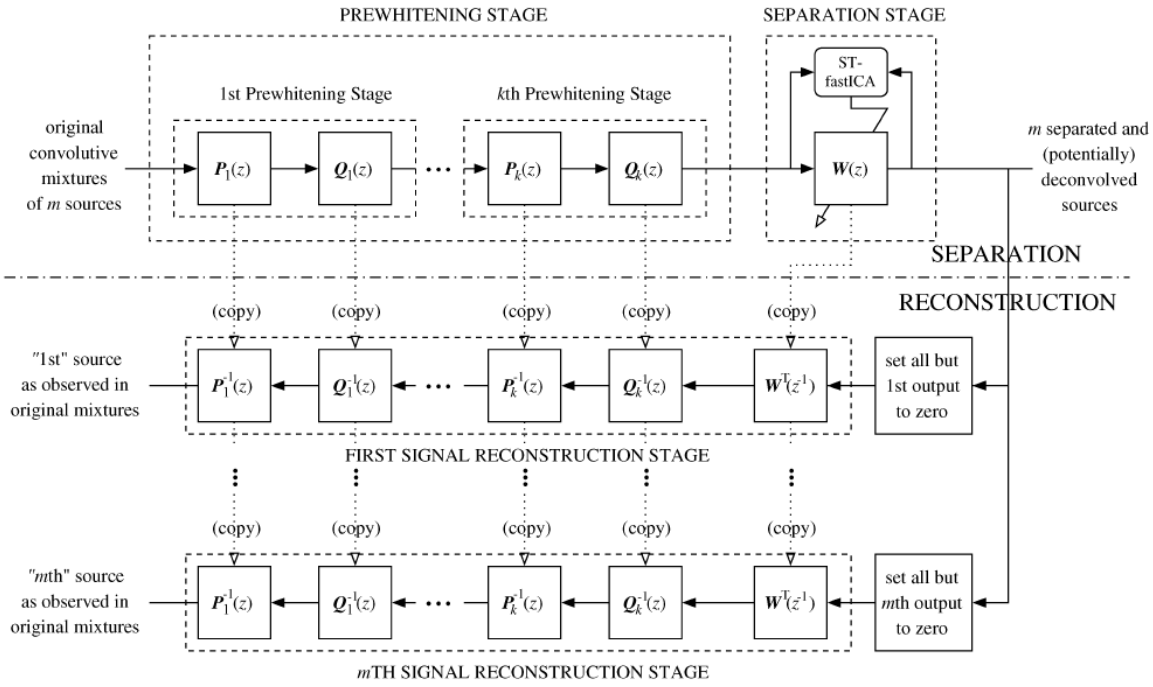


Figure 1.3 Block Diagram of the Combined Separation and Signal Reconstruction System from from Douglas, S.C.; Gupta, M.; Sawada, H.; Makino, S., "Spatio–Temporal FastICA Algorithms for the Blind Separation of Convolutive Mixtures," [13]

These proposed spatio-temporal approaches have advantages such as they do not require step size tuning, nor does it require prior knowledge of source distribution, and this approach has fast convergence especially for i.i.d sources. This adaptive approach extends the usage of FastICA to situations where reverberation exists. This approach also performs fairly well when reverberation exists while traditional FastICA fails to do so. Limitations are that researchers only tested separation effects on Uniform Linear Array. Therefore performance on other microphone array layouts remains unknown.

1.4.3 Adaptive time-domain blind separation of speech signals

Many existing algorithms aim to solve convolutive BSS for static sources, while in the cocktail party scenario, sources may potentially move around, therefore sources became non-stationary. Also in time domain BSS, the demixing filter length is usually very long, which consumes long computation time. To solve both issues, Málek, Koldovský, and

Tichavský proposed an adaptive algorithm with short demixing filter length (L=30) to conduct BSS in audio environments of moving sources. This algorithm is achieved via time-domain Independent Component Analysis (ICA) [15].

Researchers aim to solve convolutive blind separation of *d* number of unknown audio sources (BASS) from *m* number of microphone recordings. Because sources are moving around, the unknown mixing process is convolutive and potentially dynamic. Researchers assumed that the systems change slowly and they considered each short time interval. In each short time interval, sources can be considered static, and the classic convolutive mixing problem holds.

An on-line method processes its input block-by-block in a serial way. The separation of dynamic mixtures is done with block-by-block on-line application to stationary mixtures. Existing on-line method consists of on-line ICA in the frequency domain, on-line time-domain based on second-order statistic cost function and sparseness based on-line algorithm working in frequency domain. Authors proposed and presented an on-line Blind Audio Source Separation (BASS) method from the time-domain blind audio source separation using advanced component clustering and reconstruction [16]. The original method separates independent components, groups independent components to clusters, and then reconstructs independent components in clusters. The new method modified in a sense that ICA and clustering algorithms adapt their internal parameters by performing one iteration per block, which makes the new method an on-line method.

The on-line procedure generates delayed copies of the microphone signals. It first conducts simplified BGSEP Algorithm [17] of Independent Component Analysis to get independent components. In order to cluster independent components to make sure that each cluster belongs to the same source, researchers computed their generalized cross-correlation coefficients using GCC-PHAT. Researchers proposed Relational Fuzzy C-Means algorithm (RFCM) to simplify the computations track the continual changes of the clusters for cluster groupings. For reconstruction, researchers used the windowing function (Hann Window) in demixing matrix to average the overlapping parts.

Researchers also ran experiments on fixed sources and moving sources to check the performance of the proposed on-line method. For fixed source experiments, on-line method is able to adapt the separating filters throughout the recordings for fixed-position sources but produces more artifacts than the off-line method. For moving sources, if microphones were 2 cm apart, the proposed separation algorithm performs slightly worse than the frequency domain algorithm with regards to SIR values, but performs better if the microphone distance is 6cm apart. Researchers concluded that the proposed on-line method outperforms the frequency-domain method when spatial aliasing occurs due to larger microphone inter-distance.

The proposed time-domain method is comparable with frequency domain BSS algorithm. With short filter length, this algorithm has the advantage of less processing computation time. This algorithm can adapt to and perform separation on non-stationary speech. This new algorithm also offers a blind source separation solution for moving which is very beneficial for the cocktail party scenario. This proposed algorithm performs better when microphones are further apart which is useful for the thesis. This algorithm has the drawback of potential long computation time.

1.4.4 DOA Estimation for Multiple Sparse Sources with Arbitrarily Arranged Multiple Sensors

When the number of sources is greater than the number of sensors, the system is called underdetermined system. To conduct underdetermined blind source separation smoothly for convolutive mixtures without restricting microphone array arrangements, Arak, Sawada, Mukai, and Makino proposed and explored a method to estimate the direction of arrival (DOA) for multiple sparse sources with arbitrary arranged sensors [18]. The sensors are arbitrarily assigned in a sense that these microphones can be set up in two or three dimensions.

Commonly used DOA methods include the MUSIC (Multiple Signal Classification) algorithm, MUSIC algorithm variants and the DOA estimation method based on independent component analysis (ICA). But the MUSIC algorithm is only applicable when the number of sensors is greater than the number of sources. Independent

Component analysis DOA is applicable when the number of sources is greater or equal to the number of sensors. To find a solution for the underdetermined system, researchers proposed a DOA estimation that assumes source sparseness.

To estimate the DOAs of the N sources from the M sensor observations, researchers proposed a new method shown in Figure 1.4. It includes two assumptions: sparseness and anechoic. Researchers show that temporal/frequency sparseness holds for speech. Researchers used a short-time Fourier transform (STFT) making the convolutive mixtures instantaneous.

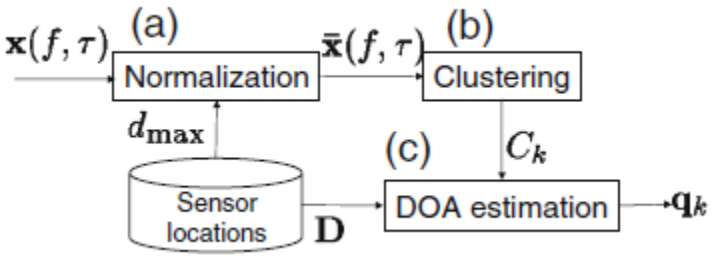


Figure 1.4 Structure of the proposed method from Araki, S., Sawada, H., Mukai, R., & Makino, S. (2011). DOA estimation for multiple sparse sources with arbitrarily arranged multiple sensors [18]

After STFT to transfer sources from time domain to frequency domain, researchers normalized **x (**f, τ**)** observation vectors so that each observation vector depends only on the source geometry. Researchers then clustered normalized vectors **˜x (**f, τ**)** to *N* clusters by minimizing the total sum of the squared distances between cluster members and their centroid. Each cluster corresponds to one source and centroid c_k has the geometry information of the source $s_{k;}$ thst is, it has the information of DOAs.

Researchers ran experiments on close microphones (4 cm apart) with reverberation time RT=120 ms. Estimation results are reasonable. Through experiments, researchers found that MUSIC and the proposed method both performed well when two sources are apart while the proposed method outperforms MUSIC when two sources are close to each other. Researchers found that when distances between sources and sensors are large and reverberation time is long, the source sparseness assumptions seem to be corrupted [18].

This paper is very informative. Researchers conducted multiple experiments in multiple settings which provided convincing results. The results of the new method are based on an assumption of source sparseness, but this assumption can be weakened when reverberation time is high and/or sensors and source distances are high. This paper also gave us insight of the performance with regard to microphone grouping distance.

1.4.5 The Signal Separation Evaluation Campaign (2007–2010): Achievements and Remaining Challenges

In this paper, Vincent, Araki, Theis, Nolte, Bofill, Sawada, ..., & Duong presented the outcomes of the Signal Separation Evaluation campaigns in audio and biomedical source separation[19]. Researchers presented key results in the campaign, discussed impact of these methods on evaluation methodology and proposed future research goals.

Source separation characterizes the sources and estimates underlying source signals with given source mixtures. Source separation can be applied to chemistry, biology, audio, biomedical, telecommunication, etc. Existing techniques such as beamforming and time-frequency masking are based on spatial filtering and are now used to suppress environmental noise and/or enhance spatial rendering in mobile phones and consumer audio systems. Methodologies in this campaign are likely to be widely used in the future.

Researchers describe the reference evaluation methodology to evaluate the performance of all the new and existing algorithms for source separation and presented the key results obtained over almost all datasets provided in this campaign. To evaluate a source separation system, we need a dataset, a task to be addressed, evaluation criteria, and performance bound(s) four factors. Datasets are categorized to application- and diagnosis-oriented. Application-oriented datasets are real world signals where each dataset faces all factors of source separation at once while diagnosis-oriented are synthesized to analyze a combination of a few challenges of all factors. To access the performance gap with industrial applications, we use application-oriented dataset to analyze. To improve separation robustness, we combine diagnosis-oriented datasets to find solutions to individual challenges.

For checking audio blind source separation performance, researchers summarized four main characteristics: mixture, source, environmental, and sensing. In mixture characteristics, we need to specify parameters. In source characteristics, we categorize source signals and identify scene geometry. In environmental characteristics, we categorize noise and reverberation. Sensing characteristics refer to sampling and sensor geometry. There are also six tasks: source counting, source spatial image estimation, source feature extraction, source localization, mixing systems estimation and source signal estimation.

Researchers pointed out that regarding the evaluation of a mixing system, Amari Performance Index (PI) or Inter-Symbol Interference (ISI) is for over-determined mixing systems, i.e. biomedical data. Mixing Error Ratio (MER) criterion is applicable to all mixing systems. The amount of spatial distortion, interference and artifacts are then measured by source image to Spatial distortion Ratio(ISR), the Signal to Interference Ratio(SIR) and the Signal to Artifacts Ratio (SAR) while the total error is measured by Signal to Distortion Ratio(SDR) [19]. SDR is calculated in small bins shown below[Formula from 19]:

$$\mathrm{SDR}_j = 10\log_{10}\frac{\sum_{i=1}^{I}\sum_t s_{ij}^{\mathrm{img}}(t)^2}{\sum_{i=1}^{I}\sum_t (e_{ij}^{\mathrm{spat}}(t)+e_{ij}^{\mathrm{interf}}(t)+e_{ij}^{\mathrm{artif}}(t))^2} \tag{1.1}$$

Regarding audio, performance is more accurately measured by Target-related Perceptual Score (TPS), Interference-related Perceptual Score (IPS), Aitifact-related Perceptual Score(APS) and overall Perceptual Score(OPS). The evaluation criteria related to source feature extraction are highly specific to the considered features.

Then researchers tried to summarize the key results regarding source separation with the main focus on source signal estimation and source spatial image estimation tasks. With regard to Under-determined speech and music mixtures dataset, multichannel Nonnegtive Matrix Factorization (NMF) or flexible probabilistic modeling framework performs better than Spare Component Analysis (SCA) on instantaneous mixtures, but the new methods NMF and SCA remain inferior to SCA on live recordings. Researchers

concluded that a great deal of research could be done to simulate room effects to study about audio effects in rooms.

Then researchers summarized performance on other audio datasets. Researchers pointed out that the best separation result is on noiseless over-determined mixtures via frequency-domain ICA. 2-channel noise mixtures of 2 sources with mixtures either short or dynamic can be separated via frequency-domain ICA as well but with the presence of significant filtering distortion of the source signals. Performance becomes worse on 4-channel mixtures of 4 sources. The separation performance degrades when background noise presents. Researchers pointed out that none of the above methods is truly blind as all assume prior knowledge of number of sources and how sources are mixed (instantaneous or convolutive). Apart from audio, blind source separation can also be performed on biomedical sources.

Finally, researchers summarized the remaining challenges. These challenges involve evaluation methodology but we can create a dataset to evaluate audio source separation system. Future challenges involve developing a more close to real life mixing model that takes more factors into consideration, designing accurate source localization methods and developing a model selection method with truly blind separation and adapt to the appropriate source and mixture model at hand while finding the number of sources.

Researchers summarized the whole campaign in different aspects in detail. This paper is a very good summarizing paper. It gave us broad perspective of the campaign and presented updated research on source separation with regard to performance and measurement criteria especially in audio. Researchers pointed out major future research directions in source separation, which is very valuable. I wish researchers would explain how some of the key algorithms function before doing the cross comparison.

In this chapter, a broad range of techniques related to ICA are covered, with advantages and disadvantages stated. In chapter 2, we are going to emphasize on FastICA.

Chapter 2 : FastICA

2.1 ICA Algorithm and its Literature Review

The ICA model can be generalized into two basic parts: the mixing model part and the separation model aspect as shown in block diagram Figure 2.1. Generally speaking, the ICA model consists of instantaneous ICA and convolutional ICA two methods.

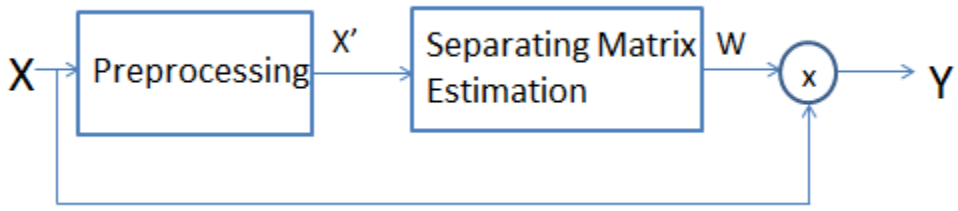


Figure 2.1: ICA Procedures Block Diagram

In Figure 2.0, we have mixtures X; after steps of preprocessing, we have whitened mixture X'. We use whitened mixture X' to estimate Separating Matrix Estimation W, we multiply matrix W to mixture Matrix X yielding a Matrix Y with all underlying Independent Components (ICs).

In the instantaneous blind signal separation approach including instantaneous ICA, we have the model

$$\mathbf{x}=\mathbf{A}*\mathbf{s} \tag{2.1}$$

where **x** is the mixture matrix, **A** is the mixing matrix with each coefficients in matrix A a scalar and **s** is the sources/speakers matrix with each column/row an individual source. This model is referred to as the instantaneous blind source separation model due to the mixing matrix **A** being instantaneous in a sense that no delays are present (signals arrive at the sensors at the same time), no dispersive effects (reverberation, echoes) are taken into consideration, and no microphone sensor noise presents.

Independent Component Analysis was relatively thoroughly covered by Aapo Hybarinen, Juha Karhunen, Erkki Oja from Helsinki University of Technology [6]. Independent Component Analysis (ICA) is a method of Blind Source Separation. Blind refers to the fact that we have very little or no prior knowledge of the original sources and mixing process but only the mixtures and we try to recover the Independent Components (ICs) or underlying sources. Specifically in the ICA model, we have the observed multivariate data variables. These variables are linear or nonlinear mixtures of some unknown latent variables with unknown mixing systems. We estimate the mixing matrix based on the statistical analysis of the mixtures and there are two common ways to recover the mixing matrix: minimize the mutual information and maximize the non-Gaussianity.

In ICA, we assume components are statistically independent and carry out preprocessing procedures before the main ICA method. Generally, there are three preprocessing processes: centering the observed data (also called removing mean), dimension reduction by principal component analysis (PCA) and whitening the observed data. The preprocessing process is always carried out in the above order. First we need to center multivariate data variables by removing their mean values, while speech signals always have a mean value of zero, we always eliminate this step in audio signal processing.

Principal Component Analysis (PCA) decorrelates a set of correlated variable mixtures into linearly uncorrelated variables referred to as principal components. PCA does not perform as well as Independent Component Analysis (ICA) individually, but PCA is an effective way to do dimension reduction, which can be used in the preprocessing of data before passing them through the FastICA algorithm. Reducing dimension of data by PCA helps to reduce noise and prevents overlearning. PCA may solve the problem that we have less ICs than mixtures.

2.1.1 ICA Basic Model

We have Original Signal matrix **S** with each column an independent source $\mathbf{s}_1$,$\mathbf{s}_2$, $\mathbf{s}_3$,…$\mathbf{s}_n$. $\mathbf{s}_1$, $\mathbf{s}_2$, $\mathbf{s}_3$,…,$\mathbf{s}_n$ are column vectors and **S**=($\mathbf{s}_1$,$\mathbf{s}_2$, $\mathbf{s}_3$,…$\mathbf{s}_n$). The unknown mixing system, matrix A is a square matrix. The observed matrix X corresponds to microphone

recordings and each column $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n$ is observed from each microphone where $\mathbf{X}=(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$. We have

$$\mathbf{X}=\mathbf{A}*\mathbf{S}. \tag{2.2}$$

In order to use the ICA algorithm to find the underlying independent sources, we also have to run preprocessing which will be covered in details later this thesis on microphone recordings meaning the preprocess matrix **X** for relatively good performance. Preprocesses include removing room noise/effects, removing mean from the mixtures, using principal component analysis (PCA) or Singular Value Decomposition (SVD) to find the eigenvalues and eigenvectors of the mixture for further use to recover the latent sources. We use a high pass filter to filter out room noise.

Since audio signals always have a mean value of zero, the step of removing mean from the microphone recording mixtures can be neglected. In order to use PCA for eigenvalue decomposition, we need to find the covariance matrix Cx of the recorded mixture matrix X first, and it can be calculated using the equation below

$$Cx=E\{(\mathbf{X}-m_x)(\mathbf{X}-m_x)^T\} \tag{2.3}$$

It can be calculated element-by-element using the following equation

$$C_{ij}=E\{(x_i-m_i)(x_j-m_j)\} \tag{2.4}$$

Cx is covariance of matrix **X** and mx is the mean of the matrix **X**.

The independence of components is maximized through the ICA algorithm by minimization of mutual information or maximization of component non-Gaussianity. Minimization of mutual information consists of algorithms such as Kullback-Leibler Divergence and maximum entropy. Maximization of the non-Gaussianity algorithm considers kurtosis and negentropy and tries to reverse the central limit theorem. Some popular BSS methods are FastICA, Time Frequency Masking, Direction of Arrival, ConvolutiveBSS, optimized informax, and optimized kurtosis based methods [20]. After estimating the mixing matrix M, we can directly apply the mixing matrix to the original

data to get independent components, but for better source separation, we introduce preprocessing steps.

2.2 Preprocessing steps for BSS/ICA

When directly applying the ICA algorithm to real data, several problems will arise including overlearning and noise. So we introduce preprocessing steps such as centering, whitening, and dimension reduction to cope with the problems mentioned above as well as simplify the main iterative ICA algorithm. Centering is done by subtracting the mean of the signal from the original signal and can be neglected in audio signal processing due to the fact that audio signals always have a mean of zero. But when we consider image processing, centering is a must. Whitening is usually done with eigenvalue decomposition. This step tries to make the source signal as orthogonal to each other as possible. Dimension reduction aims at focusing on the signals/mixtures with most of the information and discards mixtures with the least information and mainly noise.

2.2.1 Filtering

We use a Butterworth high pass filter with a cutoff frequency of fc= 100 Hz to remove the low frequency room noise. Why do we need high pass filter?

Room noise presents in a typical room environment. Even in a fairly quiet room, there exists power line carrier frequency disturbance, molecule movement, electronic devices disturbances, etc. Noise generated from a source in a room will undergo frequency dependent propagation, absorption and reflection, creating multi-path (which is an issue in telecommunication, cellular), reverberation and echoes [6]. In Telecommunication, the multipath phenomenon exists and channel models that have multipath propagation cause acoustic processing-reverberation. We try to take care of these issues in the FastICA algorithm.

For better process results, we use a filter to preprocess the microphone recordings to remove as much room noise as possible. We also have to consider the effects that filtering can bring to the source separation process. Luckily, linear filtering of the signals will not change the ICA model itself but different kinds of filters such as low-pass filter and high-pass filter affect the ICA model differently. Low-pass filtering removes slowly

changing trends of the data to smooth the data and helps to reduce noise in the data. But low pass filter can also reduce information in the data causing the loss of fast-changing, high-frequency features of the data, which leads to reduction of independency. High-pass filtering or computing innovation processes are useful to increase the independent and non-Gaussianity of the components. It increases the independence of the components. That is to say, the high pass Butterworth filter we introduced can remove room noise as well as improve the separation results.

2.2.2 Preprocessing via Dimension Reduction through Principal Component Analysis

In Chapter 13 Practical Considerations of ICA of the book *Independent Component Analysis* by Aapo Hyvarienen, Juha Karhunen and Erkki Oja, it says that to prevent overlearning and reduction of noise of the data set, preprocessing techniques such as dimension reduction by Principal Component Analysis, and time filtering are useful.

It states that dimension deduction helps prevent overlearning of the data, we should choose the minimum number of principal components that explain the data well enough such as containing 90% of the variance. But there are no theoretical guidelines so we need to choose the dimension for PCA by trial and error. Since PCA always contains the risk of not including the ICAs in the reduced data so we also do not want to reduce the dimension of PCA too much hence there is no good guideline to choose how many ICs to be estimated. For my understanding, if we have 5 sources, about 40 microphone recordings, we may estimate three components that have good performance (i.e. easy to identify words that each source is speaking) using ICA, in this case 3 sources. There also exists trade-off between filtering the data to reduce noise and choosing the number of principal components to be retained to prevent overlearning.

So we perform Principal Component Analysis (PCA) to reduce dimension of the data to the number of independent components we desire. While PCA dimension reduction helps prevent overlearning of the data, it has limitations such that PCA is sensitive to the noise and some weak ICs may be lost during the PCA process. So we have to choose the minimum number of principal components wisely such that it can explain the data well. In a statistical sense, we choose the number of independent components that contains 90%

of the variance. This can be achieved by choosing rational eigenvalue range or eigenvalue dimension after we conduct eigenvalue decomposition (EVD) of the covariance matrix of observed data variable **x**.

2.2.3 ICA Preprocessing through Whitening

After PCA, we whiten the data by the formula

$$\tilde{\mathbf{x}} = \mathbf{E}\,\mathbf{D}^{-1/2}\mathbf{E}^{T}\mathbf{x} \tag{2.5}$$

where **D** is the diagonal eigenvalue matrix of covariance matrix $E\{\mathbf{x}\mathbf{x}^{T}\}$($E\{\}$ is the expectation function operation) and **E** is the orthogonal eigenvectors of the covariance matrix. Whitening helps solve half of the ICA problem because whitening reduces the number of parameters to be estimated, therefore reducing the complexity of the problem. This can be easily seen in the two-dimensional data example. After whitening the two-dimensional data, we just need to find the rotation angle and use this angle to rotate back the distribution to get independent components. Whitening basically makes each underlying sources as orthogonal to each other as possible.

2.3 ICA/FastICA Main Algorithm

Now the non-Gaussianity concept is introduced and is crucial for the establishment of ICA method. According to the Central Limit Theorem, the distribution of sum of multiple random variables looks closer to Gaussian distribution than the distribution of each individual random variable. Now finding an estimator to give good approximation so as to find the underlying independent components means that we need to find an estimator to make each independent Component more non-Gaussian. The main algorithm of the FastICA helps estimate Separating Matrix W in Block Diagram Figure 2.1 so as to recover independent components. FastICA uses a set of fixed-point iterative procedures that extract independent components using a non-Gaussianity signal measure.

There are two main quantitative measures of non-Gaussianity of a random variable kurtosis and negentropy. Kurtosis is a fourth-order cumulant and the kurtosis of random variable x is defined as

$$\text{Kurt}(\mathbf{x}) = E\{\mathbf{x}^4\} - 3(E\{\mathbf{x}^2\})^2 \quad (2.6)$$

Typically, we use the absolute value of kurtosis to measure non-Gaussinity so as to identify the independent component. Kurtosis is simple to use both computationally and theoretically, but is not very robust due to its sensitivitiy to outliers. Negentropy J is defined as

$$J(\mathbf{x}) = H(\mathbf{x}_{\mathbf{gauss}}) - H(\mathbf{x}) \quad (2.7)$$

Where H(x) is the entropy of the random variable **x**, $\mathbf{x}_{\text{gauss}}$ is a Gaussian random variable of the same covariance matrix as **x**. For continuous-valued random variables and vectors, differential entropy H(**x**) shows how unpredictable and unstructured the random variable **x** is and differential entropy H(**x**) with density f(**x**) is defined as

$$H(\mathbf{x}) = -\int f(\mathbf{x}) \log f(\mathbf{x}) d\mathbf{x} \quad (2.8)$$

According to information theory, for differential entropy continuous distribution Gaussian variable has the largest entropy among all random variables with the same variance. So the higher the negentropy value, the more non-Gaussian the random variable x is so negentropy can be used to find the independent component. But it brings computational and estimation difficulties when using negentropy as an estimator of non-Gaussianity. So we approximate negentropy using higher-order moments shown as

$$J(\mathbf{x}) \approx \frac{1}{12} E\{\mathbf{x}^3\}^2 + \frac{1}{48} \text{kurt}(\mathbf{x})^2 \quad (2.9)$$

but this classical approximation is not robust due to the usage of kurtosis and the limitation of kurtosis mentioned above. Luckily Hyvarinen came up with a new approximation in 1998 based on maximum-entropy principle shown as

$$J(\mathbf{x}) \approx \sum_{i=1}^{p} k_i [E\{G_i(\mathbf{x})\} - E\{G_i(\mathbf{v})\}]^2 \quad (2.10)$$

where k_i are some positive constant and we can just treat it as a plus sign. **v** is a zero-mean unit variance Gaussian variable. **x** is zero mean unit variance variable. G_i are non-quadratic nonlinearity general purpose functions that help robustly estimate the negentropy. Variable p is the total number of functions G_i that is used in the negentropy approximation. In the estimation process, if we use the same G, the above approximation can be simplified as

$$J(\mathbf{x}) \approx [E\{G(\mathbf{x})\} - E\{G(\mathbf{v})\}]^2 \quad (2.11)$$

Depending on different distributions and by choosing function G wisely, we can get a very robust approximation of the negentropy which is very useful in the FastICA

algorithm. For each fixed non-quadratic function G, the E{G(**v**)}value is fixed, which is due to the definition of negentropy.

2.3.1 FastICA for one computational unit

FastICA learning rule finds a direction: a unit vector w that the projection $\mathbf{w}^T\mathbf{x}$ maximizes non-Gaussianity with non-Gaussianity measures by the negentropy J($\mathbf{w}^T\mathbf{x}$). After conducting the Gradient algorithm and the Newton Method, finding the optima of the Lagrangian by Newton's method, simplification, and other mathematical manipulations, the basic iteration in FastICA is shown as

$$\mathbf{w} \leftarrow E\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\}-E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}$$

g is the derivative of G in eq. 2.11**.** For example, we take g(u) = tanh(au) , 1≤a≤2, and often we take a =1.

After mathematical approximation and algorithm derivation, the steps mentioned above, the FastICA algorithm for single component (vector **w**) extraction has steps below

1. Choose an initial random unit norm vector **w**
2. Let $\mathbf{w}_{new}=E\{\mathbf{x}g(\mathbf{w}^T\mathbf{x})\}-E\{g'(\mathbf{w}^T\mathbf{x})\}\mathbf{w}$
3. Norm w by letting $\mathbf{w}=\mathbf{w}_{new}/\|\mathbf{w}_{new}\|$
4. If w not converged, go back to step 2

g is the derivative of the non-quadratic general purpose function G in equation 2.10 and g' is the derivative g. Convergence is calculated based on whether the norm distance between **w** and **w** in the last iteration is less than the value of epsilon (ε **), which is very small**. Convergence also means that old and new values of **w** point in the same direction.

2.3.2 FastICA for several computational units

To extract several independent components using FastICA, we need to run one-unit FastICA using several units of weight vectors $\mathbf{w_1}$**, ..,** $\mathbf{w_n}$**.** To prevent different vectors converging to the same maxima, orthogonalized vectors $\mathbf{w_1}$,$\mathbf{w_2}$,**...,** $\mathbf{w_n}$ after each iteration

are a must. We can conduct deflationary or symmetric orthogonalization (decorrelation). Deflation decorrelation estimates ICs one by one, while Symmetric Decorrelation parallelly computes ICs [6].

For the deflation algorithm, when we have estimated p independent components, or p vectors $\mathbf{w}_1,\ldots,\mathbf{w}_p$, we run the one-unit fixed-point algorithm for $\mathbf{w}_{p+1}$, and after every iteration subtract from $\mathbf{w}_{p+1}$ the "projections" $\mathbf{w}_{p+1}{}^{\mathrm{T}}\mathbf{w}_j\mathbf{w}_j$, $j=1,\ldots,p$ of the previously estimated p vectors, and then renormalize $\mathbf{w}_{p+1,}$ shown in steps as

1. Let $\mathbf{w}_{p+1=}\ \mathbf{w}_{p+1}$ - $\sum_{j=1}^{p} \mathbf{w}p + 1\mathrm{T}\mathbf{w}j\mathbf{w}j$
2. Let $\mathbf{w}_{p+1=}\ \mathbf{w}_{p+1}/\sqrt{\mathbf{w}p + 1\mathrm{T}\mathbf{w}j\mathbf{w}j}$

For Symmetric Decorrelation, no vectors are privileged over others. The steps are as follows:

1. Let $\mathbf{W} = \mathbf{W}/\sqrt{||\mathbf{W}\mathbf{W}^{\mathbf{T}}||}$
2. Let $\mathbf{W} = \frac{\mathbf{3}}{\mathbf{2}}\mathbf{W} - \frac{\mathbf{1}}{\mathbf{2}}\mathbf{W}\mathbf{W}^{\mathbf{T}}\mathbf{W}$

Where we have **W, it** is the matrix $(\mathbf{w_1}, .., \mathbf{w_n})^{\mathrm{T}}$, Repeat 2 until convergence; that is to say, $\mathbf{W}\mathbf{W}^{\mathbf{T}}$ is the identity matrix or close enough to it. Then we estimate underlying ICs by

$$\mathbf{Y}=\mathbf{W}*\mathbf{X}. \tag{2.12}$$

Researchers chose FastICA method over other methods because it is superior over the gradient-based algorithm. When the environment is not fast changing, fast adaption to environment is not needed; the fast fixed-point Algorithm(FastICA) is much better than the gradient-based algorithm in ways such as fast convergence and no need to consider learning rate or other adjustable parameters. FastICA can also directly find independent components, can be optimized by choosing a suitable function g, can estimate independent component one by one, and is computationally simple and requires little memory space [6].

2.4 Noisy ICA model

In reality, there is always noise in the observations. Actual physical noise in the measuring devices or inaccuracies of the model causes noise. Estimating the mixing matrix seems to be quite difficult when noise is present.

The noisy model is not invertible; therefore estimation of the noise-free components requires new methods. Noisy ICA model is described as

$$\mathbf{X}=\mathbf{AS}+\mathbf{N} \tag{2.13}$$

We assumed that the noise is independent from the independent components and that the noise is Gaussian. In reality, a better approach is to reduce noise in the data before performing ICA i.e. conduct filtering of time signals or dimension reduction. This noisy model helps us understand the mixing system better [6].

2.5 Limitation of ICA/FastICA

ICA model also has drawbacks such that it will not be able to estimate the correct scaling of the sources, the order of the ICs. This is where we introduce permutation alignments.

The basic ICA model is straightforward, but in reality, it is more sophisticated and complicated than the basic model especially in an audio environment. In an acoustic signal environment i.e. the typical cocktail party scenario, it is hard to use the existing ICA model to obtain the underlying sources; researchers then come up with a convolutional ICA method to help overcome problems brought on by the audio environment. Still we have to take some factors into consideration in the modeling process. First, we need to figure out a way to measure delays in the mixtures. Sound signals propagate at different rates; different frequency bands attenuated at different rates, thus the speech signals do not arrive at the microphone at the same time. Also microphones record echoes of the speakers' voices due to reverberation from walls, ceilings and other objects in the room. All these factors have to be considered to get an accurate delay. Second, speakers easily become non-stationary. Even in our stationary cases, speakers are not strictly stationary because a speaker may slightly move their head

while talking. When this happens, we have to re-estimate the mixing matrix. If multiple speakers move their heads non-simultaneously, we have to constantly re-estimate the mixing matrix. Third, noise exists in the systems. There is actual physical noise in the devices and noise brought by the inaccuracies of the estimating model. Actual physical noise, such as sensor noise may not be Gaussian as previously assumed and this will interfere with the algorithm because high-order cumulates are used to estimate the mixing matrix which is insensitive to Gaussian noise.

To get accurate independent components, we have to modify the existing ICA toolbox and optimize based on the issues listed above. We may also consider using the convolutional ICA method on the frequency domain instead of the time domain. Also, we can introduce some pre- or post-processing techniques to help get better sound effects on underlying sources, such as introducing a high-pass filter on the mixtures to remove room noise, combining ICA method with masking method. In chapter 3, we introduce the Convolutive BSS algorithm hoping to solve these problems.

2.6 FastICA Experiment Setup

2.6.1 FastICA Parameter Configuration Procedures

The properties of ICA method depend on both the objective function and the optimization algorithm. The objective function affects the statistical properties such as consistency, symptotic variance and robustness while the optimization algorithm affects the algorithm properties such as convergence speed, memory requirements, and numerical stability. Ideally, statistical and algorithm properties are independent. To choose the algorithm, if we estimate the independent components by parallel, we can select the symmetric method; otherwise we can use the deflation method to estimate a few of them. We can use the tanh function to resolve the nonlinearity in the algorithm. On-line stochastic gradient methods can be selected to cope with the changing mixing matrix or close to real-time tracking.

Summaries about selecting the suitable function G: $G(y) = \log\cosh a_1 y (1 < a_1 < 2)$ is a good general-purpose function. $G(y) = -\exp(-y^2/2)$ works better when the Independent

Components (ICs) are highly super-Gaussian or when robustness is very important. Kurtosis as g function is very picky. It is well justified only if the ICs are sub-Gaussian and there are no outliers, we should be cautious when using kurtosis. More details are covered in the ICA book [6].

As far as different ICA algorithms, for statistical performance, the best results are obtained when using the tanh nonlinearity with any algorithm. For computation load, Fast ICA is much faster than gradient algorithms.

Noise has a strong impact on the ICA algorithm. Estimation accuracy of ICA degrades fairly smoothly until the noise power increases up to -20dB of the signal power. If noise power increases more, ICA algorithms are not able to separate all the sources. In practice, if a lot of noise is present, it can smear the separated ICs or sources, meaning the separated results are useless. Once there is even a little noise present in the data, the error strongly depends on the condition number of the mixing matrix A [6].

Researchers in the ICA book stated for real world data, the true independent components are unknown. Assumptions made in the standard ICA model may not hold or hold approximately, hence we can only compare the performances of the ICA algorithms with each other. Researchers summarized that [6]

1) ICA is a robust technique
2) The FastICA algorithm and the natural gradient ML algorithm with adaptive nonlinearity yielded usually similar results with real-world data.
3) In difficult real-world problems, it is useful to apply several different ICA algorithms, because they might reveal different ICs from the data.
4) The theorem means that we can estimate the independent components from the noisy observations by maximizing a general contrast function of the form.
5) High-order cumulates are unaffected by Gaussian noise, but high-order cumulates are sensitive to outliers which is not very useful in practice. But we do not need to know the noise covariance matrix.

6) To obtain estimates of the original independent components, we would like to obtain estimates of the original independent components and the results are somehow optimal using the MAP estimates.
7) Noisy ICA estimation can also be used to denoise. Denoise procedure is called sparse code shrinkage. It is better to first attempt to denoise the data so that basic ICA methods can be used.

2.6.2 Experiment Setup

Instantaneous and convolutive mixtures are simulated to validate and check the performance of the source separation in immersive audio environments. Parameters are optimized for separation results through paper and book reviews and numerical experiments.

Parameters are set up as below:

Approach: Symmetric, 'symm'
Nonlinearity function g: tanh ,'tanh'

2.6.2.1 Instantaneous Mixtures Separation

We randomly selected four wave files man1.wav, mam2.wav, woman1.wav and woman2.wav and treated them as four sources. After processing them, we used a 4x4 randomly generated matrix A and treated it as a pseudo-attenuation scalar to multiply the source signals yielding a pseudo-four-channel microphone recording. We then used the FastICA toolbox to process the pseudo-mixture. Please observe the envelopes of the waveforms. Please observe waveforms changes amongst original speech, one microphone channel, and resulting underlying speech.

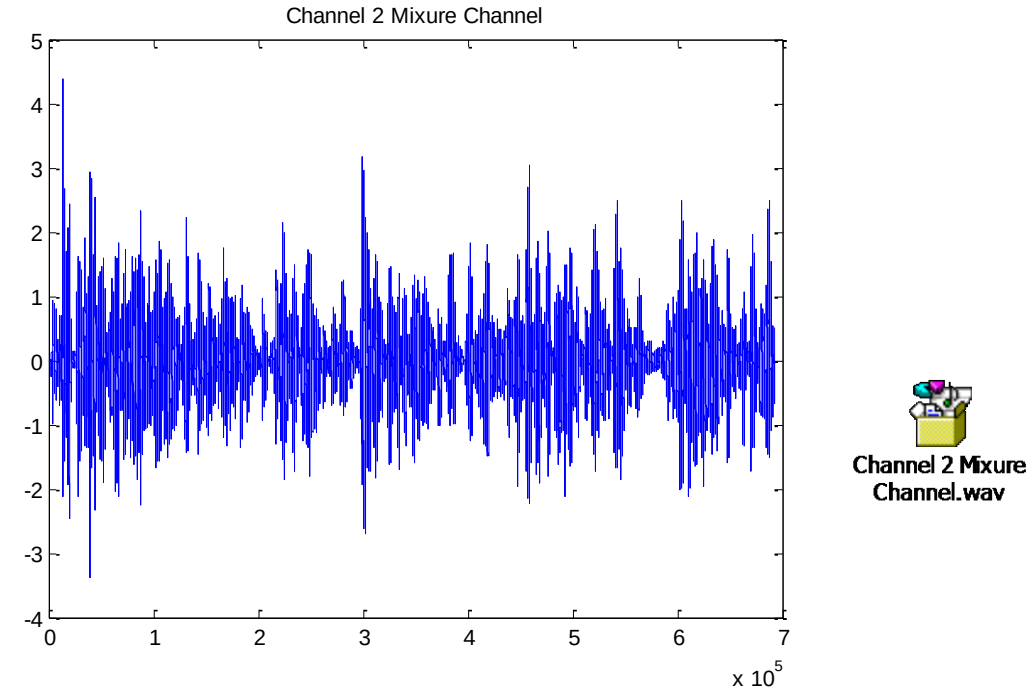


Figure 2.2: Channel 2 Mixture Channel

Figures are shown with comparison to originals as below:

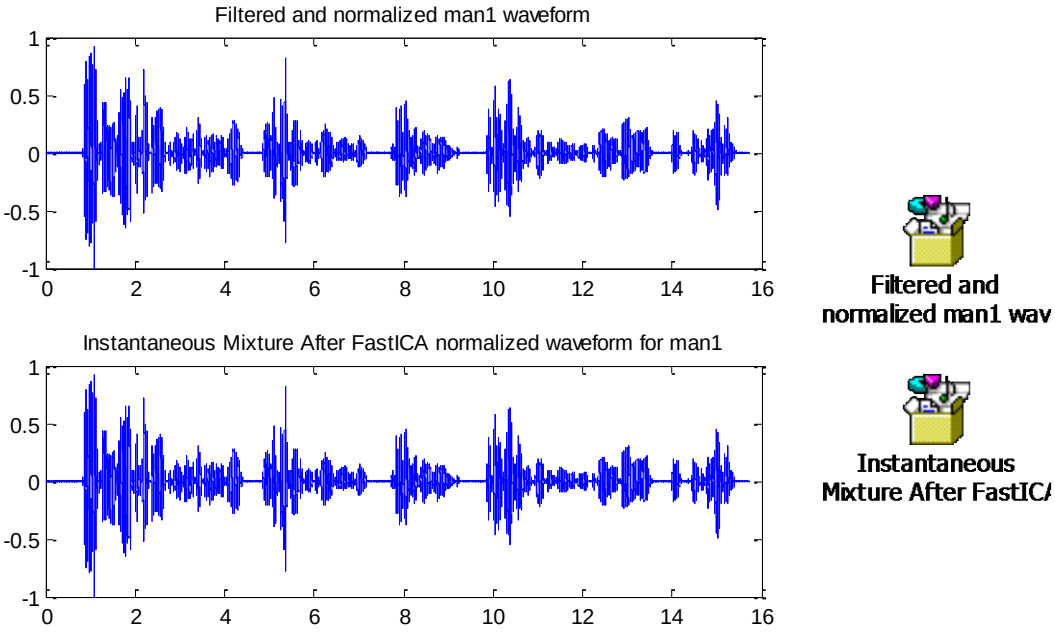


Figure 2.3: Source Man1

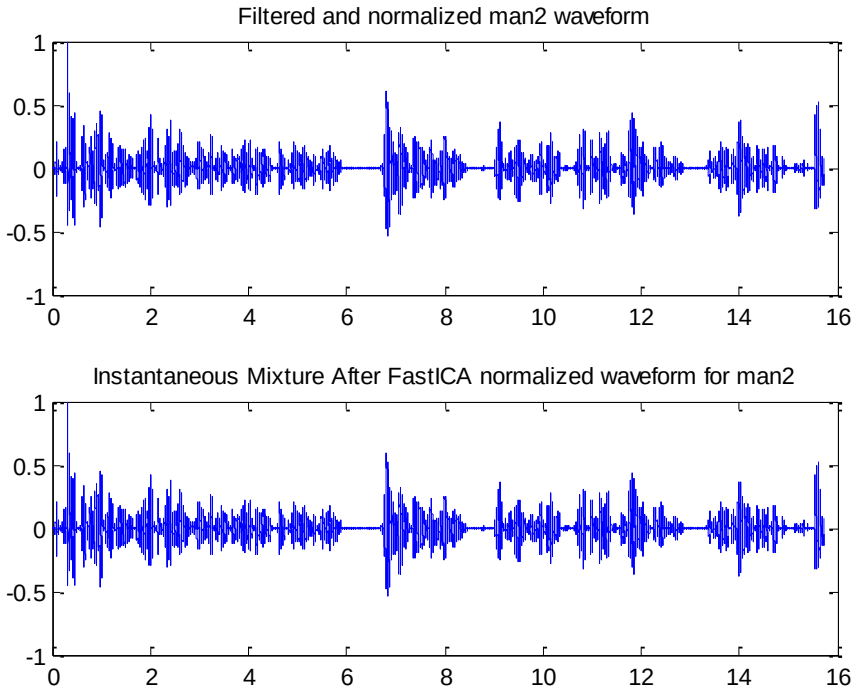


Figure 2.4: Source Man2

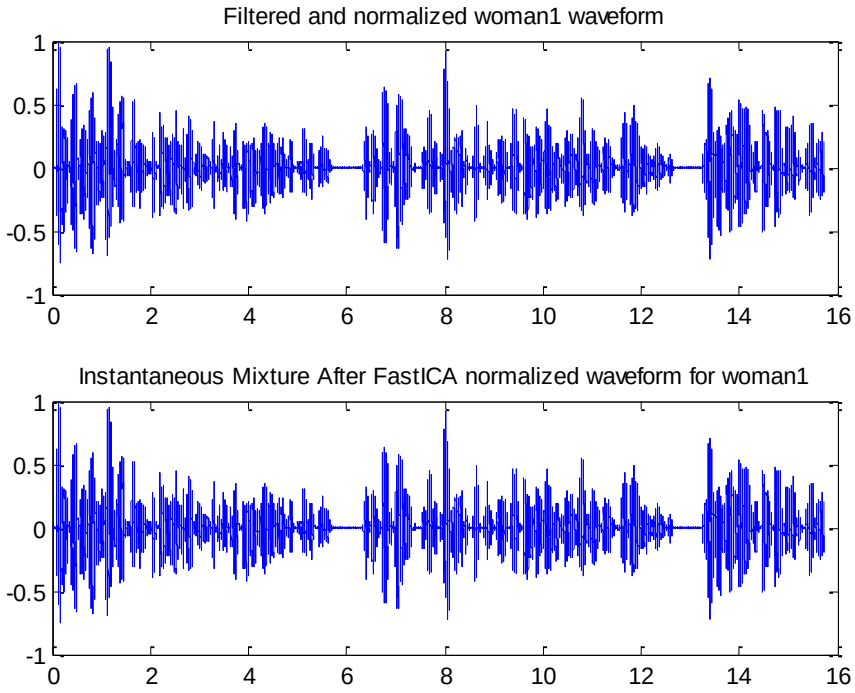


Figure 2.5: Source woman1

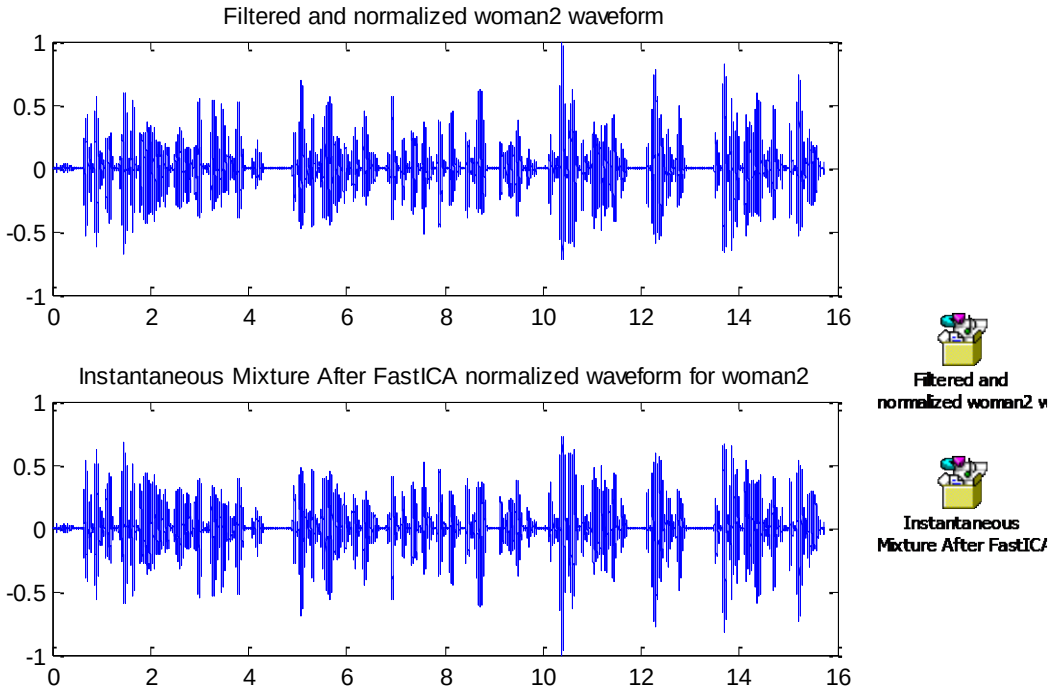


Figure 2.6: Source woman2

Through these figures, by observing envelops of the independent components before and after processing, we can see that FastICA works very well with instantaneous mixtures. Though Figure 2.6 looks like the AfterICA signal, it is flipped through the x–axis, but this does not affect what we hear.

After intensive experiments with the Convolutive BSS toolbox did not result in good separation audio qualities, this inspired us to come up with the FastICA enhancements for source separation in Convolutive Audio Mixtures.

2.6.2.2 Convolutive Mixtures Separation

We used the cocktail party simulator cocktail.m from the Array Toolbox to simulate the situation in the real world. But when we used the same parameter settings as stated in the FastICA toolbox, the signals after separation sounds were pretty much the same as the mixtures and we could not tell from which sound source the mixtures came. Please refer to linked files as below. The first file is the microphone recordings, the rest of the four

are supposed separated underlying sources. We can hear the separated sources sound about the same as the microphone channel, that is to say, no performance improvements.

2.6.3 Conclusions

Through the experiments, we observed that the FastICA toolbox is very powerful in audio source separation with instantaneous mixtures, but failed to work with the real world recording. But the better real world source separation is what we desire. In the following chapter, we are going to look in the Convolutive BSS toolbox in source separation.

Chapter 3: Convolutive BSS

3.1 Convolutive BSS Algorithm and its Literature Review

For Convolutional ICA, Independent Component Analysis (ICA) is processed on convolutional mixtures. In acoustic signal processing, the mixing process is very complex, especially in cocktail party scenario. In this scenario we have simultaneous and independent speakers, an unknown mixing process, mixtures collected at microphones and we try to recover underlying independent sources. To accurately approximate the real life situation, we use the convolutional ICA model.

In linear noise free systems, we choose suitable multi-dimensional filters based on reasonable assumptions trying to undo the mixing process and recover accurate underlying sources. Then we introduce sensor noise to the Convolutional ICA to best model the cocktail party scenario.

The basic convolutional mixing model at discrete time index t is shown as

$$\mathbf{x}_m(t) = \sum_{n=1}^{N} \sum_{k=0}^{K-1} a_{mnk}\mathbf{s}_n(t-k) + \mathbf{v}_m(t) \quad (3.1)$$

where we have N source signals $s(t) = (s_1(t), s_2(t),\ldots s_N(t))$ with each column an independent source. N sources are received by M microphones with received signals represented as $x(t) = (x_1(t), x_2(t),\ldots x_m(t))$, mixing filter coefficient a_{mnk} represents the filter coefficient relates to source s_n, sensor x_m and propagation delay k. $v_m(t)$ is the sensor noise corresponds to sensor m.

We can rewrite (3.1) in matrix format

$$\mathbf{x}(t)=\sum_{k=0}^{K-1} A_k\,\mathbf{s}(t-k) + \mathbf{v}(t) \quad (3.2)$$

where A_k is k'th filter's coefficients and is M *N matrix, $\mathbf{v}(t)$ is the sensor noise vector and is M*1. Take the z transform of (3.2), we get convolutional model in z domain

$$\mathbf{X}(z) = \mathbf{A}(z)\,\mathbf{S}(z) + \mathbf{V}(z) \quad (3.3)$$

Take the Fourier Transform of the (3.2), we get convolutional model in frequency domain

$$\mathbf{X}(\omega)=\mathbf{A}(\omega)\ \mathbf{S}(\omega)\ +\mathbf{V}(\omega) \tag{3.4}$$

where $\omega=2\pi f$, $\mathbf{A}(\omega)$ is a complex M*N mixing matrix. The dimension size of **X, S, V** stays the same as time domain **x, s, v**.

Instantaneous ICA approach is a special case of convolutional ICA approach. Other special cases for Convolutional ICA includes reverberation-free environment, noise free situation.

The separation model aims at recovering original sources without interferences from other sources, that is to say finding an estimate y(t) corresponds to original source signals s(t) one by one.

We often estimate the separation filters W_l that remove the cross-talk between signals caused by the mixing process rather than identify the mixing filters A_k specifically. Those separation filters can be modeled as feedback structure (infinite impulse response) or feed forward structure (Finite Impulse Response).

The Feed-forward Separating system is

$$\mathbf{y}_n(t)=\sum_{m=1}^{M}\ \sum_{l=0}^{L-1}\ w_{nml}\mathbf{x}_m(t-l) \tag{3.5}$$

or in matrix form

$$\mathbf{y}(t) = \sum_{l=0}^{L-1}\ W_l\mathbf{x}(t-l) \tag{3.6}$$

and z-domain transform form

$$\mathbf{Y}(z) = \mathbf{W}(z)\mathbf{X}(z) \tag{3.7}$$

where n is the number of underlying sources, L is the filter length, m is the number of microphone recordings.

Therefore, each model source signal is a filtered version of the original source signals, shown below in Z domain

$$\mathbf{Y}(z)=\mathbf{W}(z)\mathbf{A}(z)\mathbf{S}(z)=\mathbf{G}(z)\mathbf{S}(z) \quad (3.8)$$

We derive

$$\mathbf{G}(z)=\mathbf{W}(z)\mathbf{A}(z) \quad (3.9)$$

In room situation, the recorded speech signals are most likely a filtered version of the signals at the speaker due to diffraction and reverberation [21].

The difference between the linear convolutive mixing model and the linear instaneneous one is that delayed values of the source signals contribute to the output at a given time. The mixing matrix is now a multi-variant linear time-invariant(LTI) system with impulse response.

First, the propagation channel often follows a specular model. The contribution of the first souce on the first sensor is merely a superimposition of delayed/scaled replica of $s_1(n)$ and the transfer function hence reads $\sum_{l=1}^{L} \lambda_l z^{-tl}$ where L is the number of paths, and (λ_l,t) is the attenuation/ delay pair associated with the l-th path. This model is FIR and that causality then follows from the fact that the delay t_l is positive.

Convolutional ICA has the potential to solve non-stationary issues. In this chapter, we try to figure out the feasibility of the Covolutive BSS toolbox for BSS.

3.2 Using Convolutive BSS to model the Cocktail Party Scenario

In the classic cocktail-party problem, or separation of speech signals recorded by a set of microphones, the speech signals do not arrive at the microphone at the same time. This happens for two reasons. First, sound travels in the atmosphere with a very limited speed. Second, microphones usually record echoes of the speakers' voice due to reverberation from walls, ceilings and other objects in the room.

The cocktail party problem can be modeled as a convolutive BSS model. Then the mixing matrix can be modeled as a delayed filter instead of instantaneous scalar. The convolutive mixtures model is then constructed as

$$\mathbf{x}_i(t)=\sum_{j=1}^{n}\sum_{k} a_{ijk}\mathbf{s}_j(t-k) \qquad \text{for } i=1,\ldots,n \qquad (3.10)$$

which is a FIR filter model, with coefficients a_{ijk} represent each FIR filter. Here $\mathbf{x}_i(t)$ is the mixture of the microphone recordings, where we have N source signals $s(t) = (s_1(t), s_2(t),\ldots s_N(t))$ with each column an independent source. N sources are received by M microphones with received signals represented as x (t) = (x1(t), x2(t), …, xm(t)), mixing filter coefficient a_{mnk} represents the filter coefficient related to source sn, sensor xm and propagation delay k. $\mathbf{v}_m(t)$ is the sensor noise corresponds to sensor m.

To get a set of the estimates of the source signals $s_1(t), s_2(t),\ldots s_n(t)$, we introduce a set of similar FIR filters with wijk as the coefficients of the filters and $y_1(t), y_2(t),\ldots,y_n(t)$ the estimated output signals.

$$\mathbf{y}_i(t)= \sum_{j=1}^{n}\sum_{k} w_{ijk}\mathbf{x}_j(t-k) \qquad i=1,2,\ldots,n \qquad (3.11)$$

To achieve inversion accuracy, the number of coefficients in each separating filter must be hundreds or even thousands in length/order. Depending on the situation of the model, we pick feedback IIR filters or feed forward FIR filters or a combination of both.

Table 3.1: Comparison Amongst Standard Linear ICA, BSS, and Convolutive BSS

	Standard Linear ICA	BSS	Convolutive BSS	Fourier approach
Indeterminacies	Scaling, order of the ICs or sources	Scaling, order of the ICs or sources	More sever, order of estimated ICs unknown, use filter to represent scaling	Permutation and sign in each frequency band

One way to solve blind separation of convolutive mixtures is to reformulate the problem using the standard linear ICA model. Longer speech segments may help improve the quality of the separated signals, which result in Higher decibels [6].

Take Frourier Transform of equation (3.10), the convolutive mixture model in time domain is transformed to an instantaneously linear ICA model in frequency domain.

$$\mathbf{x}_i(\omega) = \sum_{j=1}^{n} A_{ij}(\omega)\mathbf{s}_i(\omega), \quad \text{for } i=1,\ldots,n \tag{3.12}$$

This mixing matrix is a function of angular frequency w. If we take short-time Fourier Transform of the data then we can utilize standard ICA in practice in Fourier Domain. Data is usually windowed by a Gaussian envelope and then Fourier Transform is applied separately to each data window. We estimate the ICA component separately for each frequency bin.

3.3 Comparison and contrast between the instantaneous and convolutional ICA approaches

Independent Component Analysis (ICA) is a blind source separation and is one of the state-of-art topics in signal processing, biomedical fields, telecommunications, neural science, etc. ICA model has two basic parts: mixing model and separation model. There are different types of ICA, such as instantaneous ICA and convolutional ICA.

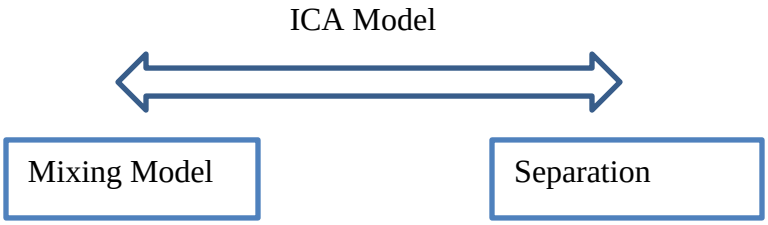


Figure 3.1: Overall ICA model

The instantaneous ICA model is the same as the instantaneous Blind Source Separation (BSS) Model while ICA is a kind of BSS. The model is constructed as

$$\mathbf{X}=\mathbf{A}*\mathbf{S} \tag{3.13}$$

where **X** is the mixture(sensor) matrix, **A** is the mixing matrix with each coefficient as an attenuation scalar and s is the source matrix with each column/row as an individual source. The model is instantaneous because the mixing matrix A is instantaneous. We assume that no delays are present (meaning signals arrive at the sensors at the same time),

no dispersive effects (reverberation, echoes) are taken into consideration, and no microphone sensor noise is present [22].

But the real world situation is very complicated especially in acoustic signal processing. Therefore, researchers introduced the convolutional ICA model to factor in delays, dispersive effects, and noise and use this convolutional model to more accurately approximate real life situations. In audio signal processing, especially in a cocktail party scenario, we have simultaneous and independent speakers, unknown mixing process, and mixtures collected at microphones, and we try to recover underlying independent sources. For Convolutional ICA, Independent Component Analysis (ICA) is processed on convolutional mixtures which help with non-stationary issues in a cocktail party scenario.

The basic convolutional mixing model at discrete time index t is

$$\mathbf{x}_m(t) = \sum_{n=1}^{N} \sum_{k=0}^{K-1} a_{mn}k\mathbf{s}_n(t-k) + \mathbf{v}_m(t) \tag{3.14}$$

where we have N number of source signals $s(t) = (s_1(t), s_2(t),\ldots s_N(t))$ with each column as an independent source. N sources are received by M microphones with received signals represented as $x(t) = (x_1(t), x_2(t),\ldots x_m(t))$, mixing filter coefficient a_{mnk} represents the filter coefficient that relates to source s_n, sensor x_m and propagation delay k. $v_m(t)$ is the sensor noise and corresponds to sensor m.

Rewrite (2) in matrix format we get

$$\mathbf{x}(t)=\sum_{k=0}^{K-1} Ak\ \mathbf{s}(t-k) + \mathbf{v}(t) \tag{3.15}$$

where A_k is k'th filter's coefficients and is a M *N matrix, v(t) is the sensor noise vector and is M*1 dimension. If we take the z transform of (3), we get convolutional model in z domain

$$\mathbf{X}(z) = \mathbf{A}\ (z)\ \mathbf{S}(z) +\mathbf{V}(z) \tag{3.16}$$

which is more straight forward.

We can also take the Fourier Transform of the (3) yielding the convolutional model in frequency domain

$$\mathbf{X}(\omega)=\mathbf{A}(\omega)\,\mathbf{S}(\omega)+\mathbf{V}(\omega) \tag{3.17}$$

where $\omega = 2\pi f$, $\mathbf{A}(\omega)$ is a complex M*N mixing matrix. The dimensions of **X**, **S**, **V** are the same as time domains **x**, **s**, **v**.

The separation model shows us how to find the underlying independent components through mixtures in the mixing model. The goal of the separation model is to recover original independent sources, that is, to find an estimate y(t) that corresponds to original source signals s(t) one by one.

To recover original source signals, we usually estimate the separation filter Wl that removes the cross-talk between signals caused by the mixing process rather than identify the mixing filter Ak specifically. Those separation filters can be modeled as a feedback structure (infinite impulse response) or a feedforward structure (Finite Impulse Response). Since in the room situations, delays are always positive, reverberation and diffraction exist. The recorded speech signals are most likely a filtered version of the signals. We use the casual feedforward structrure (Finite Impulse Response filter model) to solve the problem. In linear noise free systems, we choose suitable multi-dimensional filters based on reasonable assumptions trying to undo the mixing process and recover accurate underlying sources. Then we introduce sensor noise to the Convolutional ICA to best model the cocktail party scenario.

The Feed-forward Separating system is defined as

$$\mathbf{y}_n(t)=\sum_{m=1}^{M}\ \sum_{l=0}^{L-1}\ w_{nm}l\mathbf{x}_m(t-l) \tag{3.18}$$

We can rewrite it in matrix form as

$$\mathbf{y}(t) = \sum_{l=0}^{L-1}\ W_l\mathbf{x}(t-l) \tag{3.19}$$

and it can be modeled in z-domain form after taking z transformation shown as

$$\mathbf{Y}(z) = \mathbf{W}(z)\mathbf{X}(z) \tag{3.20}$$

where n is the number of underlying sources, L is the filter length, and m is the number of microphone recordings.

Therefore, each model source signal is a filtered version of the original source signals, shown below in Z domain

$$\mathbf{Y}(z)=\mathbf{W}(z)\mathbf{A}(z)S(z)=\mathbf{G}(z)\mathbf{S}(z) \quad (3.21)$$

Hence we derive the transfer function G(z) for the ICA process as

$$\mathbf{G}(z)=\mathbf{W}(z)\mathbf{A}(z) \quad (3.22)$$

The difference between the linear convolutive mixing model and the linear instantaneous one is that delayed values of the source signals contribute to the output at a given time. The mixing matrix is now a multi-variant linear time invariant (LTI) system with the impulse response. The instantaneous ICA approach is a special case of the convolutional ICA approach [20]. Other special cases for Convolutional ICA include a reverberation-free environment and a noise free situation. Mutiple methods are developed upon Convolutional ICA such as the time domain approach, the frequency domain approach, iterative and deflation methods, etc [20].

3.4 Convolutive BSS Experiment Setup

In this experiment, we have linear array microphones and linear array speakers; these two arrays are parallel with each other. In a room setting, we have four target speakers talking spontaneously while we have eight microphones synchronically recording the sound. We try to recover what each speaker is talking about with just microphone recordings at hand. The main algorithm we are using in this experiment is the Blind Source Separation method through the convolutive BSS toolbox (Toolbox_2.0.3). This experiment has two main goals. First, we test the separation and reconstruction sound quality/intelligibility of the four target speakers. Second, we try to explore the correlation between the quality of the reconstructed sources and the microphone/speaker spacing.

To accurately approximate the real life situation, microphones and speakers are placed inside a 3.656m*3.656m*2.29m cage. All the microphones and speakers are placed at z=1.5m plane to best approximate the height of humans' mouths. I used the cocktailsim.m file, which is edited from the runCocktailp.m file. This file was obtained

from the Audio Array Toolbox [23] on Professor Donohue's website to simulate desired situations and get the desired speaker recordings for Blind Source Separation algorithm testing. We used four wave files--man1.wav, man2.wav, woman1.wav, woman2.wav (wave files can be downloaded from Professor Donohue's website [23])--and placed them at designated speaker locations.

Parameter configurations in the simulation experiment are shown in the table below.

Table 3.2: Fixed parameters in the experiment

Features	Number/cases
Microphones	8
Speakers	4
Reverberation	2
Microphone spacing	4
Speaker spacing	2

Table 3.3: Parameters in the 16 simulations

Microphone spacing	0.25m	1.5m	2.5m	3.5m
Speaker spacing	0.5m		3.5m	
Reverberations Coefficients in this order: four walls, ceiling, floor	Low [0.5 0.5 0.5 0.5 0.5 0.5]		High [0.92 0.92 0.92 0.92 0.5 0.5]	

Two typical configurations are shown below:

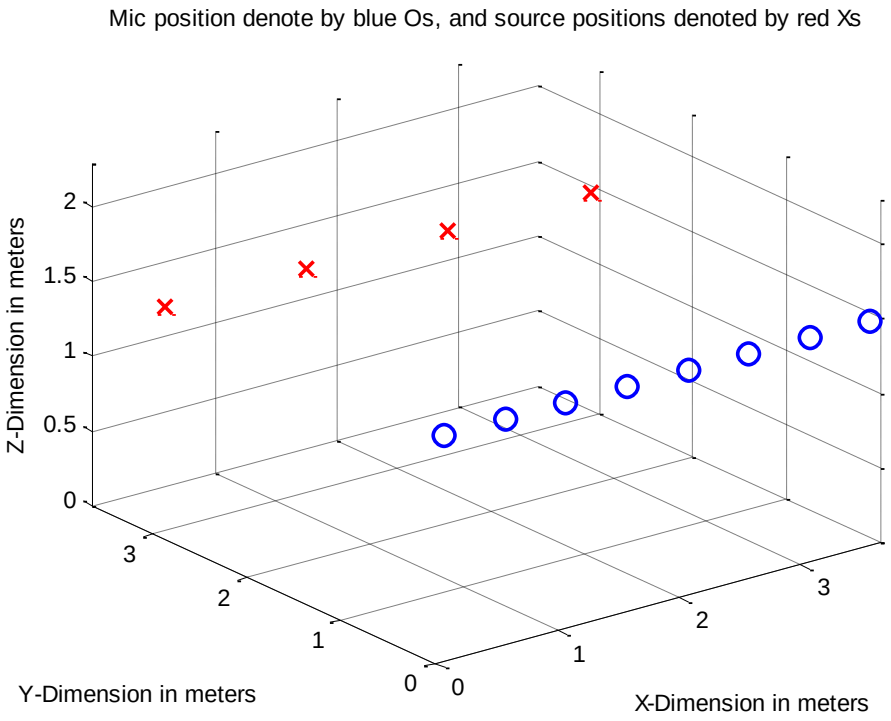


Figure 3.2: Furthest microphone apart is 3.5m; furthest speaker apart is 3.5m

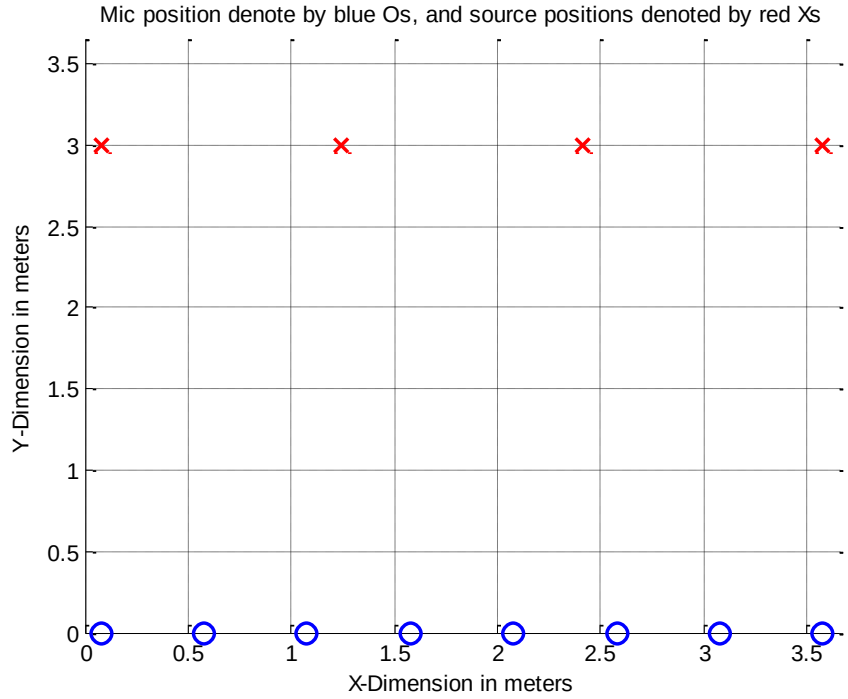


Figure 3.3: Top view of figure 3.2

Table 3.4: Speaker locations in meters for furthest speaker apart is 3.5m

	Speaker 1	Speaker 2	Speaker 3	Speaker 4
X direction	0.0780	1.2447	2.4113	3.5780
Y direction	3.0000	3.0000	3.0000	3.0000
Z direction	1.5000	1.5000	1.5000	1.5000

Table 3.5: Microphone locations in meters for furthest speaker apart is 3.5m

	Mic 1	Mic 2	Mic 3	Mic 4	Mic 5	Mic 6	Mic 7	Mic 8
X direction	0.0780	0.5780	1.0780	1.5780	2.0780	2.5780	3.0780	3.5780
Y direction	0	0	0	0	0	0	0	0
Z direction	1.5000	1.5000	1.5000	1.5000	1.5000	1.5000	1.5000	1.5000

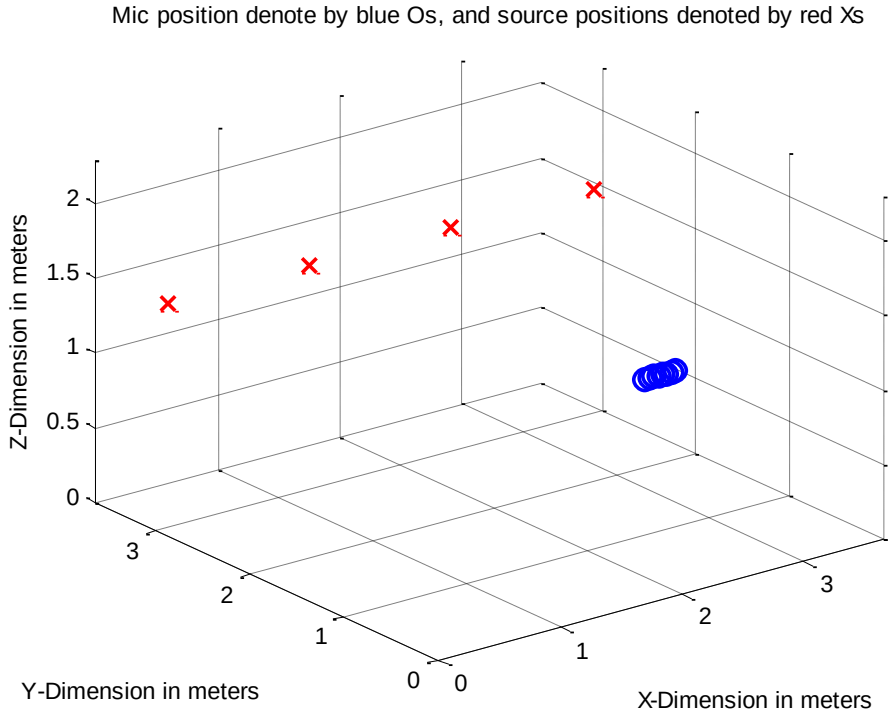


Figure 3.4: Furthest microphone apart is 3.5 m, furthest speaker apart is 0.25 m

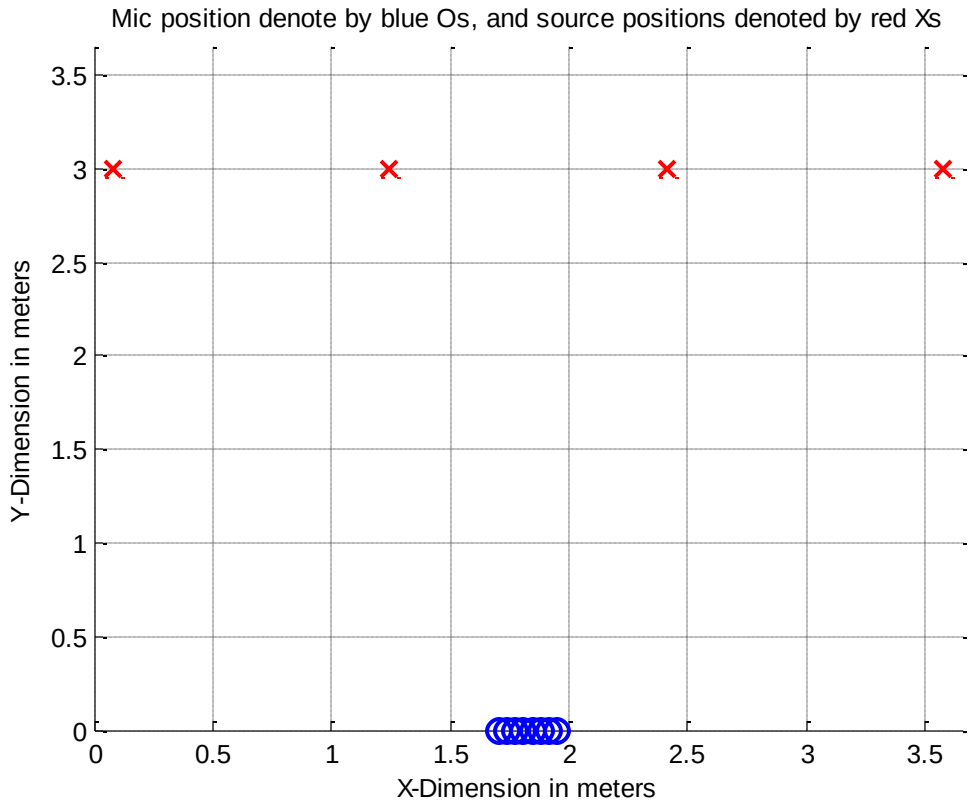


Figure 3.5: Top view of figure 3.4

Table 3.6: Speaker locations in meters for furthest speaker apart is 0.25 m

	Speaker 1	Speaker 2	Speaker 3	Speaker 4
X direction	0.0780	1.2447	2.4113	3.5780
Y direction	3.0000	3.0000	3.0000	3.0000
Z direction	1.5000	1.5000	1.5000	1.5000

Table 3.7: Microphone locations in meters for furthest speaker apart is 0.25 m

	Mic 1	Mic 2	Mic 3	Mic 4	Mic 5	Mic 6	Mic 7	Mic 8
X direction	1.7030	1.7387	1.7744	1.8101	1.8459	1.8816	1.9173	1.9530
Y direction	0	0	0	0	0	0	0	0
Z direction	1.5000	1.5000	1.5000	1.5000	1.5000	1.5000	1.5000	1.5000

After we simulated 16 different microphone recordings, we used the Conv BSS toolbox, short for convolutive blind source separation toolbox, to process simulated data in order to study the two goals mentioned in the beginning of this experiment setup.

We passed the simulated microphone data one by one through the Butterworth High-pass filter with cutoff frequency 200 Hz. Then we pass the filtered wave channels through the ConvBSS toolbox developed by M. Castella, S. Rhioui, E. Moreau and J.-C. Pesquet[24] using the deflation method. Important parameters used in convolutive BSS processing are number of sources we want to extract, deflation stopping criterion, length(order+1) of the convolutive extracting filter including anti-causal and causal parts, extraction method, and parameters specific to the chosen extraction method, such as number of sources that effectively contribute to the mixture, length of the mixing filter, and number of fixed-point-like iterations.

The number of sources we want to extract are the estimated underlying sources that contain most of the information. Deflation stopping criterion is the ratio of the power left on the sensor divided by power on the sensors initially, after a deflation step. In Convolutive BSS, this and the estimated number of sources we would like to extract act like a double threshold to help us extract the optimized extraction results as we can. Extracting filters is vital in helping us reconstruct information of underlying sources. The causal filter is a real-time filter that only depends on present and past information; anti-causal filter cannot be implemented in real-time because it depends on present and future information. Our application doesn't need to be real-time, so we use a combination of causal and anti-causal filters hoping for good separation results. Regarding the extraction method, for now we use quadratic contrast, SVD-based optimization [24].

Parameters associated with this extraction method are: number of main speakers, length of mixing filter, number of fixed-point like iteration, and gradient step method. We assign the same number to the length of the mixing filter and extracting filter. Parameter specifications used in the simulation tests are below:

Table 3.8: Values used in ConvBSS separation process

Parameters	Value
Number of Sources	4
Stop Threshold of a Deflation Step	1e-2
Length of the Extracting Filter	100
Length of Anti-causal Part of Extracting Filter	50
Length of Causal Part of Extracting Filter	50
Source Extraction Method	'quadSVD'
No of Sources Effectively Contribute to Mixtures	4
Gradient Step	'optim'

After subjective comparison by direct listening to the separated underlying sources, we decided to focus on the two extreme cases mentioned above, out of the sixteen cases, due to these comparable better separation effects.

The separated four sources in each case are in the corresponding .wav files. The separated sources are shown in the figures below.

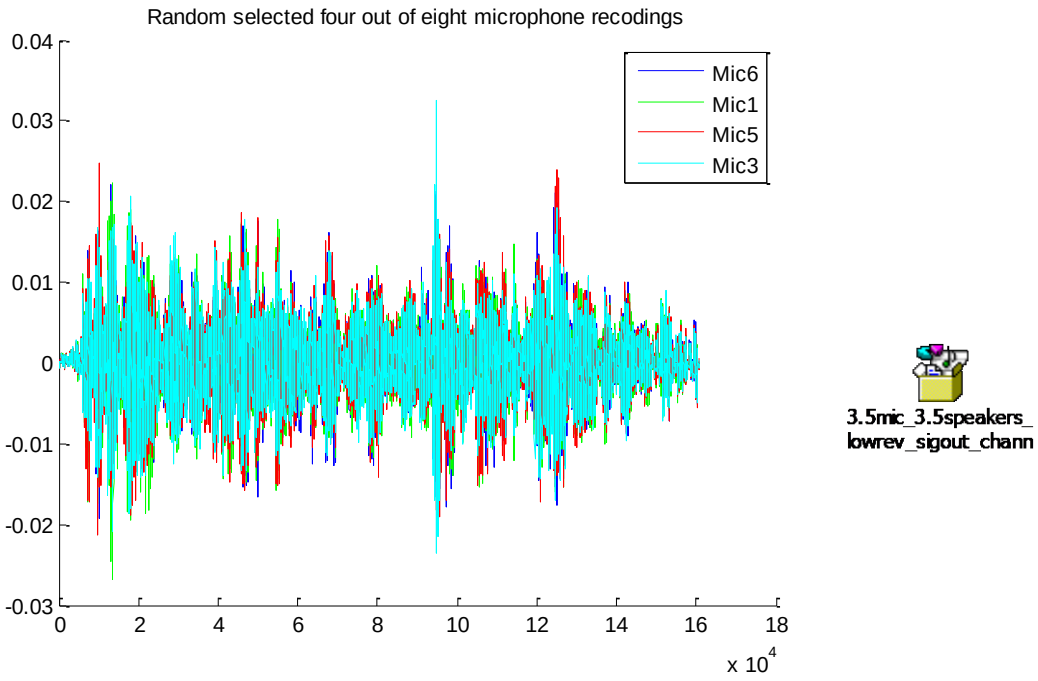


Figure 3.6: 3.5mic_3.5speakers_lowrev random selected four out of eight microphone recordings before using ConvBSS method

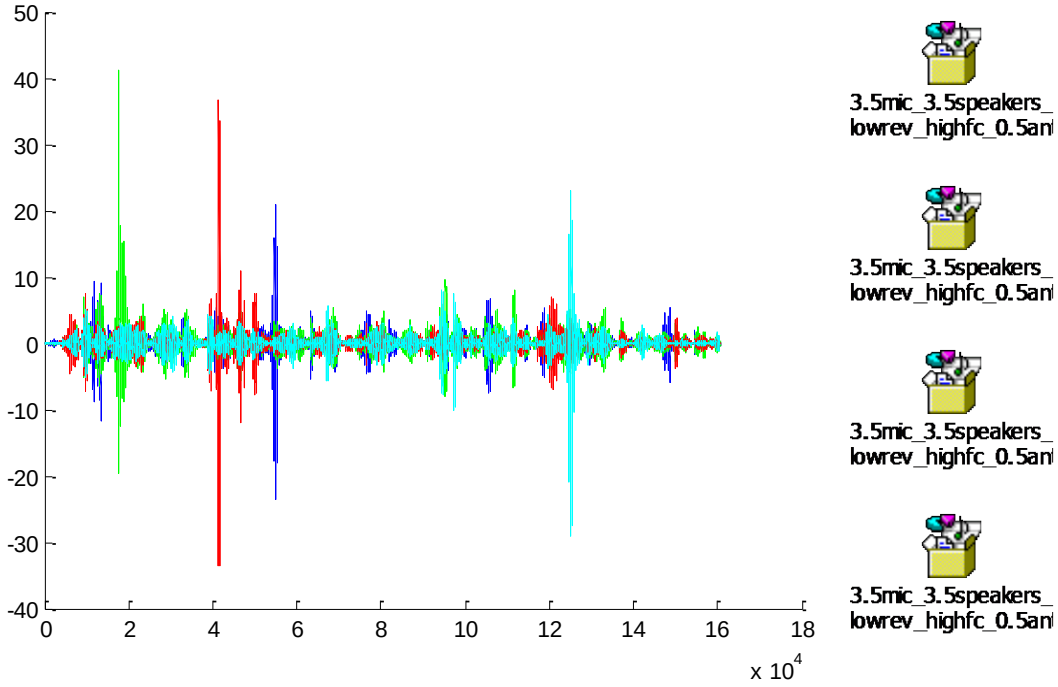


Figure 3.7: 3.5mic_3.5speakers_lowrev_highfc_0.5antin0.5causalfilt_convsepartion with every color represents one underlying source after separation using ConvBSS method

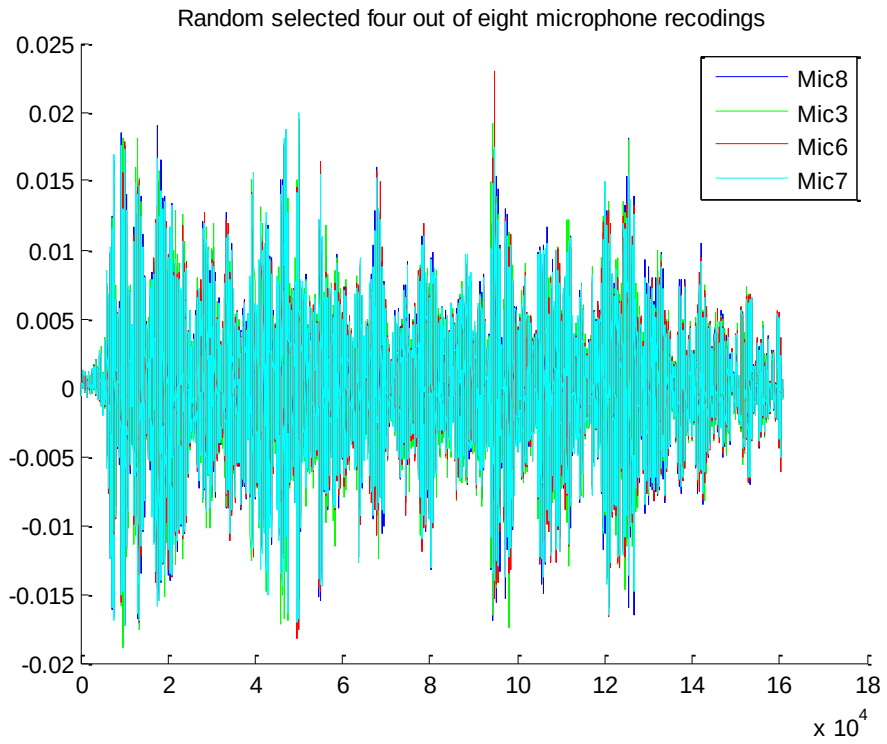


Figure 3.8: 0.25mic_3.5speakers_lowrev random selected four out of eight microphone recordings before using ConvBSS method

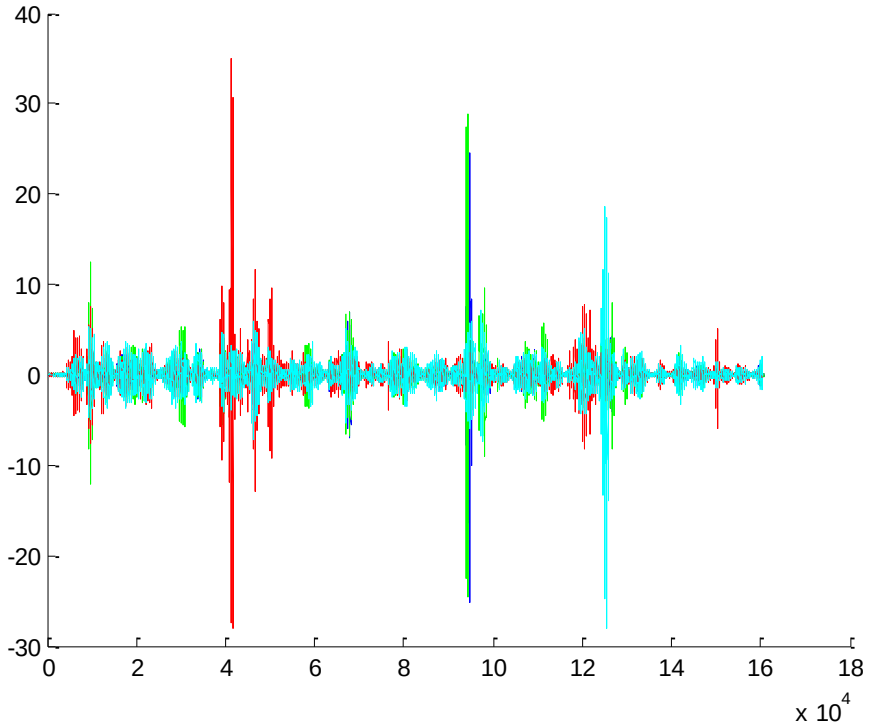


Figure 3.9: 0.25mic_3.5speakers_lowrev_highfc_0.5antin0.5causalfilt_convsepartion with every color represents one underlying source after separation using ConvBSS method.

When comparing the separated underlying sources for these two cases, we found that when the microphone apertures are 3.5 meters apart and speaker apertures are 3.5 meters apart, the estimated underlying sources sound more intelligible.

3.5 Problems Encountered When Using Convolutional BSS Toolbox

When I tried to validate the performance of the Convolutional BSS Toolbox with regards to the method mentioned in the file Goals of Experiments and Conclusion Derivation Process_w remarks, I first created an excel file called data.xlsx. Into this excel file, I manually input all the parameter names and their desired testing values. An example is shown below in Figure 3.8.

Table 3.9 Parameter values to validate the Convolutional BSS Performance

Filename	Nsources	SeuilStopAlgo	Lfilter	LSubtractFiltreAC	LSubtractFiltreC	Method	NsourcesEffectiv	Quadratic.L	Quadratic.Nifix	GradientStep
norspeakerpw4sec_3.5mic_3.5speakers_lowrev_sigout.wav	4	0.01	100	50	50	quadSVD	4	100	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_lowrev_sigout.wav	4	0.01	100	0	100	quadSVD	4	100	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_lowrev_sigout.wav	4	0.01	100	80	20	quadSVD	4	100	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_lowrev_sigout.wav	4	0.01	30	15	15	quadSVD	4	30	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_lowrev_sigout.wav	4	0.01	160	80	80	quadSVD	4	160	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_highrev_sigout.wav	4	0.01	100	50	50	quadSVD	4	100	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_highrev_sigout.wav	4	0.01	100	0	100	quadSVD	4	100	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_highrev_sigout.wav	4	0.01	100	80	20	quadSVD	4	100	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_highrev_sigout.wav	4	0.01	30	15	15	quadSVD	4	30	10	optim
norspeakerpw4sec_3.5mic_3.5speakers_highrev_sigout.wav	4	0.01	160	80	80	quadSVD	4	160	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_lowrev_sigout.wav	4	0.01	100	50	50	quadSVD	4	100	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_lowrev_sigout.wav	4	0.01	100	0	100	quadSVD	4	100	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_lowrev_sigout.wav	4	0.01	100	80	20	quadSVD	4	100	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_lowrev_sigout.wav	4	0.01	30	15	15	quadSVD	4	30	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_lowrev_sigout.wav	4	0.01	160	80	80	quadSVD	4	160	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_highrev_sigout.wav	4	0.01	100	50	50	quadSVD	4	100	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_highrev_sigout.wav	4	0.01	100	0	100	quadSVD	4	100	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_highrev_sigout.wav	4	0.01	100	80	20	quadSVD	4	100	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_highrev_sigout.wav	4	0.01	30	15	15	quadSVD	4	30	10	optim
norspeakerpw4sec_0.25mic_3.5speakers_highrev_sigout.wav	4	0.01	160	80	80	quadSVD	4	160	10	optim

Then I wrote a software script in Matab that reads in all the data from the excel file. This software script is also iterative. For every row of data, it calls the Convolutional BSS method and computes with the parameter values given using the specific method designated in the row. When finishing computing, the script will give four separated underlying sources in .wav format.

Each set of data takes approximately twenty minutes to an hour to get four underlying sources. After inner and cross comparison of the different separating results by direct listening we found that some set of the data works better than others.

We picked the four most distinct (in a sense that their timbre are quite unique and easy to distinguish from a group) sources man1, man2, woman2, and woman3. We selected four seconds based on the speech density of the wave files of these four wave files so as that we run ConvBSS algorithm testing, it does not use quite as much time, so we can get a quick idea of the performance, find the critical parameter, and validate it on the whole length speech. We then normalized the four sources to the same power level to avoid the volume interferences of the Convolutional BSS algorithm.

We also ran simulation tests on high reverberation cases. In summary, we ran simulations with regard to high/low reverberations, different numbers of microphones/speakers (meaning mixing systems are under/over determined), different microphone/speaker spacing, different parameter setup for the Convolutive Toolbox, and different filter length/types of filters (causal/anti-causual). Two typical cases are shown in Figures 3.2 through 3.9. Some of the parameter variation is shown in Table 3.8. Figure 3.2 is a layout of the best case we have through our experiments. Figure 3.3 is the top view of the layout. Even in the best case, we do not hear much performance improvement. As far as all the experiments we have tried, Convolutive BSS failed to show much improvement in source separation such as difference level of reverberation, different geometry microphone and speaker layout, different number of microphones, different filter length/types, etc. Later on, we found that Convolutive BSS has stability issues as well. The abnormal spikes in Figures 3.7 and 3.9 show stability issues. Later on, we conducted stability tests on different kinds of algorithms in the Convolutive Toolbox

(Toolbox_2.0.3); very rarely can one algorithm in Toolbox_2.0.3 make it. This test shows stability issues in Toolbox_2.0.3.

From the convolutive algorithm interpretation, it seems that theoretically the Convolutive BSS should work well dealing with real world recordings and real world recording are most often convolutive.. However, the toolbox requires many parameters to be set and often has stability issues as well as minute performance improvement.

Chapter 4: Channel Aligned Fast ICA

The FastICA toolbox works well in extracting each source when we have instantaneous mixture sources. But this toolbox failed to extract any source from mixtures when the mixture is convolutional. Then we looked into the Matlab toolbox for separation of convolutive mixtures [25], adjusted it to smoothly interact with audio signals. We also intensively ran experiments on this toolbox and tried all the separating methods in Convolutive toolbox. After many experiments as mentioned in the last chapter, we found that the toolbox is not stable when working with audio signals. As we were trying to fix this problem by researching this toolbox, we found that researchers just mentioned in their papers that this toolbox brings in low MSE when sample size was large. Researchers have not tried working with audio signals/ speech signals using this toolbox and this toolbox needs quite a bit of development work so as to be more efficient for audio signals. Other toolboxes that work well with audio signals are Flexible Audio Source Separation Toolbox (FASST) [26] and BSS Locate (A toolbox for source localization in stereo convolutive audio mixtures) [27]. FASST toolbox keen methodology is based on nonnegative matrix factorization (NMF) while BSS Locate toolbox leans more towards the estimation of Time Differences of Arrival (TDOAs) of sources. FASST does not have the smooth sound effects on Linear instantaneous mixture after separation while FastICA toolbox have smooth sound effects, it could not extract all the underlying sources in a underdetermined situation. BSS Locate Matlab toolbox estimates the Time Differences of Arrival (TDOAs) of multiple sources in a stereo audio signal recorded by a pair of omnidirectional microphones. Two different categories of source localization methods are implemented: angular spectrum-based methods and clustering-based methods. It is more powerful when combined with other algorithms using TDOAs.

For our cocktail party scenario, we took advantage of the FastICA algorithm (such as smooth separation effects, fast processing, etc.) and developed a new algorithm, Channel Aligned Fast ICA (CAICA). Since Convolutive BSS toolbox has many parameters needed to be setup, it takes time to explore suitable parameters for source separation so it is not very practical and is time cosuming to use Convoulitve BSS. While FastICA can

use just one set of parameters for source separation and it works very well with instantaneous mixtures but failed to separate Convolutive mixtures, it inspired us to align all microphone channels to make speaker sound “instantaneous” with respect to all microphone channels, and then apply FastICA to the aligned mixtures. Source separation results only have one channel with clear Source of Interest, other channels are all noise. We can then combine the results with Time Frequency Masking for effective source separation of from the mixtures. But CAICA brings up a tradeoff because Convolutive BSS does not need any prior knowledge such as the relative locations of the microphone and SOI but CAICA does require such information. With the limitation of the weighted Beamforming such that it could not generate up to the total number of microphones of meaningful channels. We also prolong the advantages of the algorithm and combine it with Time Frequency Masking for better sound extracting results (motivation of the new algorithm).

4.1 CAICA Description

A new algorithm referred to the Channel Aligned FastICA (CAICA) is introduced in the thesis. This ICA enhancement requires knowledge of the source distance to each microphone, but does not require knowledge of the noise sources.

Procedures of CAICA are:

1). Calculate delays from SOI to each microphone

2). Apply delays to align SOI signals in each microphone

3). Use Fast ICA for Source Separation of SOI

After applying delays to each microphone channels, from each microphone’s perspective of view, SOI hits each microphone at approximately the same time.

4.2 Closest Microphone(CM) recordings

Just as its name suggests, Closest Microphone (CM) is the microphone that is closest to SOI; it performs best amongst microphone arrays. CM recording is used as a reference to compare with three other algorithms CAICA, WB, CAICA with TFM. Upon comparing, we can see other algorithms have performance improvements.

4.3 Weighted Beamforming (WB):

Beamforming is a signal processing technique that uses spatial information to filter a target signal of undesired interference [Litva 1996]. Beamforming uses the measured positions of a target speaker and an array of microphones to calculate optimal methods of filtering and combining several audio tracks into one with an enhanced SNR.

Weighted Beamforming(WB) weights different microphone channel with regard to its distance to SOI. A microphone channel that is closer to SOI will have higher weights; a channel that is farther away from SOI has lower weights.

4.4 Time Frequency Masking (TFM)

Fourier transforms the SOI after processing the Channel (with interferences) and interference channels in the frequency domain[28,29].

For each time Frequency unit, compare SOI and interferences, if SOI is dominant, keep it; otherwise put value zero in this unit; that is, mask it out. Hence we have a binary time frequency mask[28, 29]. We then take the Inverse Fourier Transform to get the processed audio signals in the time domain.

4.5 CAICA with TF Masking

Furthermore, we combine CAICA with Time Frequency Masking (TFM) yielding even better SOI extraction even in a harsh environment such as a low SNR environment.

Chapter 5: Simulation Experiment

To test the effects of the CAICA and CAICA with TFM, we ran simulations, asked candidates to evaluate the separation effects and ranked the performance based on direct listening, and did statistical analysis on the gathered data.

5.1 Simulation Setup

We have eight microphones and four speakers in this set of simulation experiments.

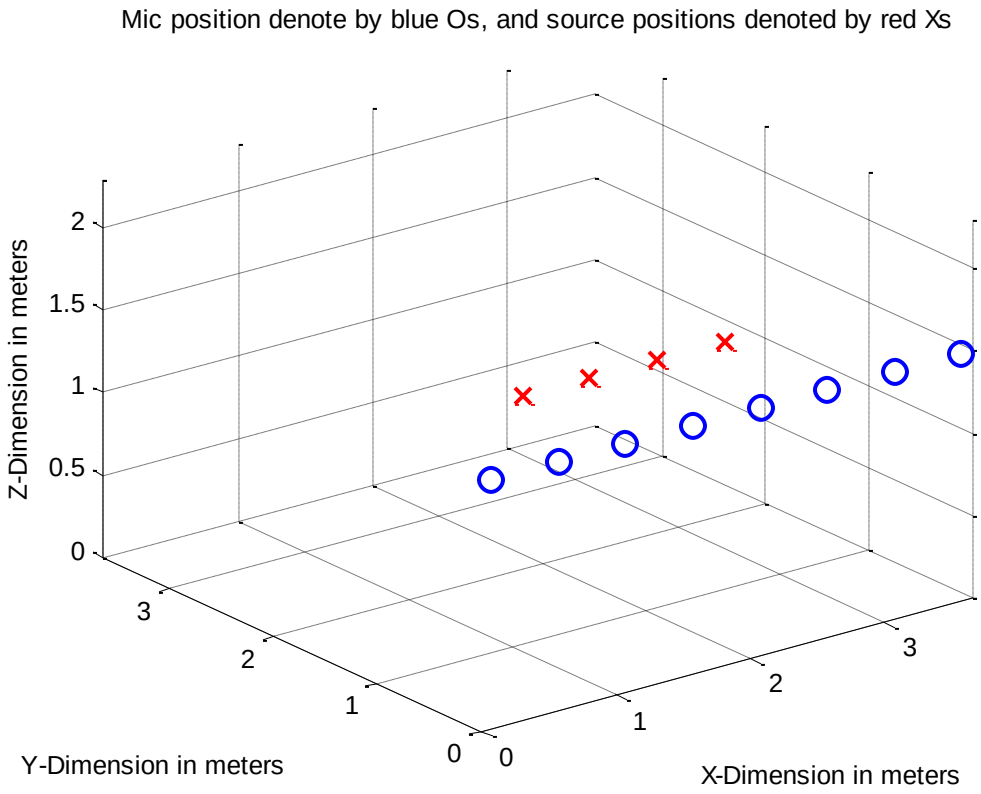


Figure 5.1: Microphones and Speakers 3-D coordinates

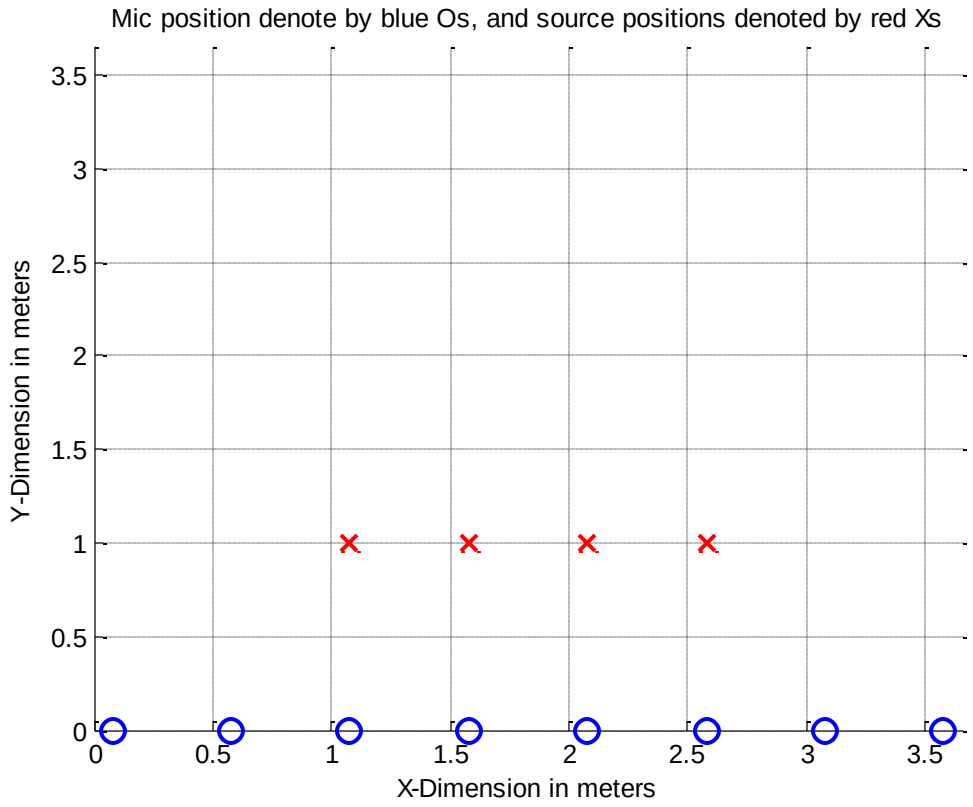


Figure 5.2: Microphones and Speakers 3-D coordinates

Table 5.1: Speaker Locations in meters for this setup

X direction	1.0780	1.5780	2.0780	2.5780
Y direction	1.0000	1.0000	1.0000	1.0000
Z direction	1.5000	1.5000	1.5000	1.5000

Table 5.2: Microphone Locations in meters for this setup

	Mic 1	Mic 2	Mic 3	Mic 4	Mic 5	Mic 6	Mic 7	Mic 8
X direction	0.0780	0.5780	1.0780	1.5780	2.0780	2.5780	3.0780	3.5780
Y direction	0	0	0	0	0	0	0	0
Z direction	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5

From left to right in Figure 5.2, we have microphone 1 to microphone 8.

5.2 Simulation Procedures

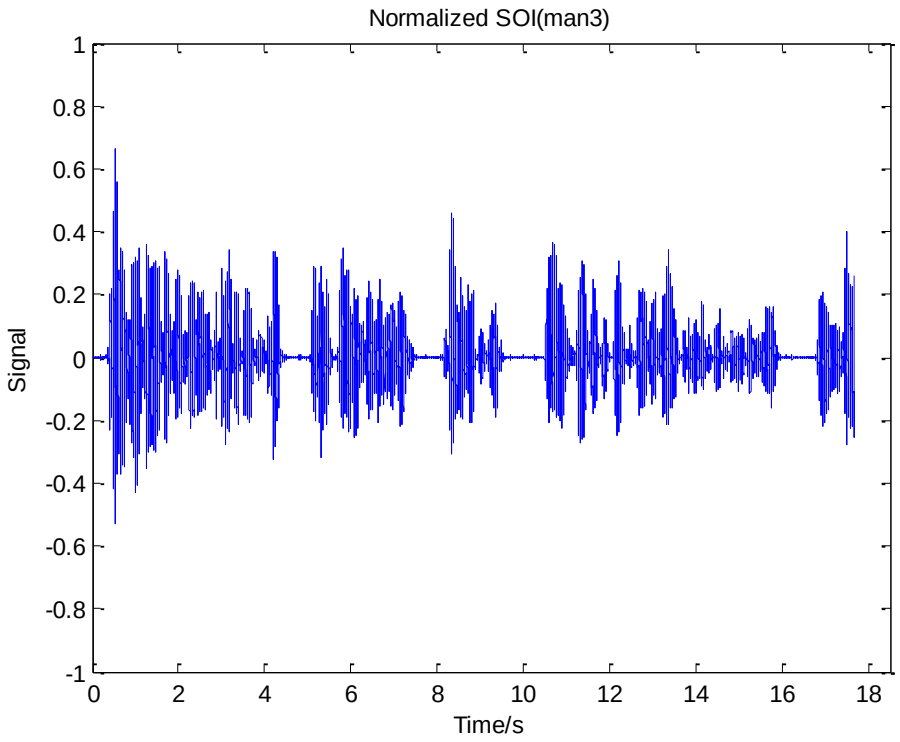
We randomly selected four out of the 12 wave clips, man1, man2, man3, man4, man5, man6, man7, man8, woman1, woman2, woman3, and woman4 without replication and put them in the selected order from left to right in four speaker spots. We put 8 microphones in the designated spots. We trimmed randomly selected speaker wave clips to the same length and passed them through a high pass filter to remove room noise. Then we normalized each speaker's power. We randomly selected a speaker location and treated it as the Speaker of Interest (SOI). We used *cocktail function cocktailp(sigin, spos, mpos, recinfo)* to simulate room effects yielding cocktail party data. Here we set *recinfo=0* for no reverberation[23].

Based on room temperature, room humidity and room pressure, we calculated the speed of sound and we found the distances from SOI to each microphone in meters. We subtracted every distance from SOI to microphone from the maximum distance and then divided by speed of sound yielding time durations that each track needs to be delayed so that SOI hits each microphone at the same time. Then we converted relative time delays to relative sample delays. We detected the closest microphone channel based on the minimal delays and labeled it. We padded the number of zeros that are equal to the relative delays samples in each track and stored data as the microphone aligned data.

We added up all the signals across the 8 microphone channels yielding SOI beamforming data. Based on the distances from SOI to sensors (microphones); we computed weights for each sensor. We weighted each channel based on these calculated weights and summed them up across all eight channels yielding the weighted beam forming (WB) data.

We processed microphone-aligned data through the FastICA toolbox with optimized parameters yielding the channel aligned FastICA data. We listened to each channel and handpicked the processed SOI channel and saved it as the CAICA SOI channel data. After identifying SOI and interference channels, we processed CAICA data through the Time Frequency Masking algorithm tfmask.m in the ASA_Toolbox. In the Time

Frequency Masking file, for each time window and frequency bin when the SOI value is larger than each interference, we kept the SOI value, otherwise we masked out (zeroed out) this frequency bin (zero out this time window) [28, 29]. Then we got the data for the CAICA with TFM. Figures associated with every algorithm and/or references are shown from Figure 5.3 through Figure 5.8. Related sound files please seen files linked next to figures.



nman3.wav

Figure 5.3: Normalized SOI (man3)

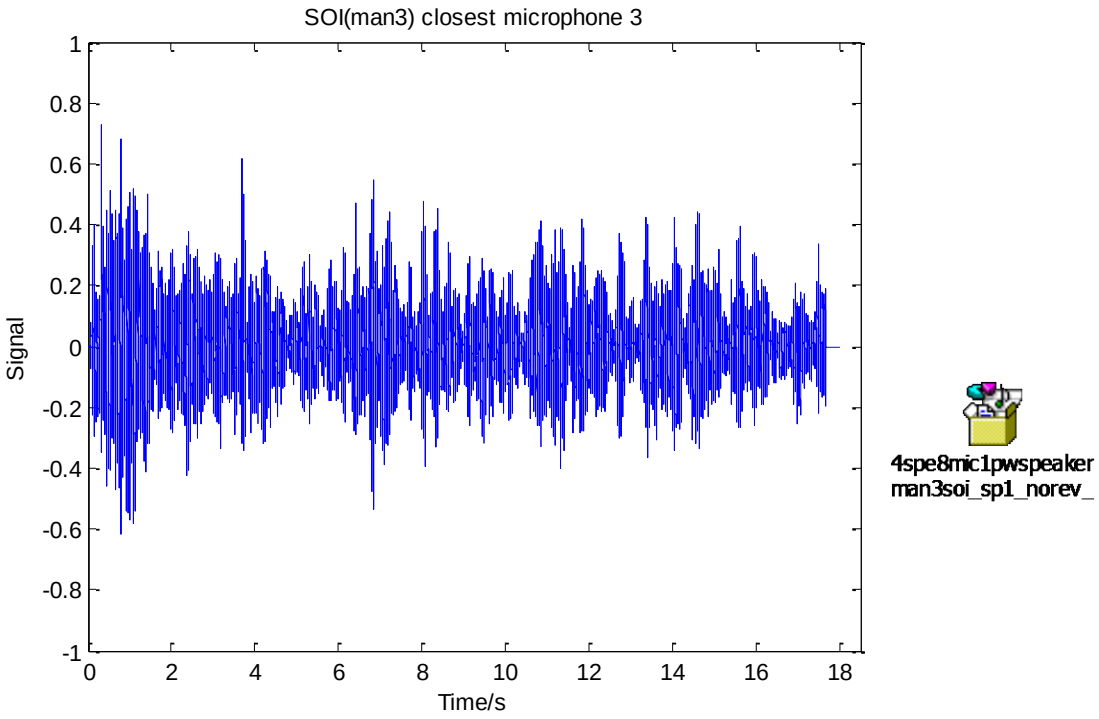


Figure 5.4: SOI(man3) closest microphone 3

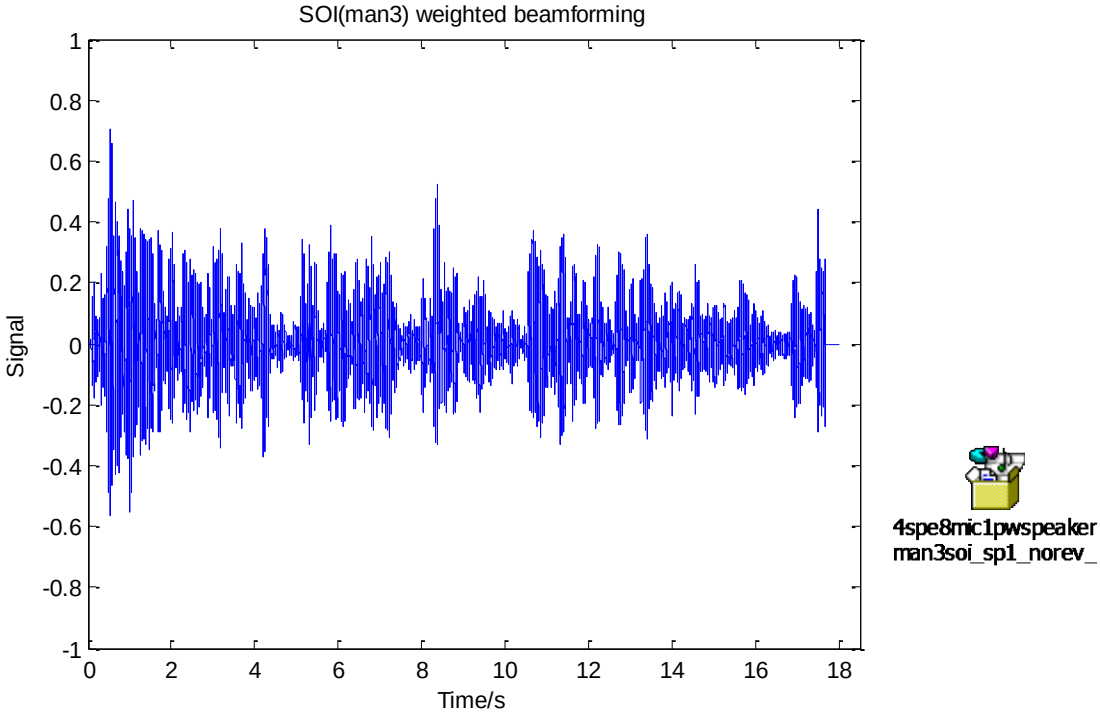


Figure 5.5: SOI(man3) weighted beamforming

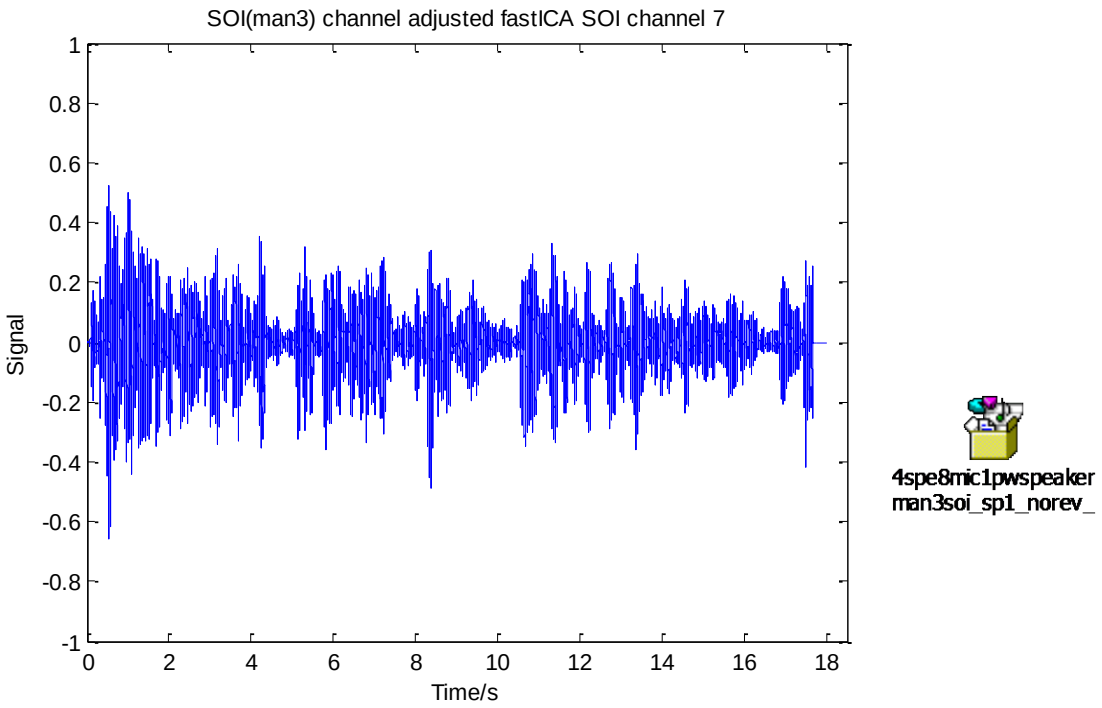


Figure 5.6: SOI (man3) channel adjusted fastICA SOI channel 7

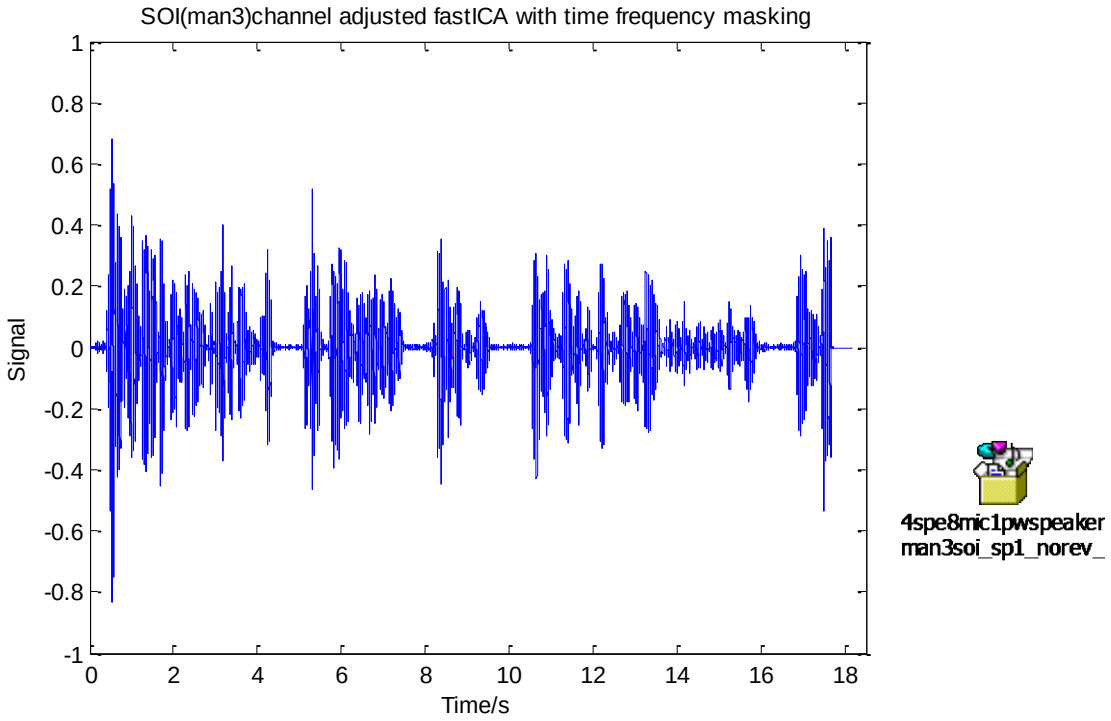


Figure 5.7: SOI(man3)channel adjusted fastICA with time frequency masking

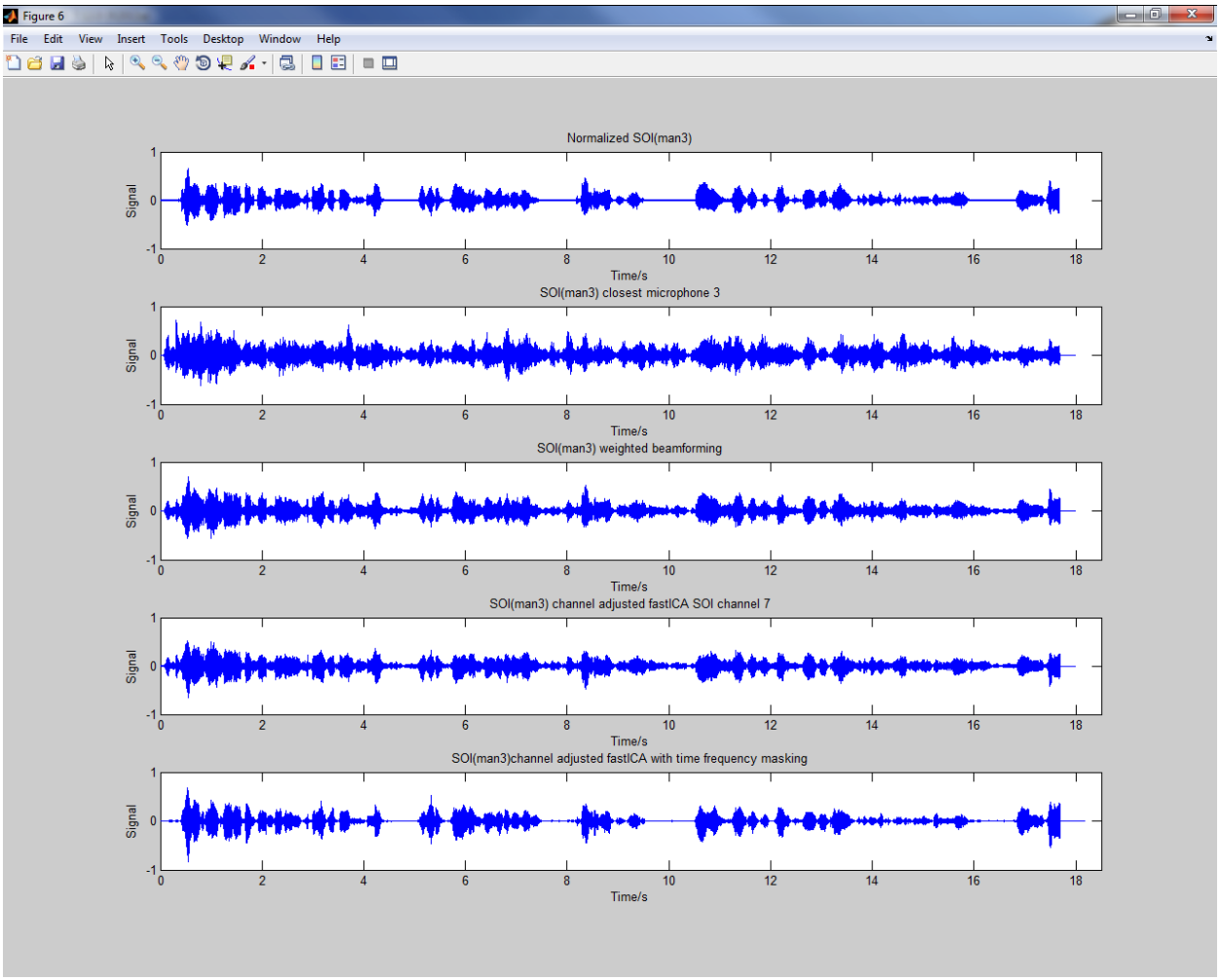


Figure 5.8: All wave forms for comparison

5.3 Experiment Approaches and Descriptions

We then ran the same experiment mentioned above but with lowered SOI volume: 50%, 40%, 35%, 30%, and 25% of the normalized power to find the critical point. When SOI is 100% of the normalized power, it roughly corresponds to -4.7712 dB SNR. 50%, 40%, 35%, 30%, and 25% of the normalized power roughly corresponds to -7.7815dB, -8.7506dB, -9.3305dB, -10dB, and -10.7918dB SNR. When it comes down to SOI 30% of normalized power (-10dB SNR), systematic errors occurred such as we cannot identify the SOI channel in the CAICA data.

100% and 35% of the normalized SOI power (-4.7712 dB and -9.3305dB SNR) were finalized to compare algorithm performance in the simulation experiments. A total of 16

sets of experiments were conducted based on the procedures mentioned above and 8 sets were with 100% of the normalized SOI power and the other 8 sets were with 35% of the normalized SOI power.

For each set of experiments, we put five sound tracks in audacity and saved the audacity file. In each audacity file, the first sound track is always the randomly selected SOI with the desired power. The rest of the four sound tracks are CM, WB, CAICA SOI channel, and CAICA with TFM, but not necessarily in the stated order. In fact, the order is random in order to better judge each algorithm's performance.

Five laboratory members participated with the goal of nonbiased testing of algorithm performance. All candidates went over the message in italics first and needed to make sure they fully understood how the experiment works and the goals before they proceeded.

Descriptions:

In this experiment, we will listen to and rate 16 sets of files. In each set of files, we have five sound tracks. The first sound track (reference sound track) is always the Source Of Insterest (SOI), the rest of the sound tracks are associated with different algorithms not appearing in the same order in each file.

Question:

Please rank the sound tracks with respect to the degree that SOI speech is extracted from the other voices with 1 being best and 4 being worst.

Remarks:

Please go back and forth until you are fairly confident with your ranking. Please record the results in the provided spreadsheet. In the case, when you feel two are the same, give them an arbitrary ranking.

Candidates will open the experiment file in the audacity with the interface as shown in Figure 5.9.

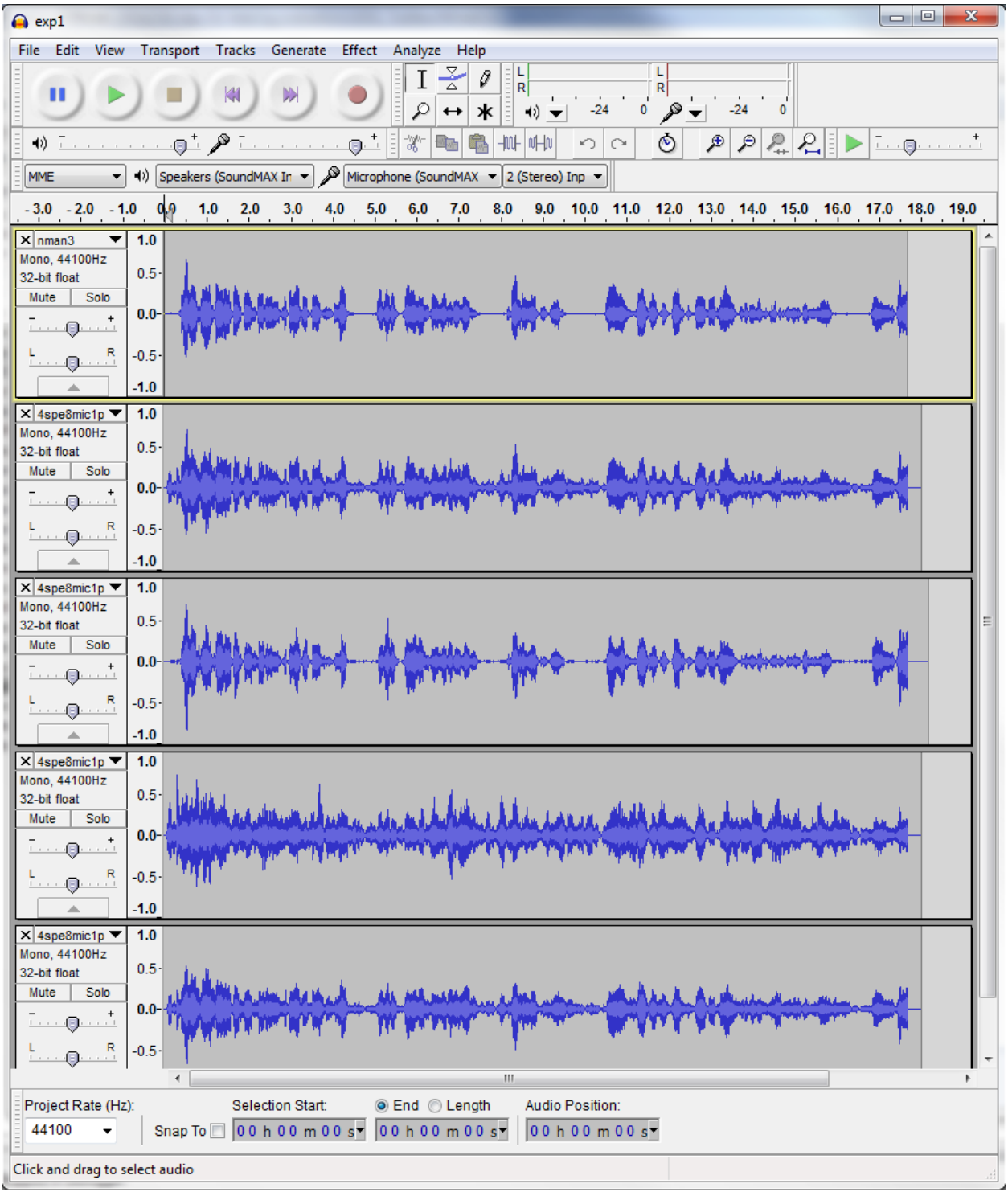


Figure 5.9: Audacity user interface for one experiment

As they went back and forth listening and comparing the quality of the algorithms, they also recorded the ranking of the sound files in an Excel file for each member. An example of a set of rankings for a single listener is shown in Table 5.3.

Table 5.3: Test_Laboratory Member A Sound Track Ranking

	Sound Track 2	Sound Track 3	Sound Track 4	Sound Track 5
EXP 1	2	1	4	3
EXP 2	2	3	4	1
EXP 3	1	2	3	4
EXP 4	3	4	2	1
EXP 5	1	4	2	3
EXP 6	3	1	2	4
EXP 7	4	2	3	1
EXP 8	2	3	4	1
EXP 9	1	2	4	3
EXP 10	4	1	3	2
EXP 11	3	2	4	1
EXP 12	2	4	3	1
EXP 13	2	1	4	3
EXP 14	2	4	3	1
EXP 15	3	4	1	2
EXP 16	3	1	4	2

Based on the name of each sound track in each experiment in Figure 5.9, Table 5.3 was converted to Table 5.4, where different algorithm ranking scores are associated with specific algorithms. Then the score sum and average were calculated for three algorithms WB, CAICA, CAICA with TFM and one reference CM.

Table 5.4: Algorithm Ranking_ Laboratory Member A's Score

	Closest Microphone	Weighted Beamforming	Channel Aligned ICA	Aligned ICA + TF Masking
exp1	4	2	3	1
exp2	4	2	3	1
exp3	4	3	2	1
exp4	4	3	2	1
exp5	4	3	2	1
exp6	4	3	2	1
exp7	4	3	2	1
exp8	4	3	2	1
exp9	4	2	3	1
exp10	3	4	2	1
exp11	4	3	2	1
exp12	4	2	3	1
exp13	4	2	3	1
exp14	4	2	3	1
exp15	4	2	3	1
exp16	4	3	2	1
Sum	63	42	39	16
Avg	3.9375	2.625	2.4375	1

5.4 Statistical Analysis

Means and standard deviations for each member and for all data sets were calculated and are shown in the tables below.

Table 5.5 Statistical Analysis

Laboratory Member A	Closest Microphone	Weighted Beamforming	Channel aligned ICA	Aligned ICA + TFM
Mean	3.9375	2.625	2.4375	1
Standard Deviations	0.25	0.619139187	0.512347538	0
Laboratory Member B	Closest Microphone	Weighted Beamforming	Channel aligned ICA	Aligned ICA + TFM
Mean	3.9375	2.3125	2.625	1
Standard Deviations	0.25	0.602079729	0.619139187	0
Laboratory Member C	Closest Microphone	Weighted Beamforming	Channel aligned ICA	Aligned ICA + TFM
Mean	4	2.6875	2.3125	1
Standard Deviations	0	0.478713554	0.478713554	0
Laboratory Member D	Closest Microphone	Weighted Beamforming	Channel aligned ICA	Aligned ICA + TFM
Mean	4	2.5	2.5	1
Standard Deviations	0	0.516397779	0.516397779	0
Laboratory Member E	Closest Microphone	Weighted Beamforming	Channel aligned ICA	Aligned ICA + TFM
Mean	4	2.4375	2.5625	1
Standard Deviations	0	0.512347538	0.512347538	0

Table 5.5, continued Statistical Analysis

Whole 80 sets of data	Closest Microphone	Weighted Beamforming	Channel aligned ICA	Aligned ICA + TFM
Mean	3.975	2.5125	2.4875	1
Standard Deviations	0.15711	0.5510347	0.527563062	0

5.5 Conclusions

Summarizing all the experiments conducted by all candidates, as well as calculating the mean and standard deviations mean score for CAICA with TFM is 1; the mean score for CAICA is 2.4875; the mean score for WB is 2.5125; and the mean score for CM is 3.975. Standard deviations for each algorithm and reference are 0, 0.53, 0.55, and 0.16 respectively. The mean score for the whole set of experiments shows that CAICA with TFM performs best in the sense of the degree that SOI speech is extracted from other voices. CAICA and WB perform next and their performance is about the same, and CM worst.

Due to the high standard deviations for WB and CAICA and minimum mean value difference between WB and CAICA, we cannot conclude which one, WB or CAICA, performs better and these two algorithms perform about the same in source separation. Since beamforming is a mature technique that has already been deployed to modern electronic devices, such as cell phones, tablets, etc., even if CAICA performs the same in source separation, it is already very impressive. The mean and standard deviation values also show that WB, CAICA, CAICA with TFM improves the performance of the SOI extraction for sure. Low or 0 standard deviations for all the experiments better support the conclusion drawn based on mean score.

Chapter 6: Algorithm Validation

We have a reference Closest Microphone (CM) for subjective listening comparisons, and we introduced three algorithms, Weighted Beam forming (WBF), Channel Aligned FastICA(CAICA) and Channel Aligned FastICA with Time Frequency Masking(CAICATFM) algorithms in the last chapter and showed their simulation results. We put emphasis on the performance of the new algorithm (CAICA) and how the new algorithm performs when combined with TF masking. In this chapter, we are going to show experimental recording results to validate algorithm performance. One experiment environment setting for experimental recordings is shown in Figures 6.1 through 6.3. Figures are from Dr. Donohue Website
http://www.engr.uky.edu/~donohue/audio/Examples/Examples.html

Figure 6.1: Cage side with Linear Microphone array, a couple of speakers, and absorptive acoustic treatment

Figure 6.2: Cage with Speakers side view

Figure 6.3: Cage with Speakers back view

6.1 Experiments Setup

We realized a cocktail party scenario in our Audio Systems Laboratory in University of Kentucky.

We used the data from the Cocktail party recording with distributed microphones (one speaker of interest embedded in 6 simultaneous speakers). Data can be downloaded from the link http://www.engr.uky.edu/~donohue/audio/Data/audioexpdata.htm. Specifically, we used the Microphone Ceiling Regular Hexagonal Grid in this validation experiment. In this experiment, we have 16 microphones and 1 SOI. Hardware and software parameters are shown below in Table 6.1.

Table 6.1 Experiment Settings

RT60 Time	0.232 s
Size of Space for speakers and microphones	3.6x3.6x2.2
Sampling Frequency	22050 Hz
Microphones	16 Behringer ECM8000 measurement microphones, condenser type, Omni direction, Frequency response, 15Hz to 20KHz [30].
Amplifiers	M-Audio AudioBuddy Dual Microphone Preamp with Phantom Power and Direct Box, frequency response: 5Hz-50 KHz[31]
Sound Card	Two 8-Channel Delta 1010 by M-Audio
Acoustic Foam Panels	Auralex MAX-WALL, noise reduction coefficient 1.05[32]
A/D conveter	M-Audio Delta 1010 Digital recording system, frequency response: 20Hz – 22KHz, 8X8 analog I/O[33]
Software	Jack audio connection kit 0.3.2, Ubuntu studio 8.04[34]

For these results presented here, we used SOI 5 and background cocktail party noise 3. The cocktail party noise is a 16 channel recording from 6 talking people. SOI is not presented in the party noise. 16 microphones are installed on the ceiling shown in blue circles with coordinates described in Table 6.3. Table 6.2 shows the mean speaker location. Speaker mean location is also marked as red cross in Figure 6.4. Figure 6.4 shows microphone and mean speaker 3-D locations. Figure 6.5 is the top view of the microphone and mean speaker location. We can see that microphone locations are like the Ceiling Regular Hexagonal Grid. We superimposed SOI and party noise recordings with different SNR values and tested the four algorithms mentioned above. We tested on three scenarios: SNR=2 dB, SNR = 0 dB, SNR = -10 dB. The 6 interferences are not marked in the microphone and speaker layout since their locations do not matter to our program and they were used as noise.

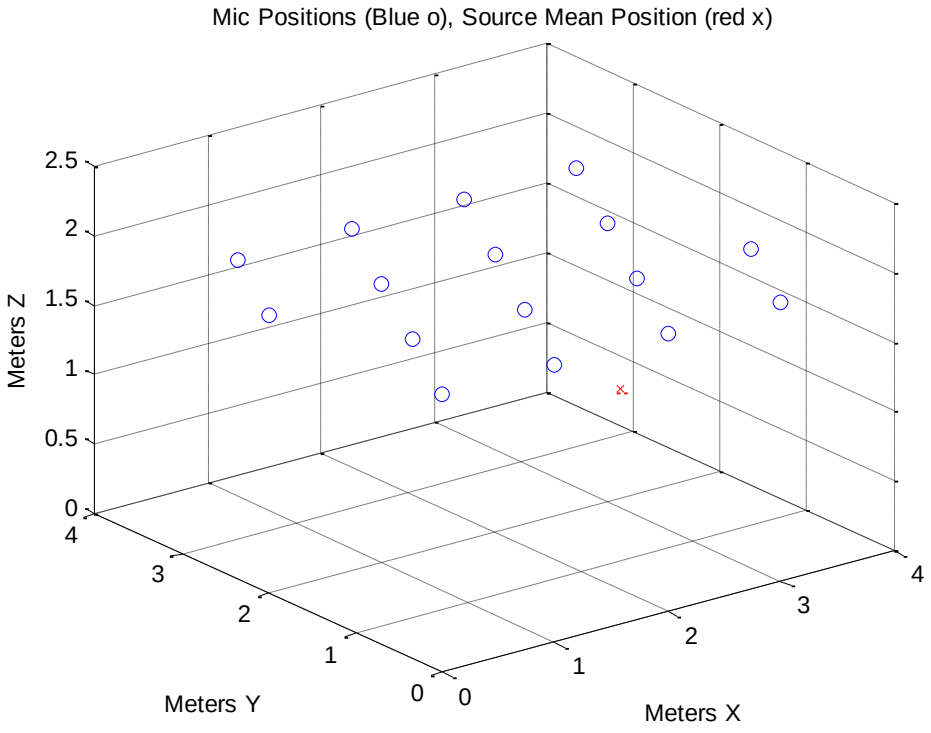


Figure 6.4: 3-D View of the microphone Locations and mean Speaker Location

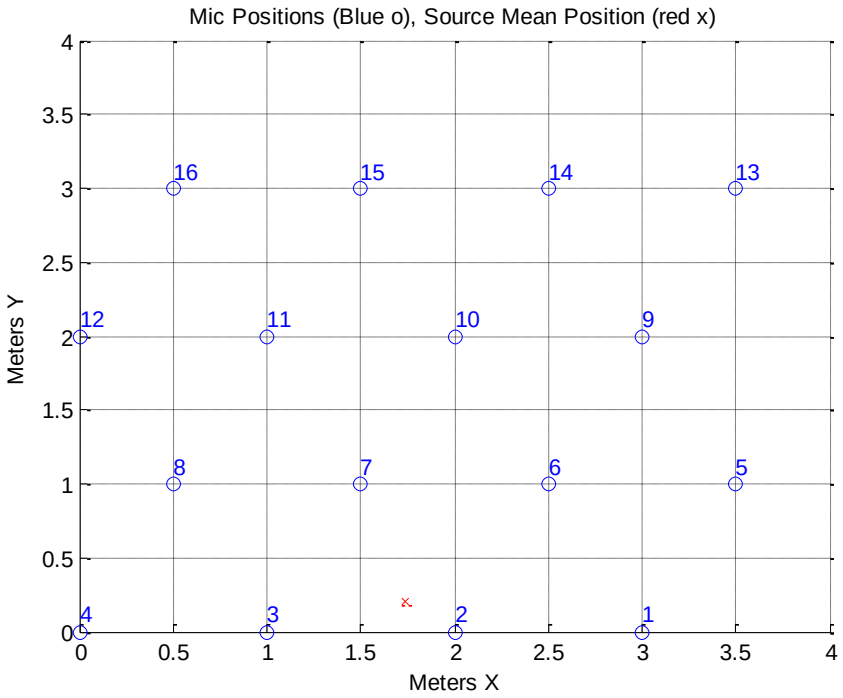


Figure 6.5: Labeled 16 Microphones and Speaker of Interest Mean Location Top view

Table 6.2: Speaker of Interest (SOI) Mean Coordinates in Meters

	SOI
X direction	1.741
Y direction	0.2101
Z direction	1.602

Table 6.3: Microphone Coordinates in meters

	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8
X direction	3	2	1	0	3.5	2.5	1.5	0.5
Y direction	0	0	0	0	1	1	1	1
Z direction	2	2	2	2	2	2	2	2
	M 9	M 10	M 11	M 12	M 13	M 14	M 15	M 16
X direction	3	2	1	0	3.5	2.5	1.5	0.5
Y direction	2	2	2	2	3	3	3	03
Z direction	2	2	2	2	2	2	2	2

6.2 Processing Procedures

After we read in the 16 channel source data and 16 channel party noise data, we adjusted the source and party noise volume with the desired SNR value and added them together as the cocktail party scene. Now we have 16-channel microphone recordings. We applied a high pass filter to the microphone recordings to remove room noise. We detected the closest microphone with respect to the speaker, in this case Microphone 2. We saved data from the closest microphone channel into a wave file. Hence we got data for the Closest Microphone (CM) algorithm. We beam-formed on the SOI and applied the adjusted coefficients to each channel yielding the data for the Weighted Beam Forming (WBF) algorithm. We then calculated distances from the speaker's mean location to all 16 microphones and converted these distances to samples and then aligned microphone recordings base on these samples. Now all microphone channels are aligned with respect to how quickly the SOI reaches each microphone at the same time instance. Then we applied FastICA with optimized parameters to the aligned microphone channels yielding the 16-channel data for the Channel Aligned FastICA algorithm (CAICA). Then we handpicked the channel with the clearest SOI from the 16-channel CAICA data, marked the channel number and saved it as SOI CAICA. We then input 16-channel CAICA to the Time-Frequency Masking. The marked channel is the SOI and other channels are interferences. Then we got the processed data and saved it as the data for the combined CAICATFM algorithm.

We compared processed sound clips for four algorithms: CM, WBF, CAICA, and combined CAICATFM. We validated the algorithm performance by directly listening and by observing the envelopes of the SOI signals from different algorithms. The extracted SOI results are shown in Figures 6.6 through 6.34.

Experiment 1: SNR =2 dB

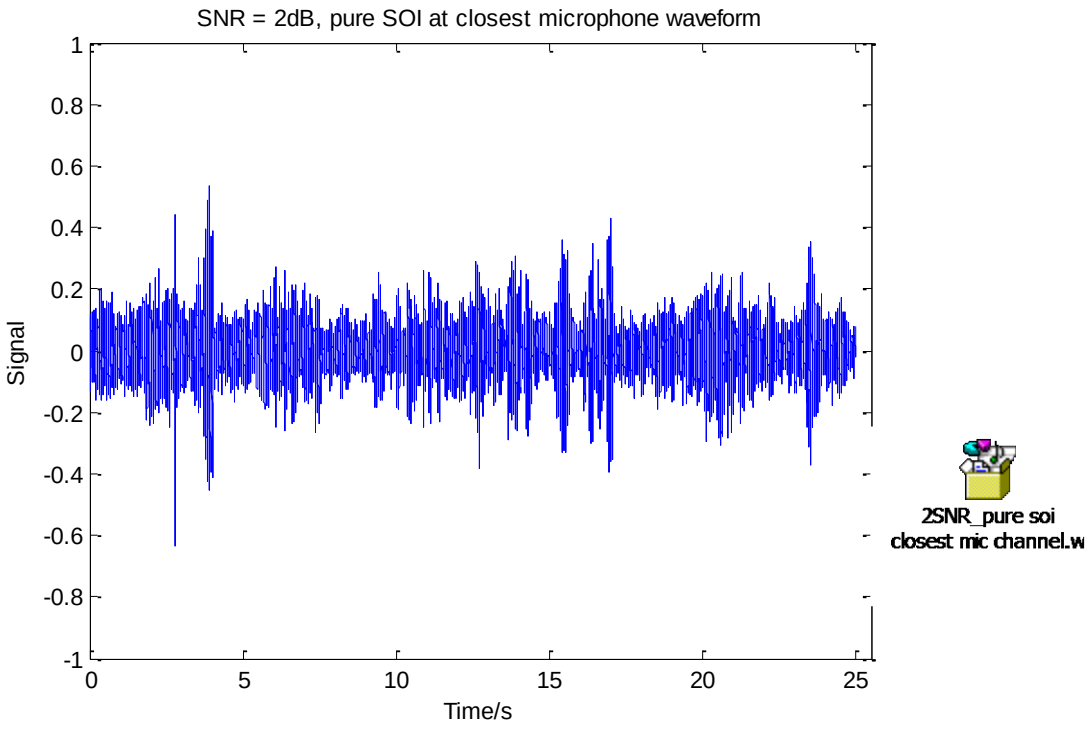


Figure 6.6: SNR=2 dB, pure SOI at closest microphone waveform

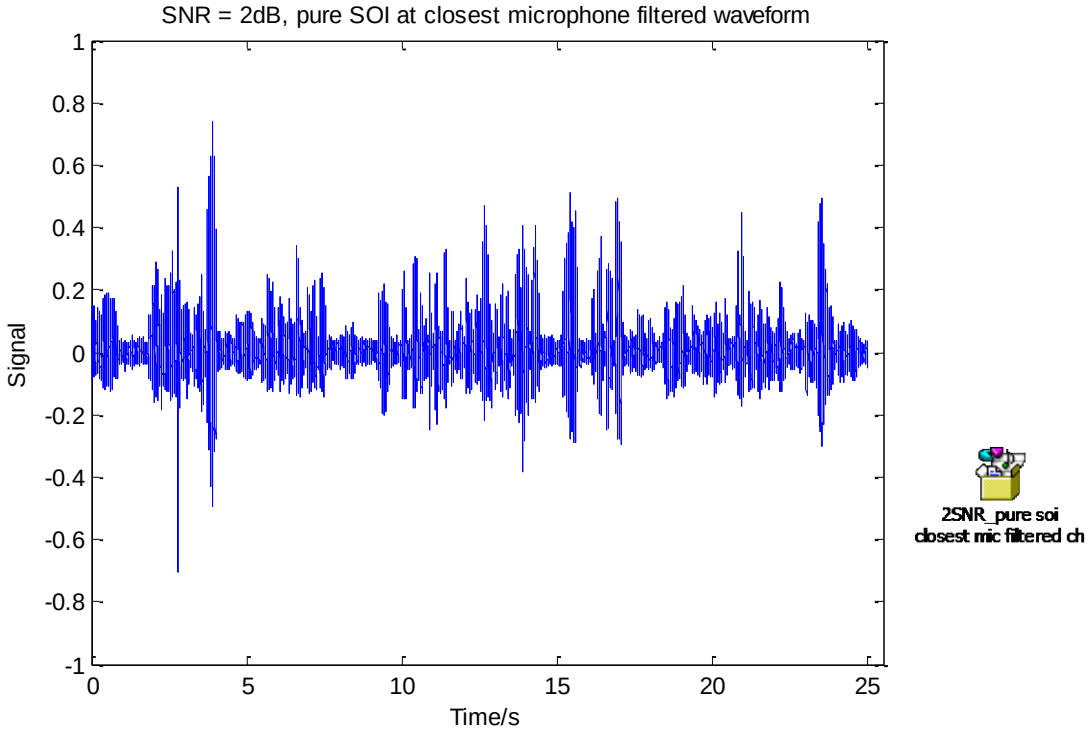


Figure 6.7: SNR=2 dB, pure SOI at closest microphone filtered waveform

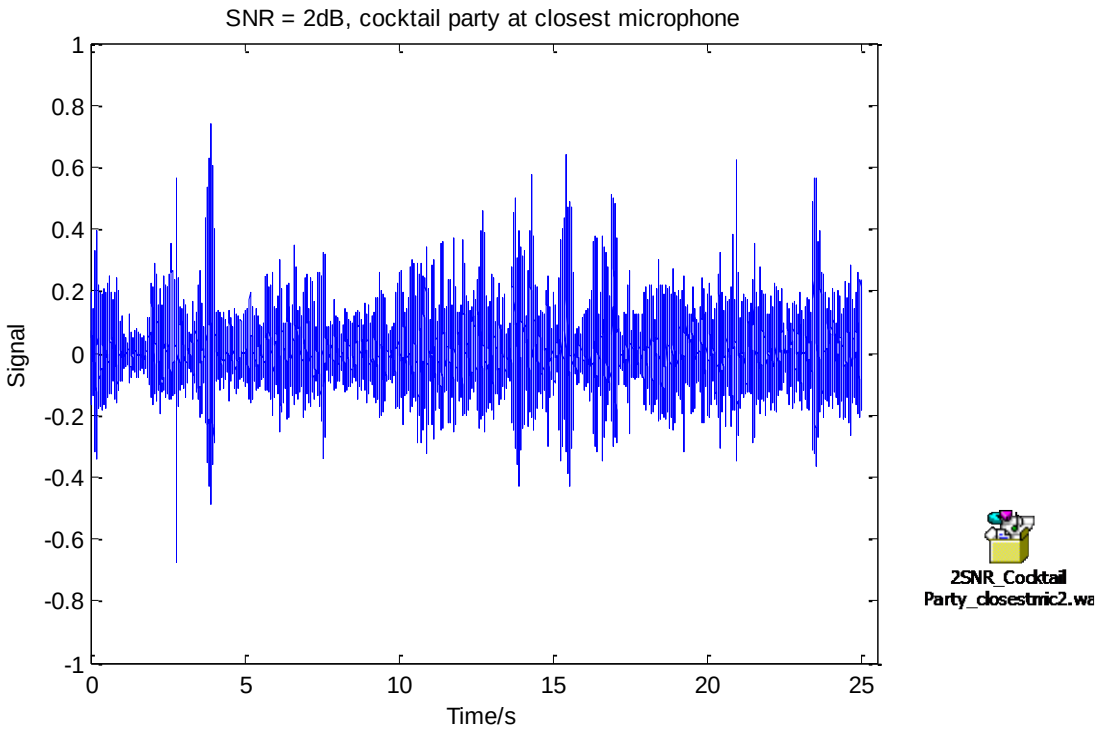


Figure 6.8: SNR=2 dB, cocktail party at closest microphone waveform

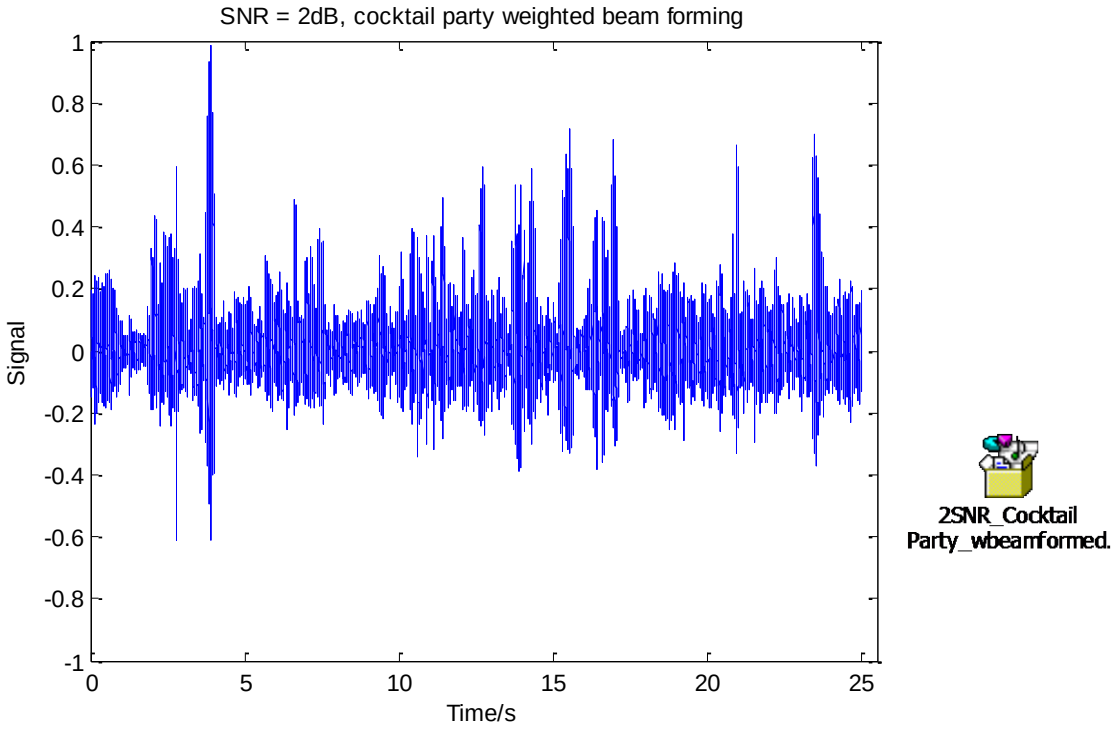


Figure 6.9: SNR=2 dB, cocktail party weighted beam forming waveform

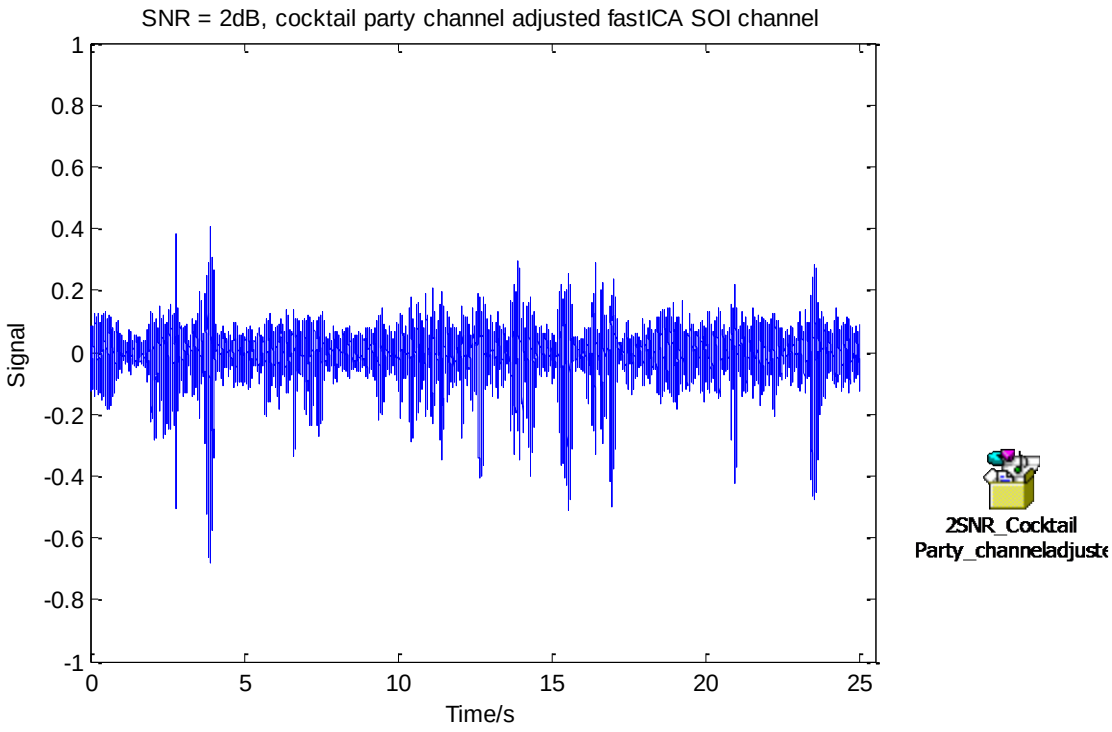


Figure 6.10: SNR=2 dB, cocktail party channel adjusted fastICA SOI channel waveform

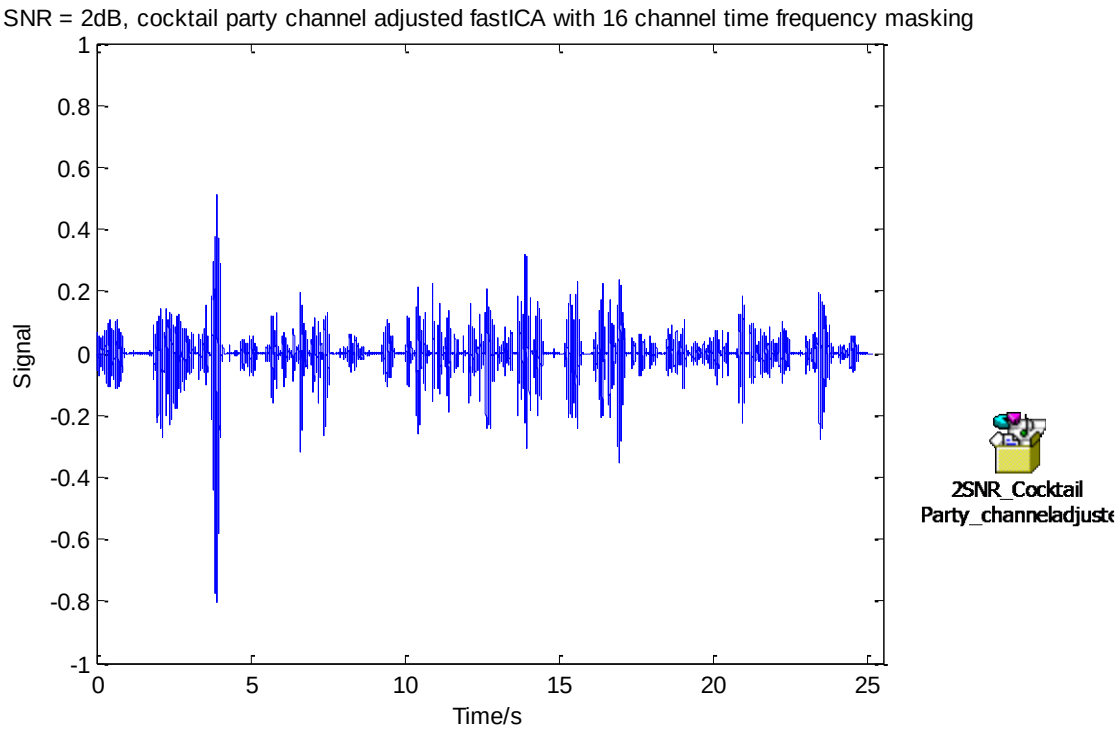


Figure 6.11: SNR = 2 dB, cocktail party channel adjusted fastICA with 16 channel TFM waveform

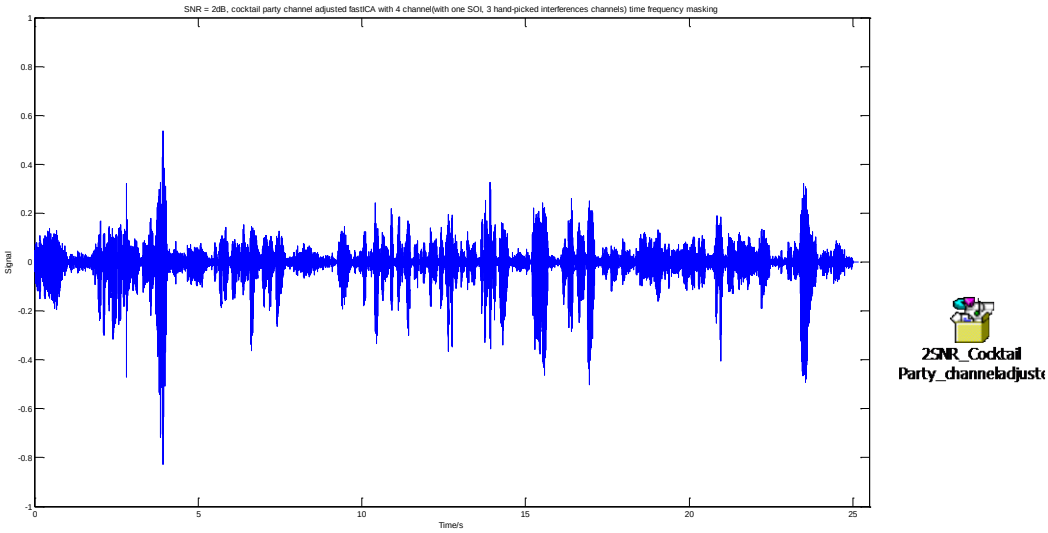


Figure 6.12: SNR = 2 dB, cocktail party channel adjusted fastICA with 4 channel (with one SOI, 3 hand-picked interferences channels) TFM waveform

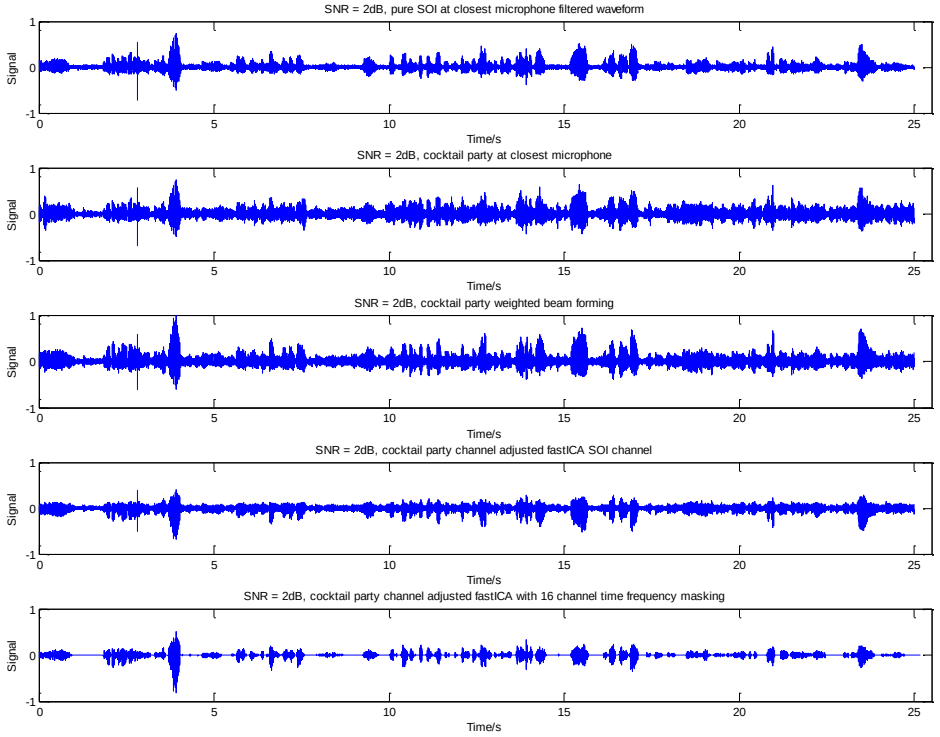


Figure 6.13: SNR = 2 dB, waveform comparisons

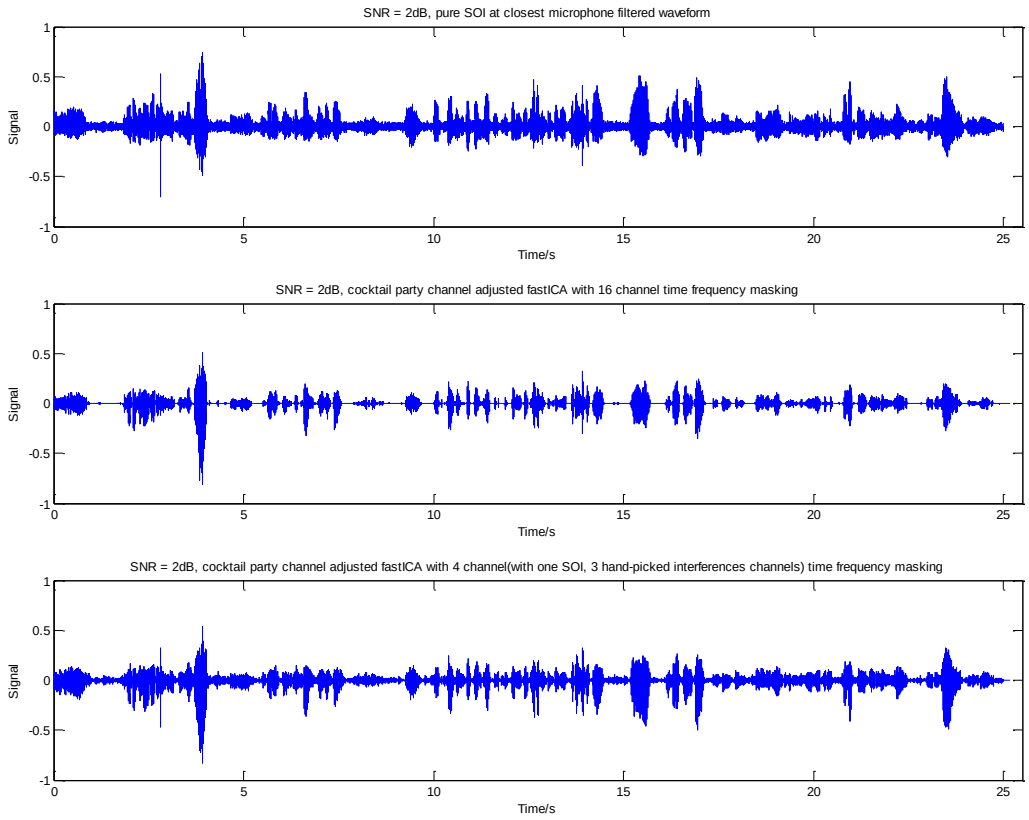


Figure 6.14: SNR = 2 dB, filtered pure SOI, channel adjusted fastICA with16-channel time frequency masking, channel adjusted fastICA with4-channel time frequency masking waveform comparisons

Experiment 2: SNR =0 dB

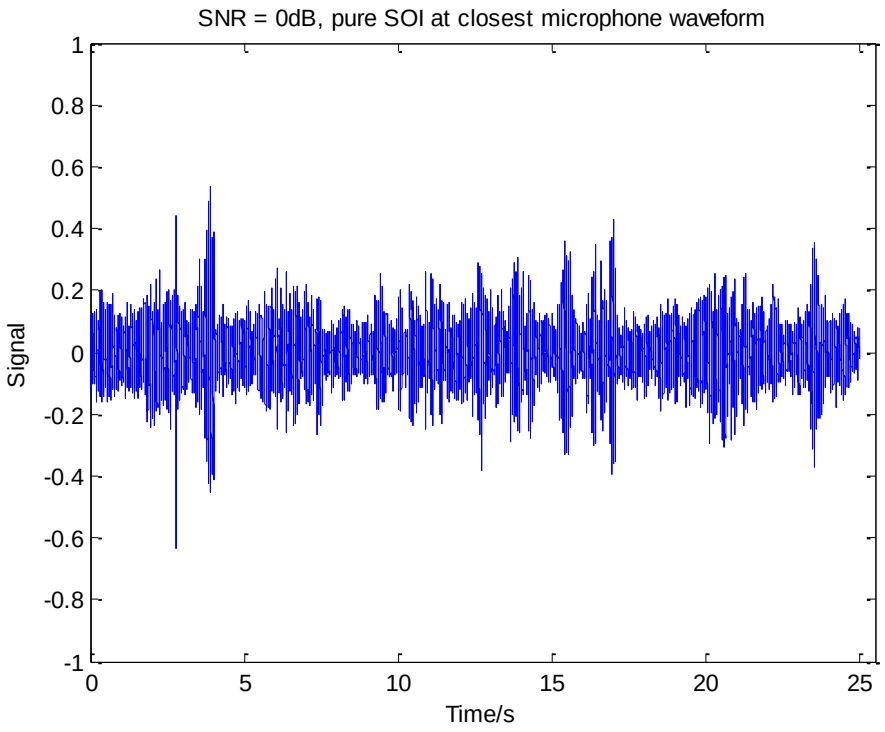


Figure 6.15: SNR=0 dB, pure SOI at closest microphone waveform

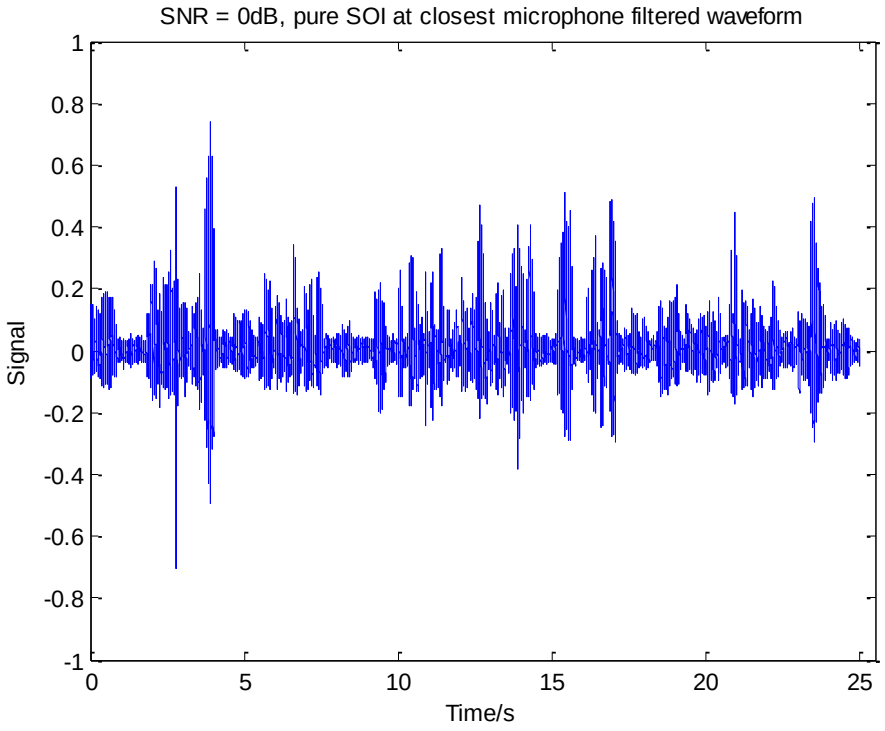


Figure 6.16: SNR=0 dB, pure SOI at closest microphone filtered waveform

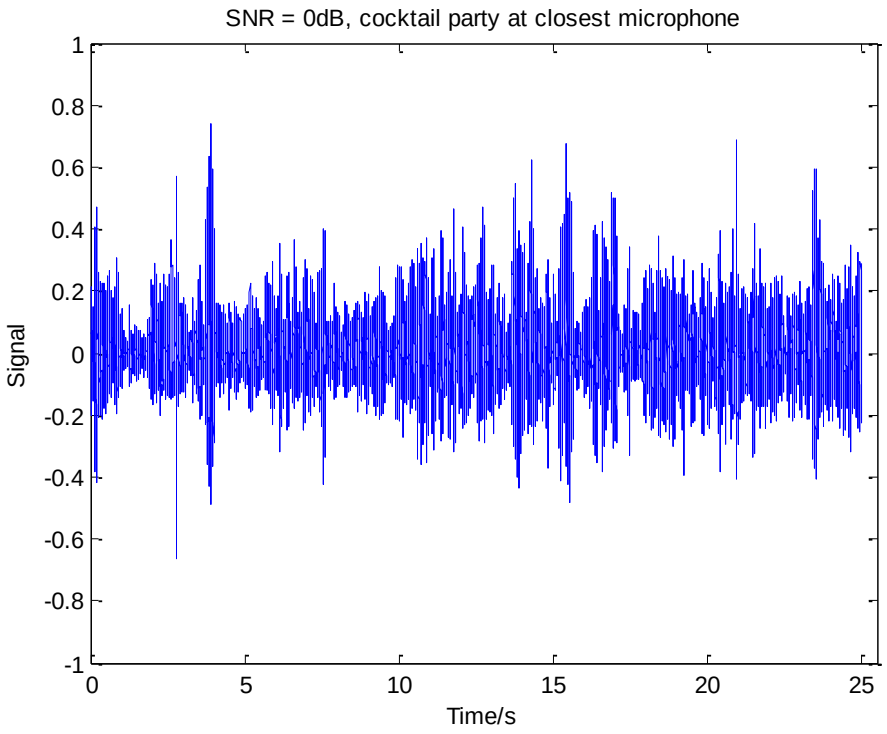


Figure 6.17: SNR=0 dB, cocktail party at closest microphone waveform

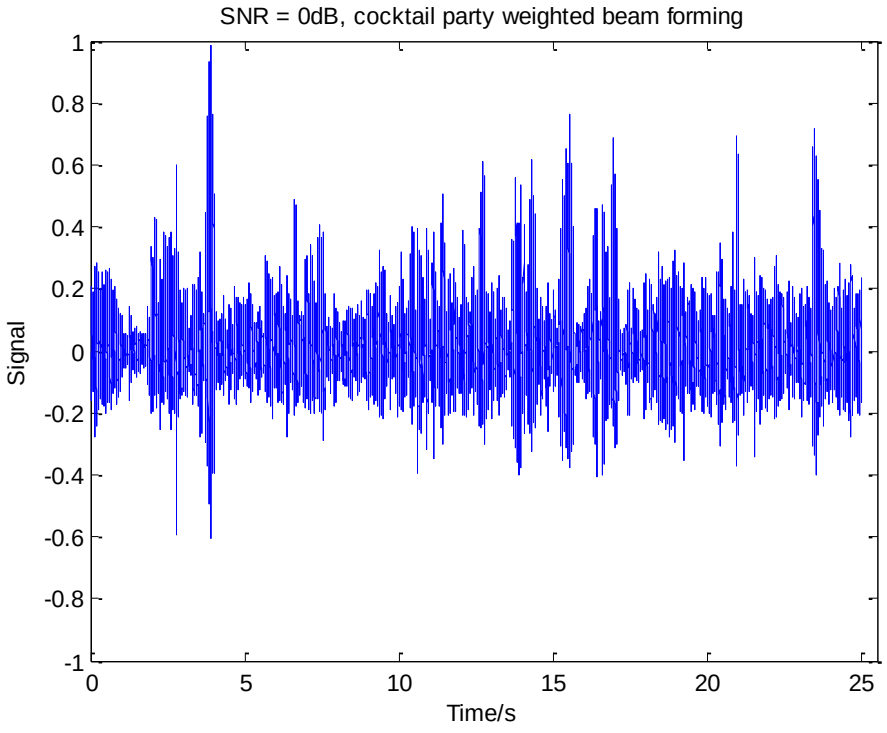


Figure 6.18: SNR=0 dB, cocktail party weighted beam forming waveform

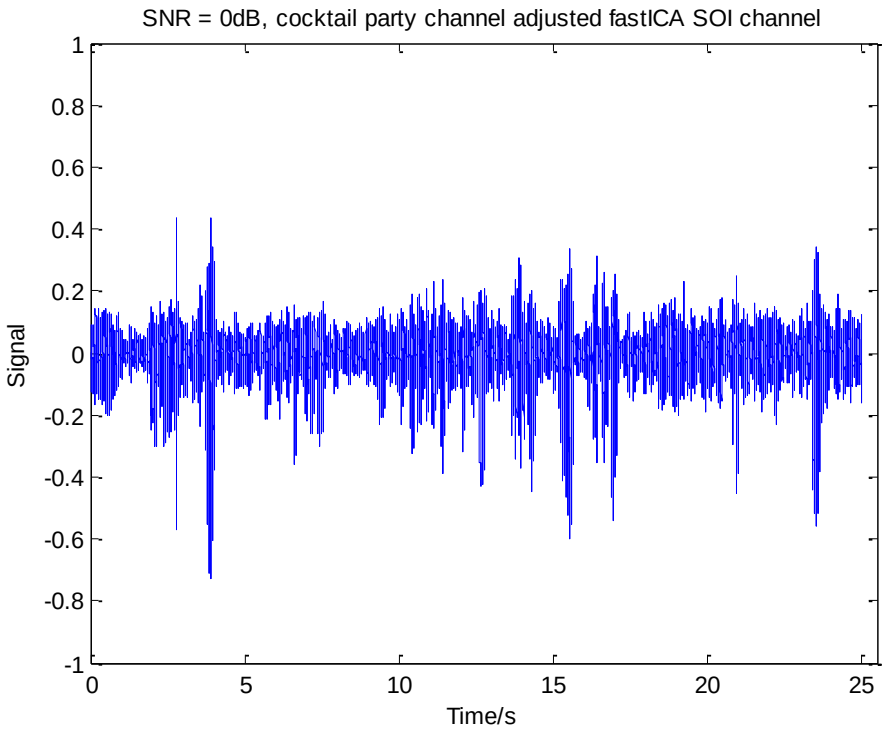


Figure 6.19: SNR=0 dB, cocktail party channel adjusted fastICA SOI channel waveform

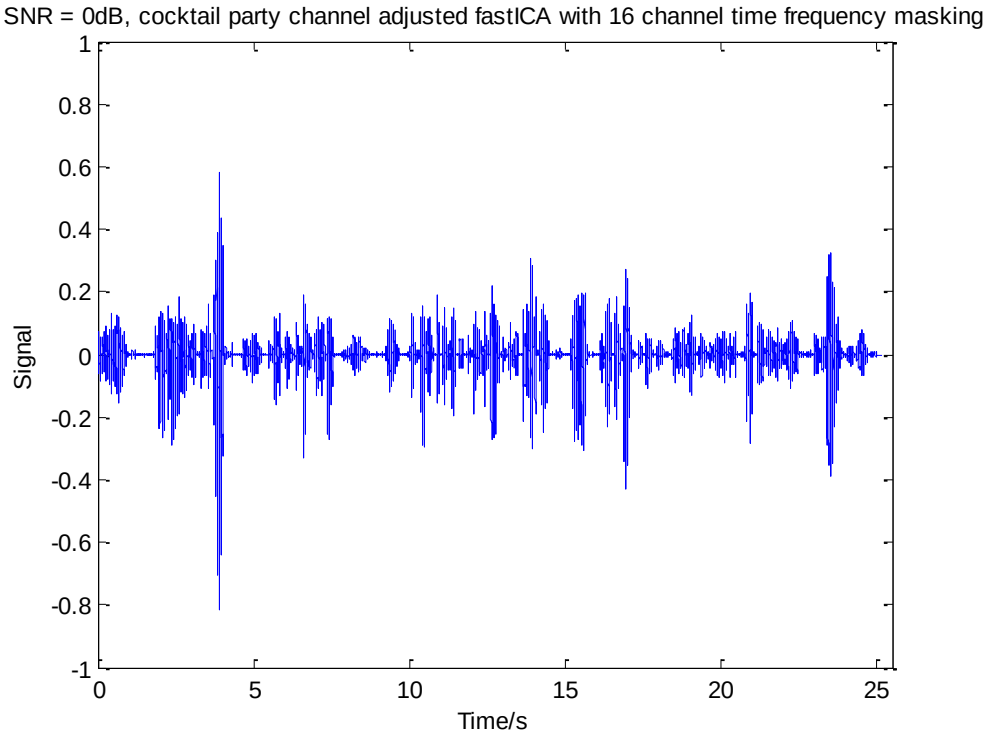


Figure 6.20: SNR = 0 dB, cocktail party channel adjusted fastICA with 16 channel time frequency masking waveform

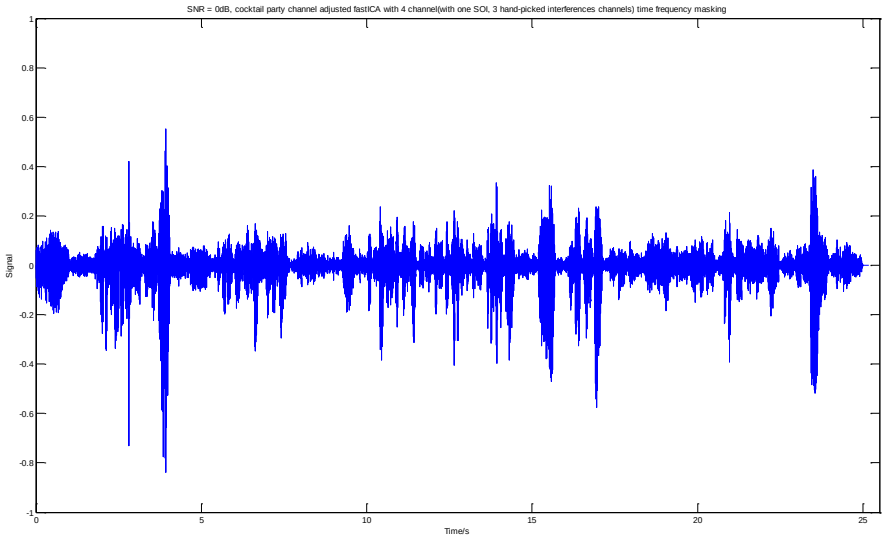


Figure 6.21: SNR = 0 dB, cocktail party channel adjusted fastICA with 4 channel (with one SOI, 3 hand-picked interferences channels) time frequency masking waveform

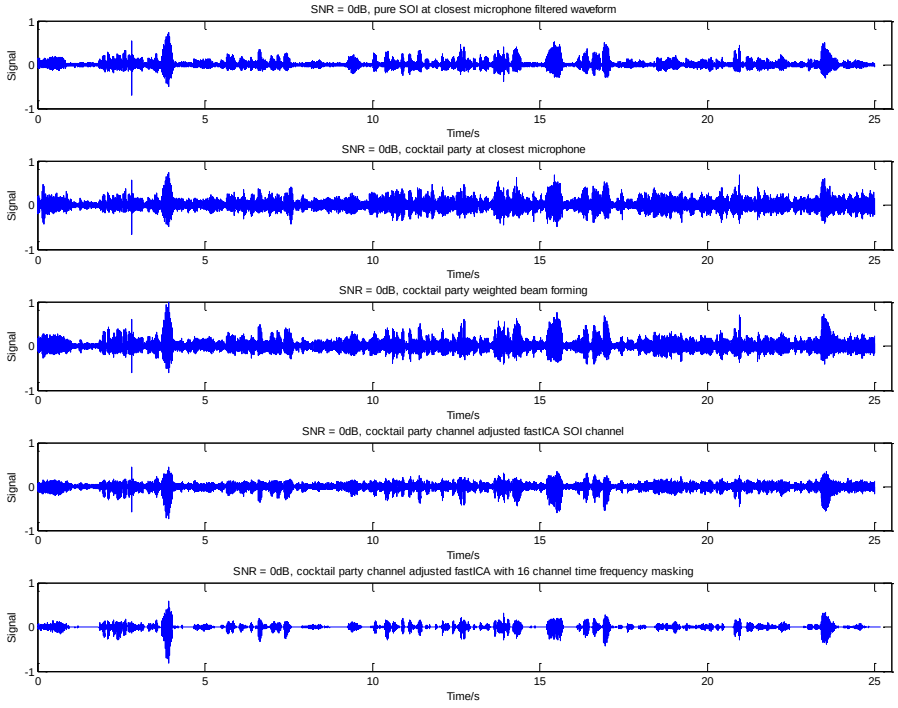


Figure 6.22: SNR = 0 dB, waveform comparisons

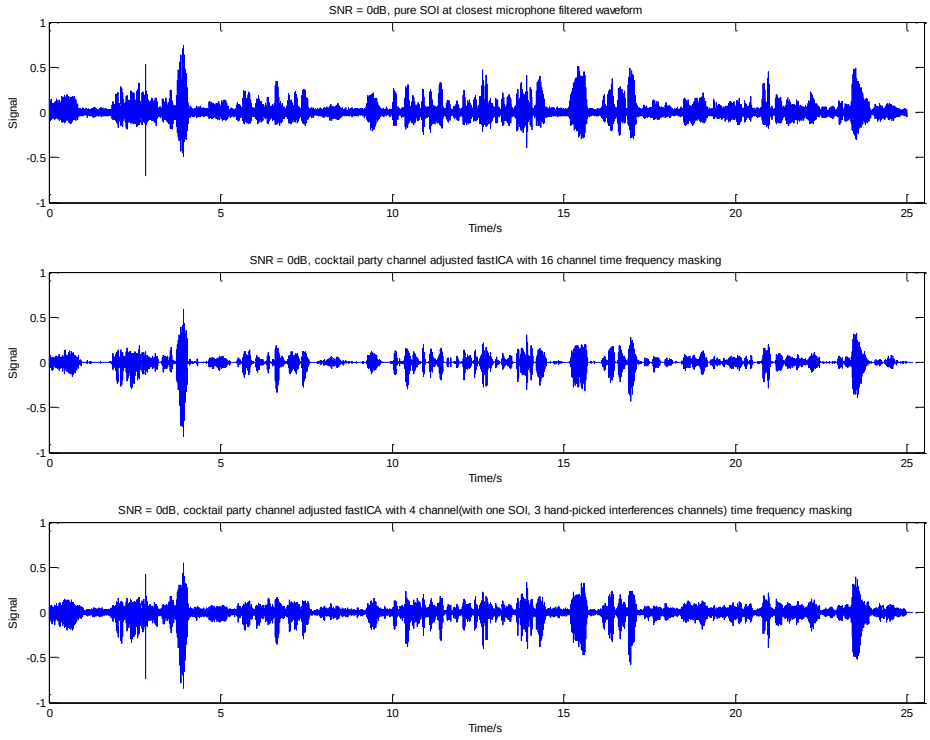


Figure 6.23: SNR = 0 dB, filtered pure SOI, channel adjusted fastICA with16 channel time frequency masking, channel adjusted fastICA with16 channel time frequency masking waveform comparisons

Experiment 3: SNR = -10 dB

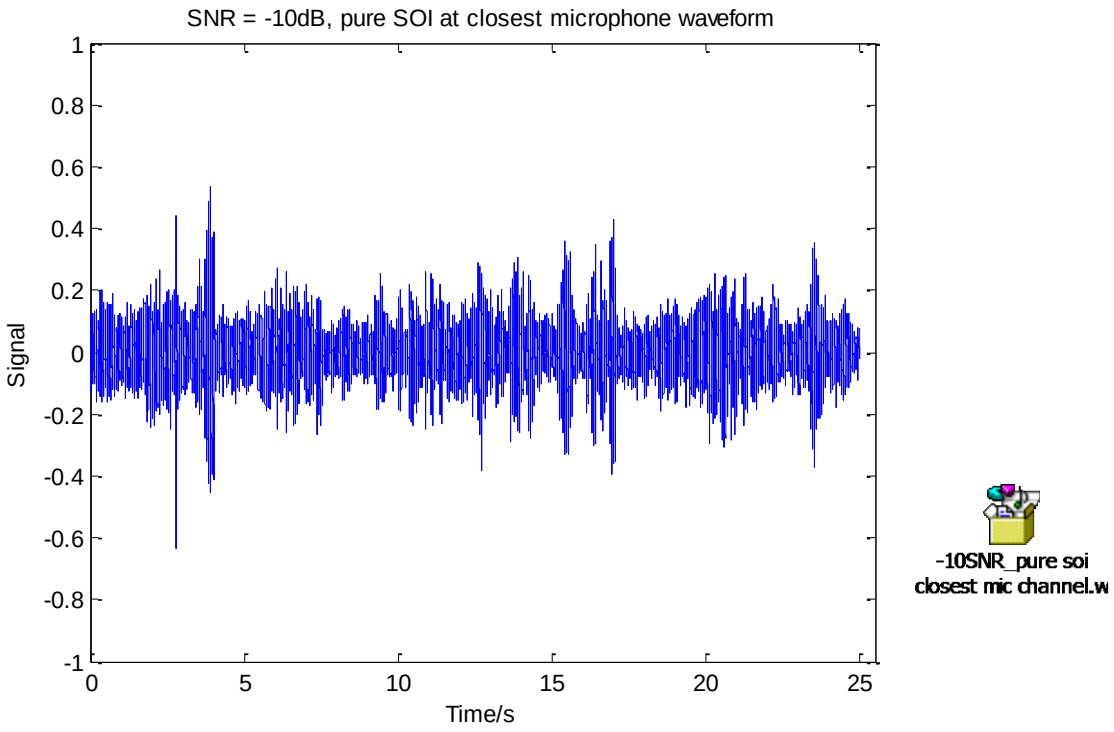


Figure 6.24: SNR=-10 dB, pure SOI at closest microphone waveform

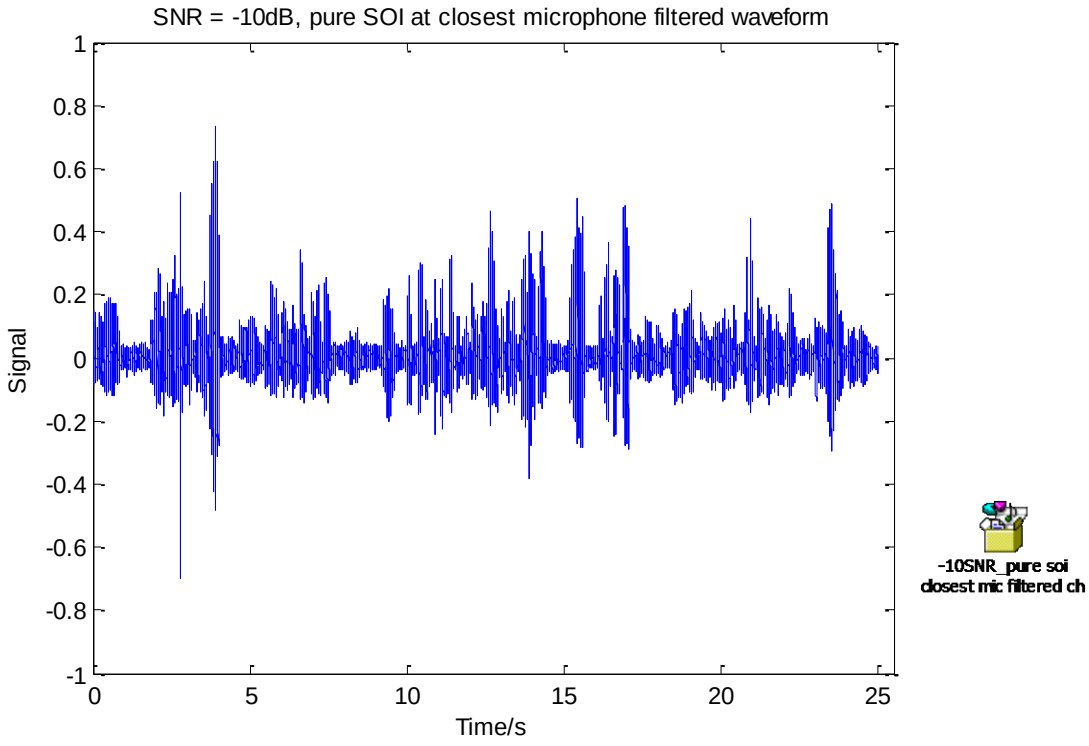


Figure 6.25: SNR=-10 dB, pure SOI at closest microphone filtered waveform

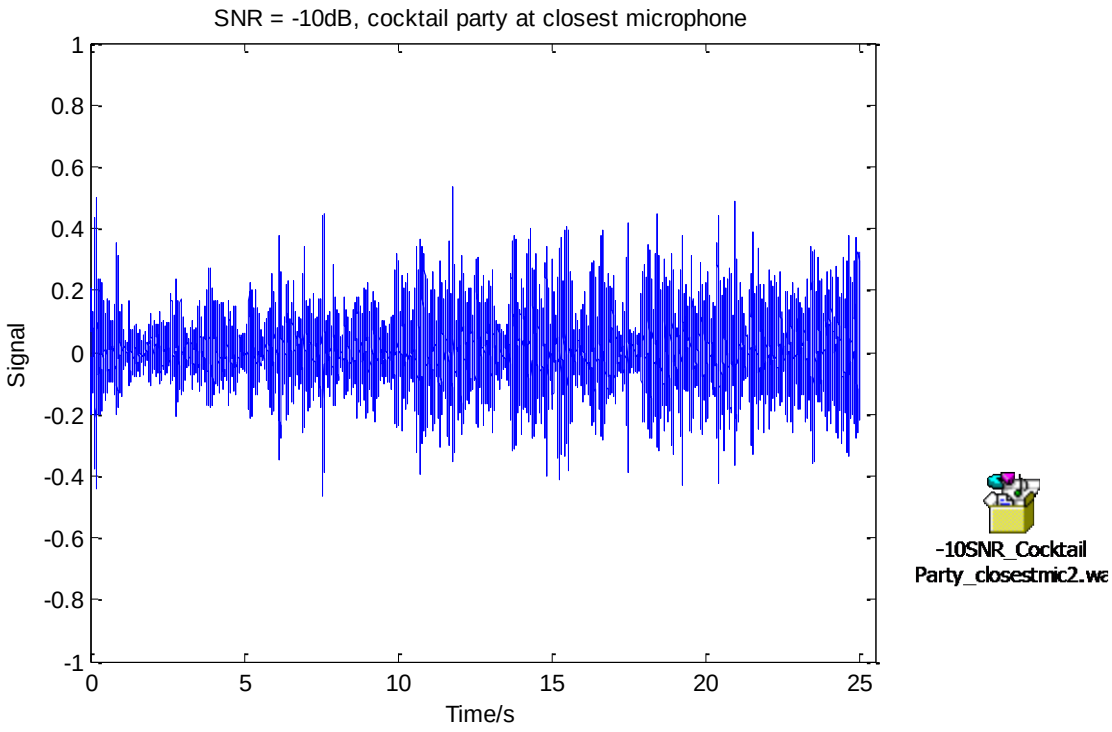


Figure 6.26: SNR=-10 dB, cocktail party at closest microphone waveform

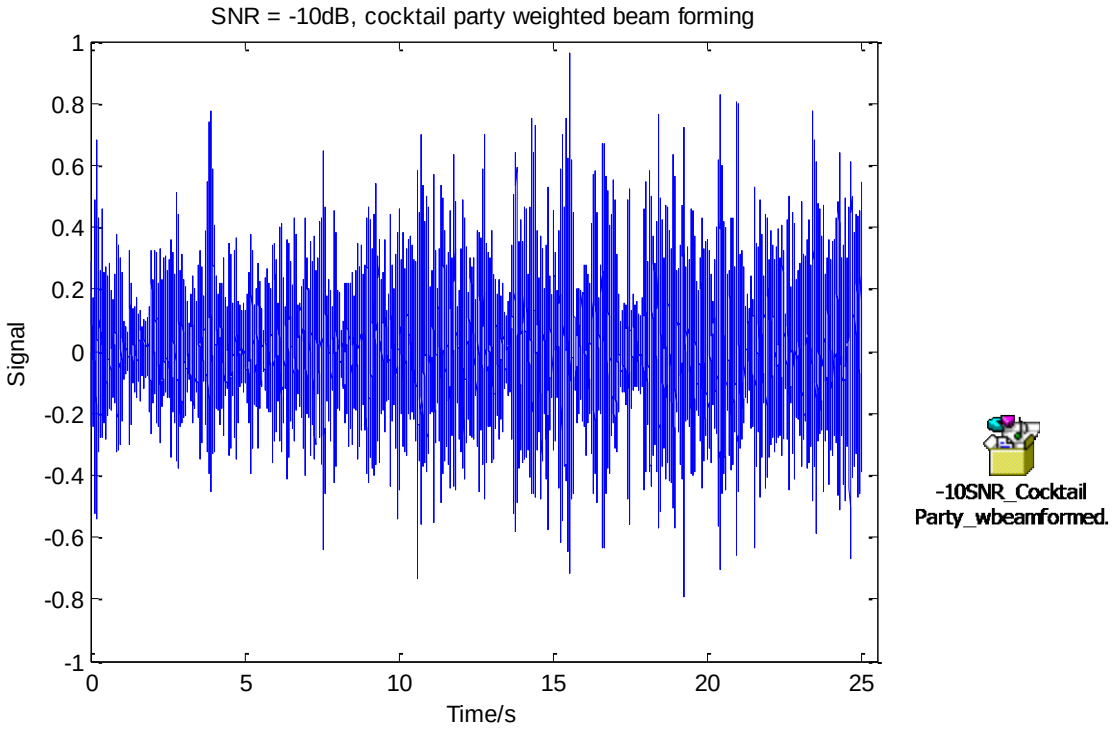


Figure 6.27: SNR=-10 dB, cocktail party weighted beam forming waveform

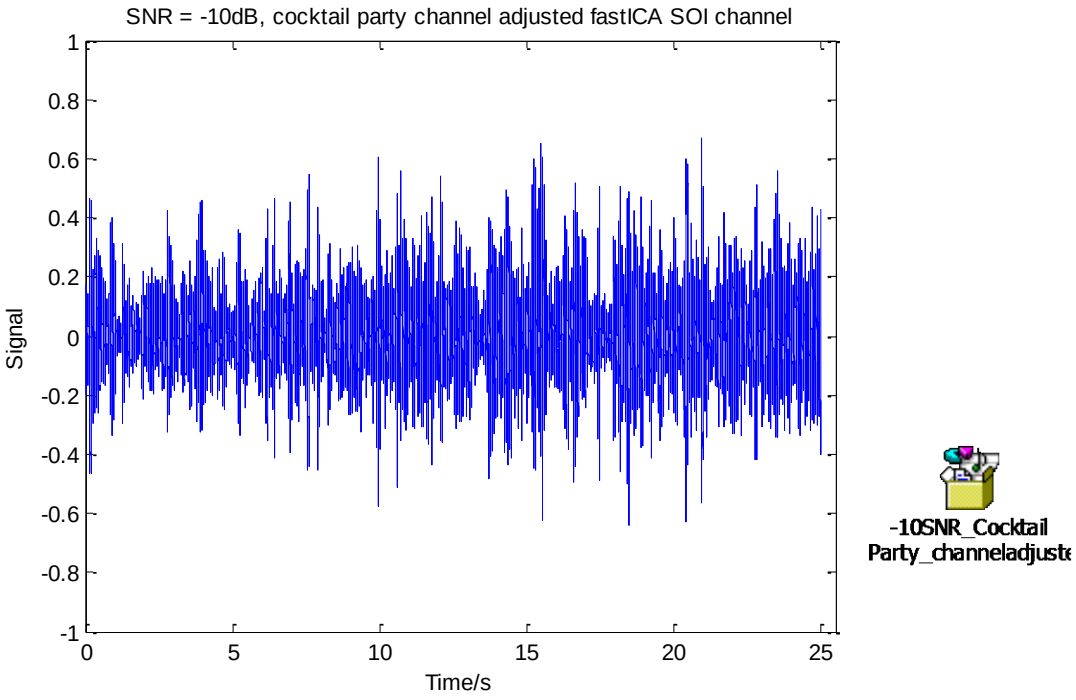


Figure 6.28: SNR=-10 dB, cocktail party channel adjusted fastICA SOI channel waveform

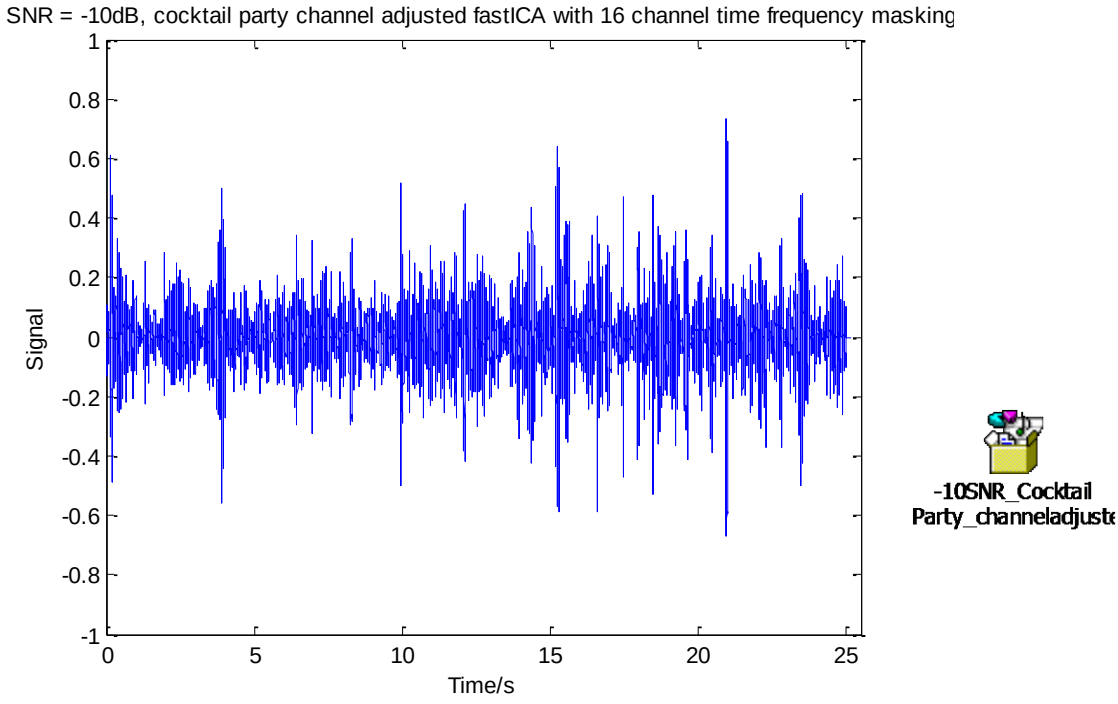


Figure 6.29: SNR = -10 dB, cocktail party channel adjusted fastICA with 16 channel time frequency masking waveform

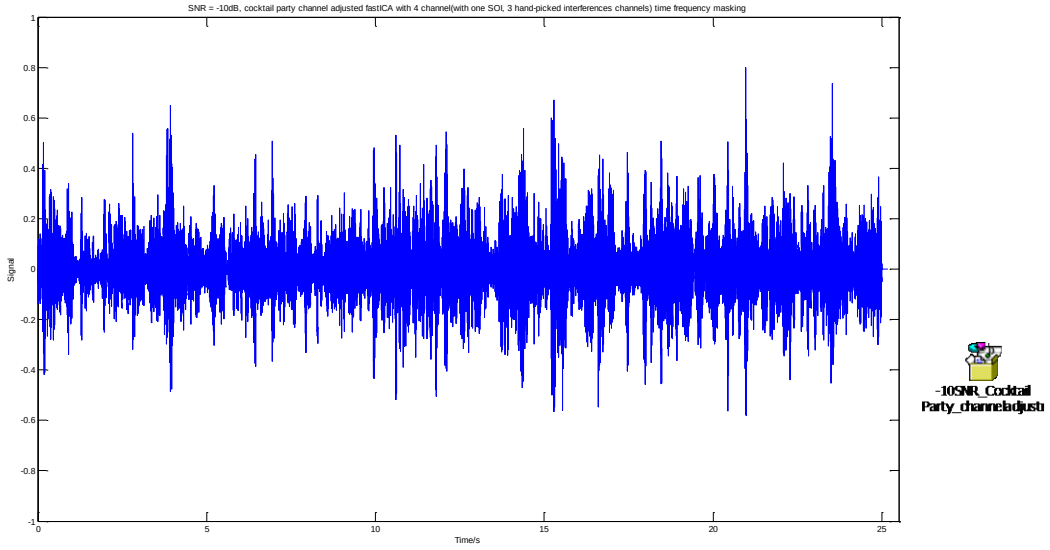


Figure 6.30: SNR = -10 dB, cocktail party channel adjusted fastICA with 4 channel (with one SOI, 3 hand-picked interferences channels) time frequency masking waveform

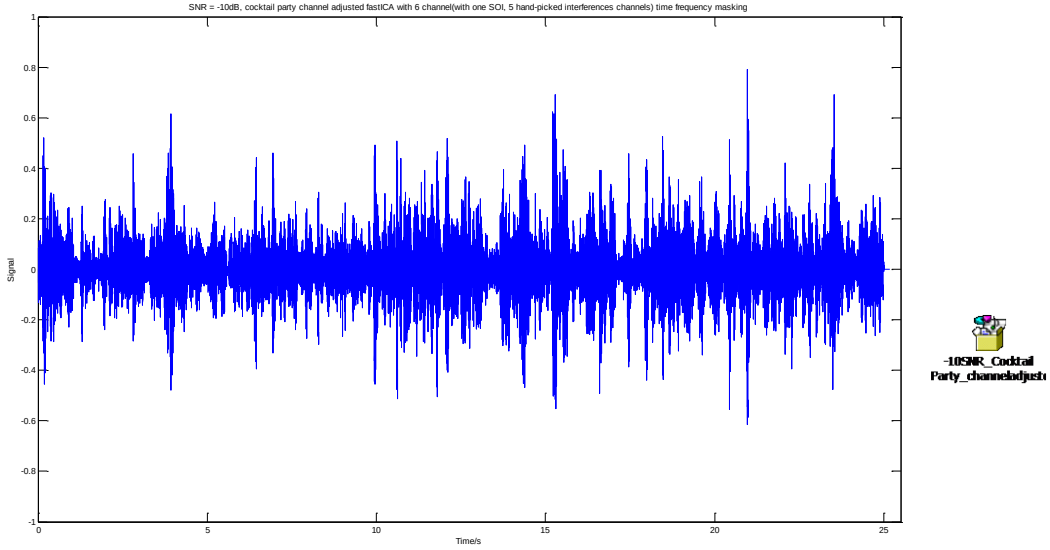


Figure 6.31: SNR = -10 dB, cocktail party channel adjusted fastICA with 6 channel (with one SOI, 5 hand-picked interferences channels) time frequency masking waveform

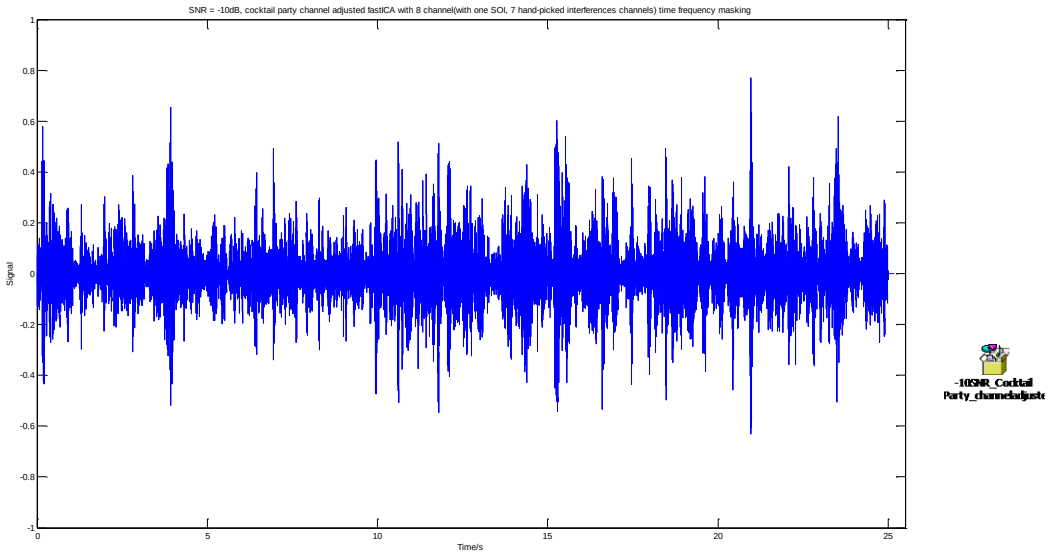


Figure 6.32: SNR = -10 dB, cocktail party channel adjusted fastICA with 8 channel (with one SOI, 7 hand-picked interferences channels) time frequency masking waveform

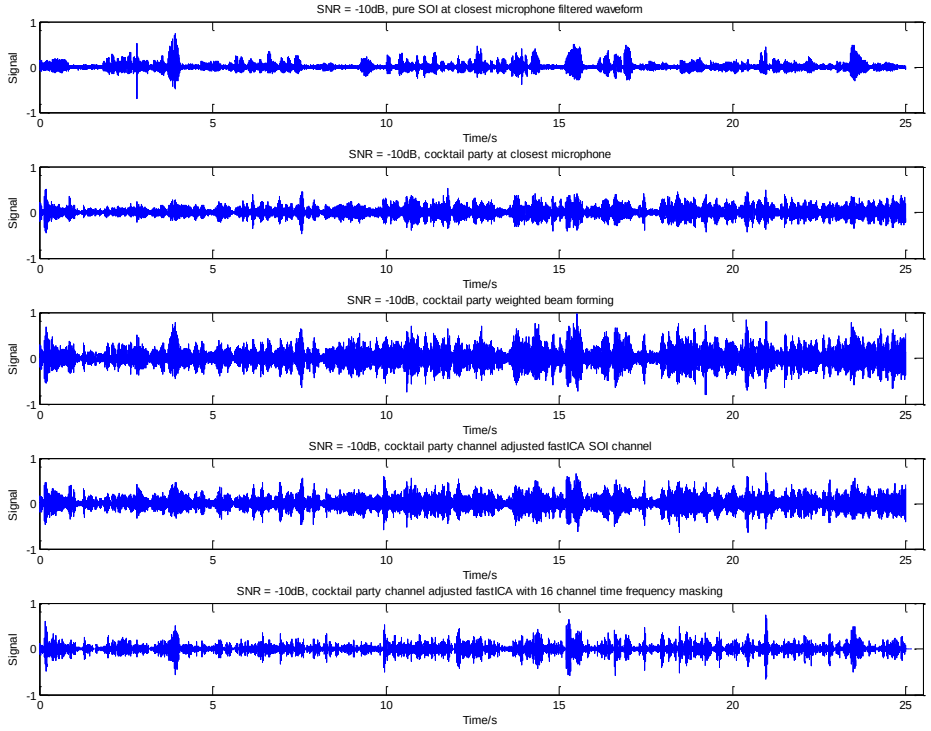


Figure 6.33: SNR = -10 dB, waveform comparisons

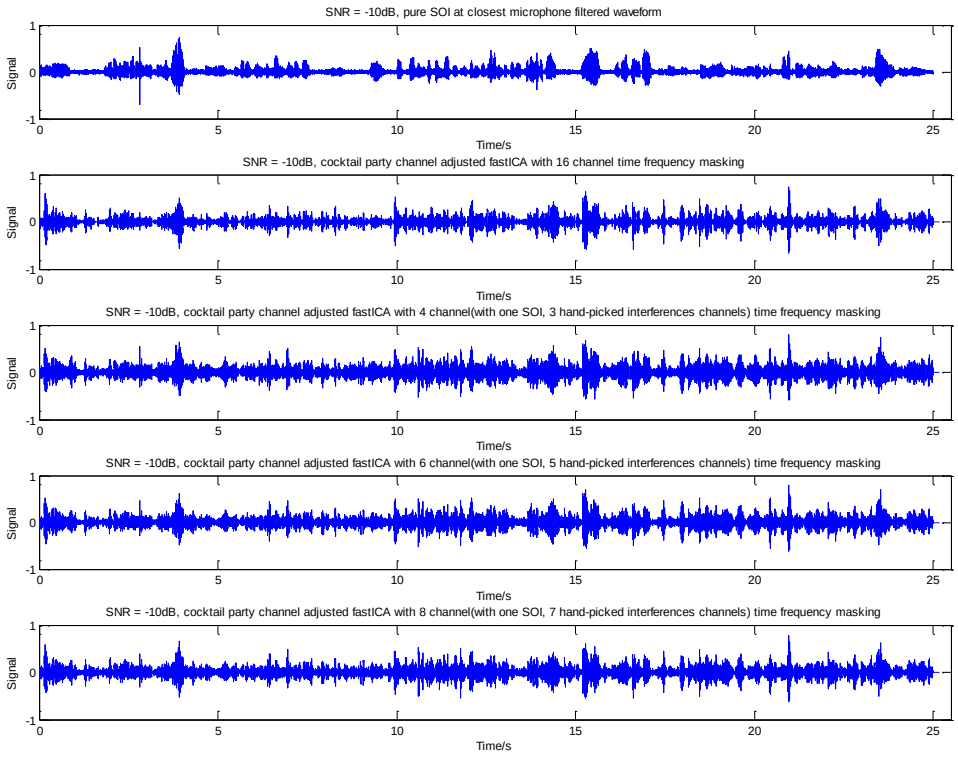


Figure 6.34: SNR = -10 dB, filtered pure SOI, channel adjusted fastICA with16-channel, 4-channel, 6-channel, 8-channel time frequency masking waveform comparisons

6.3 Results, Comments and Remarks

The pure SOI closest microphone filtered channel is passed through a high-pass filter to remove room noise. It differs very minutely from the pure SOI closest microphone channel by direct listening and it shows a cleaner envelope with important characteristics more prominent. This minute difference we heard is room noise. The pure SOI closest microphone filtered channel has lower noise in the sound clip than the pure SOI closest microphone channel, but either way the SOI is very clear. We heard interference from party noise meaning other people's speech in the cocktail party closest microphone sound clip. Party noise was also in the cocktail party weighted beamforming as well as the cocktail party channel adjusted fastICA SOI channel. But the party noise was weaker in WB and CAICA. In the meantime, SOI is most intelligible in CAICA with TFM, more

intelligible in WB and CAICA, and not very intelligible in the cocktail party closest microphone channel. I heard no interference, just the SOI, in the resulting CAICATFM.

When SNR values dropped, the SOI was buried in the party noise (6 other speakers' speech) in CM, WB, CAICA and started to immerge in 16-channel CAICATFM. CM degraded most. WB and CAICA degraded about the same, 16-channel CAICATFM only degrades slightly. Speech intelligibility is the degree that the listener can correctly understand the speech [23].

SOI was intelligible when SNR=2 dB in all cases, but CAICATFM was more intelligible than CAICA and WB and CM last. When SNR dropped, regarding the intelligibility, algorithms performed in the same order as mentioned above, but the CM became not very intelligible (a lot of noise in the sound clip and one could not tell what SOI is talking about very well), WB and CAICA were still pretty intelligible (noise was more prominent, but one can still tell what SOI is talking about if one listens closely). In the meantime, CAICA was still intelligible with very little noise interference.

For each SNR value, by observing the envelopes of the sound tracks and comparing them with the SOI in three different SNR experiments, as well as by directly listening, we find that CAICA and TFM combined algorithm performs the best, CAICA and WB perform about the same and perform second best, and closest microphone performs worst. Specifically, the CAICATFM combined algorithm performs better is in the sense of less interfering sound and prominent SOI content. This is consistent with the visual observations of the envelope of SOI of the algorithm in that it better follows the envelope of the filtered pure SOI.

When the SNR value is high, i.e. SNR=2 dB, the closest microphone has a fairly high SII, meaning the SOI is quite clear. When SNR is low, i.e. SNR =-10dB, we cannot very easily tell the SOI from the closest microphone recording anymore and then the advantages of the CAICA and combined CAICATFM, WB algorithm become more prominent.

Due to the fact that TFM uses AND operations to create binary masks to mask out interferences. We do not necessarily need to pass all 16 channels of CAICA to the TFM algorithm. When interferences have higher comparable volume, meaning when SNR is low, pass more channels to TFM results in less interference, but the extracted SOI breaks more. So the tradeoff is more significant when SNR is low. Based on the situation and desired sound effect we can adjust the total number of SOI and interference channels.

We also noticed clicking sounds in the sound track after the 16-channel TFM, and the clicking sound became more prominent when SNR values dropped in the processed 16-channel CAICA with TFM. This happens due to the AND operations in TFM process. When SNR is low, SOI is less dominant. In the time frequency domain, SOI is dominant in less time frequency units; that is to say, more time frequency units got masked out, creating the clicking sounds. For fixed low SNR values, after we passed less processed CAICA channels(SOI with some interferences and handpicked interferences channels) to the TFM, we observe the envelopes of estimated underlying sources in Figures 6.26 through 6.29. We saw that if less channels (i.e. 4,6,8 total channels,)are used, the resulting signal seems to contain more noise, that is, the shapes of signal envelopes differs from pure SOI more. When SNR is low, such as SNR =-10 dB, by directly listening to [file name], we hear when more channels are passed through TFM, i.e. 16 channels (1 SOI, 15 interferences). SOI stands out more and has less interferences, but the clicking sound effects are more severe. When less channels are passed through TFM, i.e. 4 channels (1 SOI, 3 handpicked interferences), the resulting signals have more interference, but the clicking sound effects are less severe. Hence there exists a trade-off between resulting sound qualities and SII for SOI. The results of passing 6/8 channels to TFM also validated the stated trade off. Experimental Recording results are consistent with simulation results and statistical analysis.

Chapter 7: Final Conclusions and Future Work

7.1 Conclusions

The goal of this thesis was to explore the Blind Source Separation in Immersive Audio Environments and specifically Independent Component Analysis in Cocktail Party Scenario. After researching and testing on feasibility of a variety of algorithms, FastICA toolbox stands out with regard to fast convergence, smooth separated audio sound tracks, does not need feature training and so on. It also works well in separating instantaneous mixtures, but it comes with limitations as do all algorithms. To estimate all the underlying sources, FastICA needs the system to be over-determined (mixture channels are greater and equal to source channels). The estimated underlying source channel is not fixed after each FastICA algorithm run. To cope with it, we can use auto-correlation to find the matching pairs.

When we applied the cocktail party recordings, FastICA toolbox failed to recover sources.Cocktail party recordings are always convolutive and real world recordings are convolutive as well.The Convolutive BSS algorithm theoretically should be powerful in source separation for real world recording, but the associated Convolutive BSS toolbox requires setting up many parameters and often has stability issues. And this toolbox improves minute source intelligence after we applied the toolbox to the simulated microphone mixtures.

Then we analyzed factors that make FastICA break in real world settings and after trial and error, we came up with the Channel Aligned FastICA (CAICA) that enhanced the FastICA source separation when mixtures are convolutive. In addition, we combined CAICA with TFM for an even better source separation and recovered source interligibility. Simulation experimental recording validation are conducted to compare existing and mature audio source separation Weighted Beam-forming (WB),CAICA and CAICA with TFM. These experiments as well as statistical analysis prove that CAICA with TFM works great in source separation as well as high intelligibility recovery and

this algorithm is very powerful. CAICA performs slightly better than WB, which is impressive. All three algorithms perform better than closest microphone (CM), meaning there are improvements in source separation.

7.2 Future Work

Potentially we can observe the silence period from each algorithm and compare the silent period with the source of interest to calculate the performance metric. We can also take down the masker scale level in the TFM so as to pass a few interference channels, but to achieve the desired TFM effects more interference channels are needed.

Design a graphic user interface (GUI) so as users can play with all the source separation method mentioned. In that way, users can get more involved in the underlying source separation process. Furthermore, we can break the whole process into layers, cocktail party simulation layer, filtering processing layer, and source separation layers. In the source separation layer, users can choose WB, CAICA, and CAICA with TFM and listen to each separation effect. All these layers can be wrapped up in one panel. Users can select, mix or match these three main parts for the desired effects. For example, users can import their data and then process their data through the filtering processing layer and source separation layer to listen to different algorithms' sound effects. Researchers can also use the layer they desire to conveniently test their algorithms.

A median filter or adaptive filters can potentially be added to smooth out the time domain audio signals obtained after TFM so as to reduce the clicking sounds for smoother sound quality. We can potentially fix the ConvBSS toolbox so it works with Audio signals. Explore the other mentioned algorithms and see how well each algorithm performs regarding source separation. Researchers can also explore what the separation performance will be like when combining a few of these separation algorithms. We can also develop an automated selected tool to select a more proper algorithm for the specific scenarios. Scenarios can be categorized to number of microphones, number of speakers, systems is over-determined or underdetermined, number of sources we would like to

extract from the signal mixtures, relative locations of microphones and/ or speakers, and how microphone / speakers are grouped.

Researchers can also explore how we can deploy these techniques modern electronic devices such as cellphones and tablets as well as explore how these techniques are applied to surveillance. Researchers can also see how we can download these algorithms to embedded systems such as Digital Signal Processors for commercial usages.

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