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DEVELOPING A SYSTEM FOR BLIND ACOUSTIC SOURCE LOCALIZATION AND SEPARATION

by

RAGHAVENDRA KULKARNI

THESIS

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

in partial fulfillment of the requirements

for the degree of

MASTER OF SCIENCE

2013

MAJOR: MECHANICAL ENGINEERING

Approved by:

_____

Advisor Date

DEDICATION

I dedicate my thesis research to my parents. Without their understanding, support and patience, this research would not have been possible.

ACKNOWLEDGMENTS

This thesis would not have been possible without the guidance and the help of several individuals who in one way or another contributed and extended their valuable assistance in the preparation and completion of this study. Thank you:

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Human or Animal ears are able to perceive the sound or the direction that a sound is coming from. The ears can recognize the direction of sound by the combination of different signals that are arriving at them. For instance, consider a situation in a cocktail party wherein the person is trying to make an attempt to focus on a single voice among difference conversations along with some music and background noise. The party effect explains about the focus that one has on a single person talking and ignoring the mixture of other conversations and background noise, which are of different frequencies. As mentioned above, human/animal ears have extraordinary ability that enables them to talk and catch a particular sound at the same time in a dissonance of different sounds.

Our ears have exceptional ability to catch any type of sound in a disturbed environment. For example, if we consider cocktail party, we pay attention to a single talker avoiding the unwanted sources surrounding us. If someone in the party room calls out our name, our ears immediately switch over to the direction of that sound and respond to it within no time. This is because it has been found that [1] the acoustic source, on which the human ears concentrate, is three times louder than the ambient noise. This phenomenon happens irrespective of number of sources surrounding us, making different sounds simultaneously. The ears can detect all the sounds of different frequencies. So, it can be stated that the ears act as a Band pass filter and it can concentrate on one particular sound of any desired frequency ignoring all other sounds. In general, the auditory system follows three steps in detecting sound:

1. It detects the sound above a certain threshold frequency or level.
2. It resolves the sound in to different frequencies bands.
3. Depending on above two points, it calculates the phase and direction of the sound.

After learning about all these capabilities of a human ear, there arises an eagerness to study about the phenomenon that our ear follows for sound separation.

Considering the case in a cocktail party, we can think of developing a technique to locate the sources of our choice in any kind of environment. This type of technique can be built using a number of microphones, data acquisition device and a laptop to see the results. This system can be used to locate and extract any particular sound from a mixture of different sounds which are being produced by several other sources simultaneously.

The location of the sources and separation has become an important field in recent years. With growing population and technology, one needs to cope up with the technology with day to day basis. There are many cases where the sound source localization and extraction of sound is used. For example, consider a case in a mob where police officers need to handle such a big crowd. There is every possibility of gunshots being fired from both the ends. The investigation then try to track the exact location from where that gunshots were fired. The exact location of the accident has to be known as to continue with the investigation. The extraction of the sound is also very important in many cases. Many industries nowadays are using this technique for quality control inspection on the shop floor by pin pointing the machineries that make more sound or are less efficient. The above technology is used to remove the back ground noise from the mixture of different sounds.

1.2 Problem definition

In the examples mentioned above regarding Cocktail party, Mob and Industrial applications, there is a need to detect the sound and extract a particular sound. But in all these cases, there is no prior knowledge of sources, the sounds or the characteristics of the surroundings. This method where the sound is extracted without any knowledge is known as Blind source separation [2, 3, 4, 5]. This is one of the challenging tasks in sound separation. As mentioned above, there is absolutely no knowledge about the surroundings or the sources. Every source might produce sound with different amplitude and each receiver or the microphones can get multiple multipaths from the sources. There might be reverberations, diffractions or sound reflections that might change the entire situation. The sound might get reflected from a chair, table, wall etc.

In this thesis a new technology is developed that will enable us to capture the exact location of multiple sources irrespective of any surroundings. We use a technology called Short-time source localization and separation to locate the exact locations of the sources and extract the target acoustic signals from the mixed signals that are measured directly.

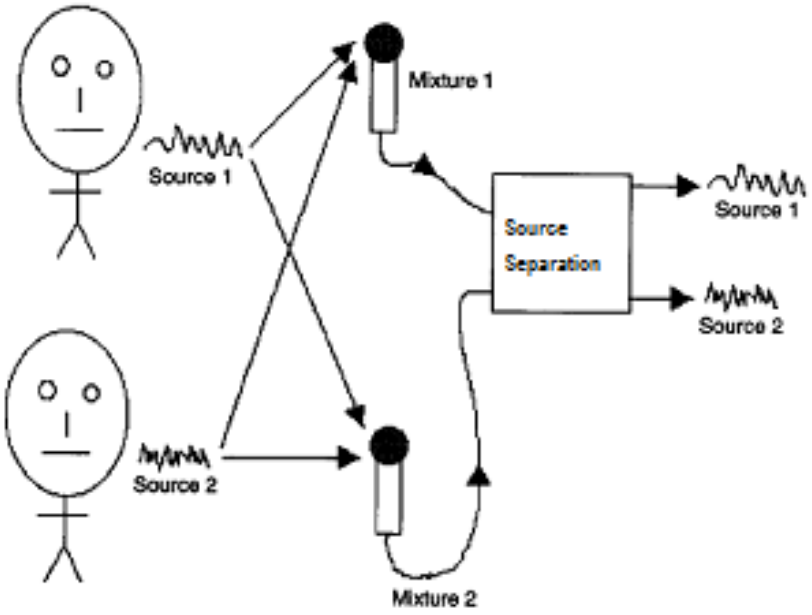


Figure 1.1: Simplest mixing model

Consider a simplest case shown in Figure 1.1. It shows two sources and two receivers. The signals from both sources are captured by receivers. Now both the receivers have mixture of two signals from two sources. Then the Blind source separation is used to separate both the signals from the mixture.

1.3 Goals and objectives of the thesis

The review explained in Section 1.2 indicates that new technology has to be developed and implemented in order to address the issues regarding source locations and separation. We should be in a position to arbitrarily locate any sources and extract the desired signal from the measured signal. This research addresses the above problems by developing a new technique to locate sound sources in real time and to separate the target signals from any mixed data.

1.4 Thesis Organization

The thesis is organized as follows. In chapter 2, we discuss various techniques used for source localization such the theory of Triangulation, Beam-forming and Time-reversal. Cross-Correlation, Auto-Correlation functions are also discussed.

In chapter 3, the mathematical formulation to link Auto and Cross correlation are mentioned which are used to find the accurate source localization. The multipath functions between the source and the receiver are presented in some detail.

In chapter 4, separation of target sound from directly measured mixed signals is discussed. A new technology known as Short-time source localization and separation is discussed along with various concerned parameters such as Fourier transform, Short time Fourier transform and Window function.

In chapter 5, the experimental validations are carried out in Acoustics, Vibrations and Noise Control (AVNC) lab, Wayne State University. The source localization is carried out using Auto Correlation and Cross Correlation functions. Error analysis is performed by comparing the localization results with the benchmark values obtained from 3-D digitizer. We then carry out the process for separation of signals using SLAS technique and three different cases are presented along with their time-domain and Spectrogram graphs.

In chapter 6, we draw conclusions and discuss the significance of the results obtained and finally in chapter 7, future work that could be carried out in this field is discussed.

CHAPTER 2

LITERATURE REVIEW

The algorithms used for source localization used multiple receivers that are microphones in this thesis. They are used to detect the signal emitted by different sources.

In this thesis, a different approach for source separation is developed, which enables one to separate mixtures of any type of frequency domain signals. Experimental validations of the proposed source localization method, source separation are conducted in the Acoustics, Vibration, and Noise Control (AVNC) laboratory.

2.1 Sound sources localization

There are currently three methodologies developed for the sound source localization problem, namely, triangulation [6, 7, 8], beamforming [9, 10, 11], and time reversal [12, 13, 14] algorithms. These methodologies are reviewed below.

2.1 (a) Triangulation

Triangulation is commonly used for source localization and most triangulation applications are based on intersection of the bearing direction to locate a source on a two-dimensional plane. It works on an assumption that the sound wave travels between two points in a straight line. For any impulsive sound source, this method works best in Time difference of arrival (TDOA) estimation. As the sound wave travels in straight path in an impulse sound, we get single sharp peak in the cross correlation function. But in case of arbitrary waveforms, where you have multiple sound reflection and diffraction, this method can’t be used as the number of peaks in the cross correlation function is more than one. There is no possible way to know which peak to be used for TDOA estimation unless we use Auto- Correlation functions. The number of

sensors needed in this method is typically small compared to other methods.

2.1 (b) Beamforming

Beamforming is a method which assumes that the sound source is at a far distance so that incident wave front is planar. Beamforming employs delay and sum algorithms to specify the direction of an incident sound wave travelling in space. This can be explained with an example of two dimensional array of microphones mounted at a fixed position. The incident sound wave at an angle impinges on the microphone array. This angle of incidence will produce different times of arrival (TOA). The signals in all channels are delayed until they are all in phase. These signals are then summed up to form a peak which gives the source location. The drawback using this method is that range of a target cannot be determined and also the microphones array has to be inclined towards the source which needs to be located which is not feasible in all the cases.

2.1 (c) Time reversal

Compared to the above methods, time reversal (TR) method is relatively simple. It employs a different approach which is playing back the time reversed signals which are emitted from the same point and then summing them up in space which will lead to the exact source location. The method is relatively simple and has good applications in the field of underwater acoustics and reverberant conditions. This method is used whenever the Signal to Noise ratio is low.

The main disadvantage of TR is that numerical computations are much more time consuming than the other two methodologies. This is because TR needs to scan every point in space to find the source.

2.2 Cross-correlation

The time delay of a signal between two microphones is the difference between the times of arrival of the signal at the two microphones. We studied the geometry of the problem by assuming that we know the time delay of the source between any pair of microphones. Cross correlation [15, 16, 17, 18] is a routine signal processing technique that can be applied to find such time delays by using the two copies of a signal registered at a pair of microphones as inputs. A cross correlation routine outputs set of cross correlation coefficients, which correspond to different time delays. These coefficients are sum of products of corresponding portions of the signals, as one signal slides on top of another one. Each cross correlation coefficient corresponds to a particular possible time delay of a signal between the two microphones. The maximum cross correlation coefficient indicates the portions of the signals with the maximum correlation. Therefore, the maximum coefficient can be used to deduce the time delay between the two copies of the same signal recorded by a pair of microphones. Accurate computation of delay is the basis for final source location with high accuracy. In the first step, time delay of arrival is estimated for each pair of microphones.

Assume time domain signals $x(t)$ and $y(t)$ are observed at two measurement positions. The cross correlation of these two signals $R_{xy}(t)$ can be expressed as:

$$R_{xy}(t) = x(t) \otimes y(t) = \int_{-\infty}^{\infty} x^*(\tau) \cdot y(t+\tau) d\tau \tag{2.1}$$

where the symbol " $*$" indicate the complex conjugate.

Consider a case in an anechoic chamber with two micro-phones capturing the time domain signals from two different micro-phones kept at a distance of 1m from each other. Figure: 2.1 shows the cross-correlation between two microphones that captured the time domain

signals.

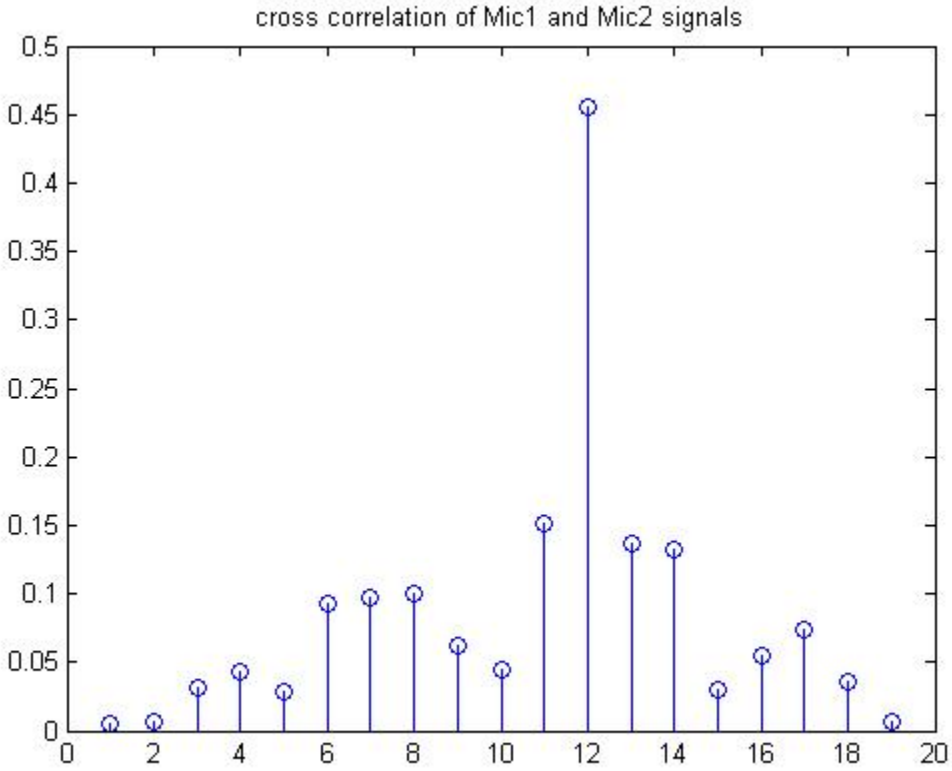


Figure: 2.1 Cross- correlations between two channels in an Anechoic Chamber.

In practice, the environment is non-ideal and inferring background noise can strongly affect the cross correlation results, therefore fluctuation or random peaks may happen in the cross correlation graphs. The cross correlation method is applicable to most of the sound types, including transient, continuous, broadband, and narrowband sounds. However, it cannot be used in the cases of a single frequency and its multiple frequencies, because the peaks in cross correlation results for these cases are neither significant nor reliable.

Now consider the above case in different environment where there are lots of reflections and two microphones separated by 1m are capturing the time domain signals from a stationary

source. The plot below shows the cross correlation between the two microphones.

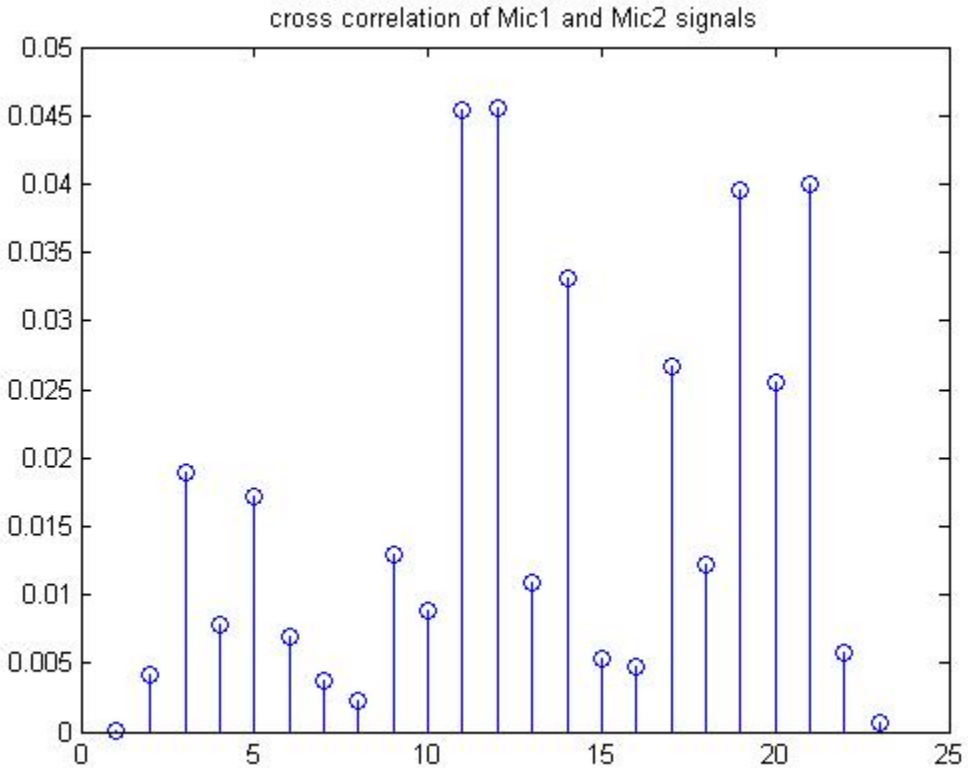


Figure: 2.2 Cross- correlations between two channels outside an Anechoic Chamber.

In Figure: 2.2 it can be seen clearly that the cross correlation peak or the Time difference of arrival (TDOA) [19] which is the important parameter for sound source localization cannot be determined accurately. There is every possibility of choosing the wrong peak in calculating the TDOA. As a result, a new technology has been developed which enables us to choose the exact peak in calculation the TDOA which in-turn localizes the source correctly. The algorithm and TDOA estimation is discussed below.

2.3 Auto- correlation

As shown in Figure: 2.2, it is impossible to tell which peak is to be chosen to calculate the TDOA when the cross correlation is taken between the output of two widely separated receivers. There might be different multipath [20, 21, 22, 23, 24] with amplitudes which make it more difficult to choose the exact peak in calculating the TDOA. In such a situation auto-correlation functions gives sufficient information to identify the relative arrival times of all the multipaths at each receiver. Cross correlation is used to estimate the arrival time of a signal between two microphones. However, if there are echoes and reflections which reach the receiver along with the direct path, there are many peaks in the cross-correlation function

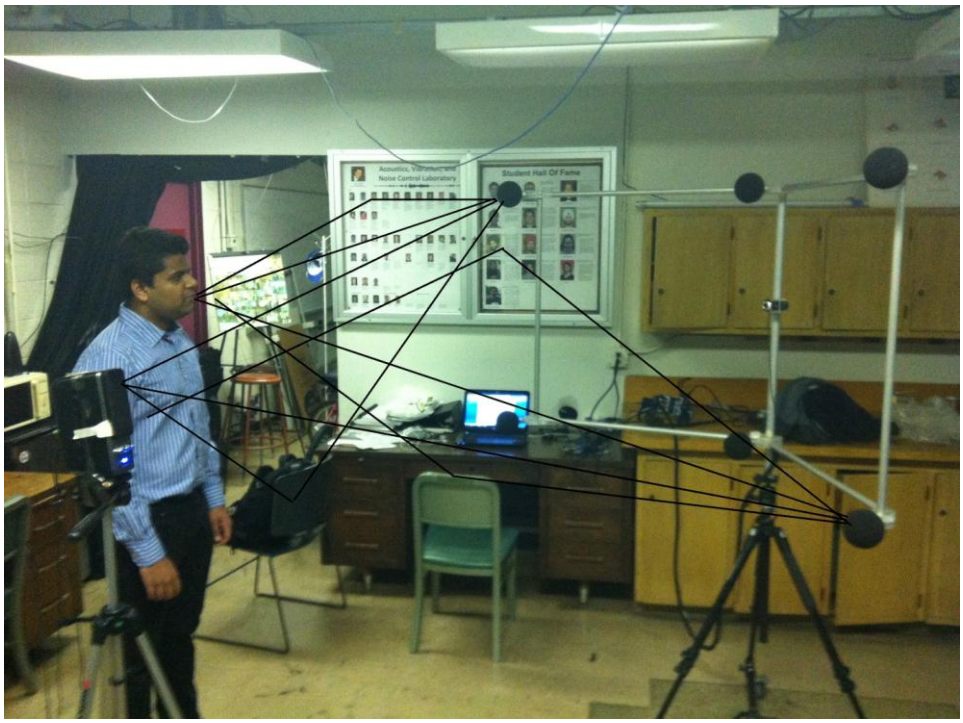


Figure 2.3 : Signals from Man and Speaker to the receiver in AVNC lab

Figure: 2.3 shows a snap shot from Acoustics, vibration and Noise control Laboratory where the Man is talking and the music is been played on the speaker beside him. There are six

microphones which act as receivers and each microphone captures the signals from the Man and the speaker. For simplicity, only two microphones are shown in the Figure 2.3 receiving the signals from two sources. Apart from the straight path between the source and receiver, the signals go through many reverberations and reflections before reaching the receivers. As seen in the Figure: 2.3, the signal from the Man reached the two Microphones is at different time interval. Apart from that the Man's voice reflects from chair, table, glass and the wall and then reaches the two microphones. Assume same case with the signal from the speaker. If we consider Microphone 1 and 2, there are three multipaths from Man's voice to these two speakers. Therefore the number of cross correlation peaks between these two receivers is 3 x 3 = 9. In many cases, the first arrival, which may be nearly straight, may be the only useful path for localization since the geometry of the other paths originating from echoes may be difficult to estimate. Cross-correlation does not tell us which peak to choose. To address this issue, a new method is used which identifies the cross-correlation peak corresponding to the difference in arrival time between the first arrivals at each receiver in the presence of echoes. Its numerical implementation is efficient. The key to unlocking the multipath problem with cross correlation is to consider the extra information residing in the reception's auto-correlationfunctions. They often provide enough information to identify the relative arrival times of all the multipaths at each receiver and between receivers.

CHAPTER 3

SOUND SOURCE LOCALIZATION

3.1 Acoustic model based triangulation

Sound source localization is based on acoustic modeling in this thesis. It has been assumed that in a free field, sound is generated by a point source and the amplitude of the sound wave follows the law of spherical spreading [25,33,35,36]. If we consider only one source, then the sound pressure can be written as [33,35,36]:

$$p = \frac{1}{r} f\left(t - c^{-1} r, \theta, \phi\right) \tag{3.1}$$

where p indicates the sound pressure at time t at geometric location (r, θ, ϕ) in polar coordinates, r is the distance between the measurement and the source location, θ and φ are the polar and azimuthal angle of the measurement position with regard to the source and c is the speed of sound which can be calculated by the following equation:

$$c = 331 + 0.6T_C \tag{3.2}$$

where T_C is the value of temperature in Celsius.

Assuming that M microphones are employed in the prototype device of sound source localization [33,35,36], one can derive a general equation [33,35,36] that governs the distance from the source to the microphone in terms of TOA as follows:

$$r_{js} = c\Delta t_{js} \tag{3.3}$$

where the subscript j indicates the j^{th} microphone, s indicates the source, and r_{js} is the distance between the j^{th} microphone and the sound source. Δt_{js} is the TOA of measurement due to the time concern of the signal traveling in the media.

Similarly, TOA of the k[th] microphone can be written as [33,35,36]:

$$r_{ks} = c\Delta t_{ks} \tag{3.4}$$

Using the Equation (3.4) minus Equation (3.3), thus

$$r_{ks} - r_{js} = c\left(\Delta t_{ks} - \Delta t_{js}\right) \tag{3.5}$$

This can be further simplified as:

$$r_{js} - r_{js} = c\Delta t_{ki} \tag{3.6}$$

As mentioned in Chapter 2, it is impractical to model the sound which propagates along multipath because the environment is poorly known. Cross-correlation between a pair of microphones contain multiple peaks from sources and it is difficult to estimate the time difference of arrival as the highest peak may not correspond to the difference in path lengths between the source and the microphones. Hence, a new technology is developed which uses the information from Auto-correlation function to determine the exact cross correlation peak which will help in source localization.

3.2 Estimating travel time differences of first arrivals

Consider a source that emits a signal at time zero. Assume the call is described by s(t) where t is time. Therefore the signal emitted is at t=0. Sound reaches receiver j along N_j paths in space, called multipaths. The first arrival is often one that does not reflect from boundaries. It may be the path which most closely approximates the straight line between the source and the receiver, and thus be useful for localization. The remaining $(N_j - 1)$ [31] paths reach the receiver afterward either by undergoing refraction in the medium or by interacting with boundaries such as chairs, table, walls etc as shown in Figure: 2.3.

Assume the pressure field at receiver j is described by

$$r_j(t) = \sum_{n=1}^{N_j} a_j[n]s\big(t - t_j[n]\big) + e_j(t) \tag{3.7}$$

where the amplitude and travel time of the nth multipath are $a_j[n]$, and $t_j[n]$respectively. The noise is$e_j[t]$.

The autocorrelation function ACF of the signal at channel j is

$$R_{jj}(\tau) = \int r_j(t) r_j(t-\tau) dt \tag{3.8}$$

From Eq: 3.7 and Eq: 3.8 we get,

$$R_{jj}(\tau) = \sum_{n=1}^{N_j} \sum_{m=1}^{N_j} a_j[n] a_j[m] \int s\big(t - t_j[n]\big) \times s\big(t - t_j[m] - \tau\big) dt + \int e_j(t) e_j(t-\tau) dt \tag{3.9}$$

where the sample ACF between the noise and the signal, that is, $\int ej(t)s(t)dt$, is assumed to be negligible [32].

In order to see how to proceed to find the desired arrival time difference, $t_j[1] - t_k[1]$, consider the case with three multipaths at each channel j and k. The peaks occur in the ACF of channels j and k for

$$\tau_{jj}[2,1] = t_j[2] - t_j[1] \tag{3.10}$$

$$\tau_{jj}[3,1] = t_j[3] - t_j[1] \tag{3.11}$$

$$\tau_{jj}[3,2] = t_j[3] - t_j[2] \tag{3.12}$$

And

$$\tau_{kk}[2,1] = t_k[2] - t_k[1] \tag{3.13}$$

$$\tau_{kk}[3,1] = t_k[3] - t_k[1] \tag{3.14}$$

$$\tau_{kk}[3,2] = t_k[3] - t_k[2] \tag{3.15}$$

The peaks in CCF occurs in lags,

$$\tau_{jk}[1,1] = t_j[1] - t_k[1] \quad (3.16)$$

$$\tau_{jk}[1,2] = t_j[1] - t_k[2] \quad (3.17)$$

$$\tau_{jk}[1,3] = t_j[1] - t_k[3] \quad (3.18)$$

$$\tau_{jk}[2,1] = t_j[2] - t_k[1] \quad (3.19)$$

$$\tau_{jk}[2,2] = t_j[2] - t_k[2] \quad (3.20)$$

$$\tau_{jk}[2,3] = t_j[2] - t_k[3] \quad (3.21)$$

$$\tau_{jk}[3,1] = t_j[3] - t_k[1] \quad (3.22)$$

$$\tau_{jk}[3,2] = t_j[3] - t_k[2] \quad (3.23)$$

$$\tau_{jk}[3,3] = t_j[3] - t_k[3] \quad (3.24)$$

We can measure any lags that appear in the ACF and CCF, but for which lags do we know the associated pair of arrival times by inspection? There are four such lags [31, 32].

They are

- $\tau_{jj}[N_j,1]$: the peak with most positive lag in the ACF of channel j. It is due to the arrival time difference between the first and last multipath.
- τ_{kk} $[N_k,1]$: the peak with most positive lag in the ACF of channel k. It is due to the arrival time difference between the first and last multipath.
- τ_{jk} $[1,N_k]$: the peak with most negative lag in the CCF occurs at the arrival time of the first multipath in channel j minus the arrival time of the last multipath in channel k.
- $\tau_{jk}[N_j,1]$: the peak with most positive lag in the CCF occurs at the arrival time of the last multipath in channel j minus the arrival time of the first multipath in channel k. The desired arrival time difference is given by a linear combination of subsets of these four lags.

The desired arrival time difference is given by a linear combination of subsets of these four lags.

3.3 The relative arrival times in auto- and cross-correlation functions

Some or all of the paths of other than the first arrival may sometimes is useful for localizing signals and mapping the environment with tomography.

3.3.1. Estimating Nj and Nk

The maximum number of peaks [31, 32] in the ACF at positive lag is given by

$$P_j = \frac{N_j(N_j-1)}{2} \tag{3.25}$$

This does not include the peak at zero lag. If there are less than $P_j$peaks, then more than one pair of multipath has similar arrival time differences.

.The lower limit comes from the fact that $N_j - 1$ signals can never yield as many asP_j positively lagged peaks in the ACF. On the other hand, arrival time degeneracy leads to $P_j^{'}$<P_j.

3.3.2. Estimating all the relative arrival times in the ACF and CCF

The most positively lagged peak in the ACF,$\Delta_{jj}(P^{'}_{j})$, is defined as $t_j[N_j] - t_j[1]$. Now, $(P_k - 1)$ peaks require identification in the ACF of channel k. For$N_j > 2$, the ACF of channel j has $P_j - 1$ as yet unidentified positively lagged peaks. We need estimates of the following $N_j - 2$ values of relative arrival times:

$$t_j[2] - t_j[1] \tag{3.26}$$

$$t_j[3] - t_j[1] \tag{3.27}$$

$$t_j[4] - t_j[1] \tag{3.28}$$

$$t_j[N_j - 1] - t_j[1] \tag{3.29}$$

There are

$$Q_j \equiv \frac{(P'_j-1)!}{\left(P'_j-1-(N_j-2)\right)!(N_j-2)!} \tag{3.30}$$

ways to pick these N_j-2 elements, without replacement, from a set of P_j-1 elements.

The realization yields trial estimates for the relative arrival times in the ACF [31],

$$t_j[2] - t_j[1] = \Delta_{jj}[l(1)] \tag{3.31}$$

$$t_j[3] - t_j[1] = \Delta_{jj}[l(2)] \tag{3.32}$$

$$t_j[4] - t_j[1] = \Delta_{jj}[l(3)] \tag{3.33}$$

etc.,

$$t_j[N_j - 1] - t_j[1] = \Delta_{jj}[l(N_j - 2)] \tag{3.34}$$

Now, for channel k, there are

$$Q_k \equiv \frac{(P'_k-1)!}{\left(P'_k-1-(N_k-2)\right)!(N_k-2)!} \tag{3.35}$$

ways to pick $N_k - 2$ elements, without replacement, from a set of $P_k - 1$ elements.

Each realization yields trial estimates of the positively lagged peaks in the ACF,

$$t_k[2] - t_k[1] = \Delta_{kk}[l(1)] \tag{3.36}$$

$$t_k[3] - t_k[1] = \Delta_{kk}[l(2)] \tag{3.37}$$

$$t_k[4] - t_k[1] = \Delta_{kk}[l(3)] \tag{3.38}$$

etc.,

$$t_k[N_k - 1] - t_k[1] = \Delta_{kk}[l(N_k - 2)] \tag{3.39}$$

For each realization of relative arrival times for channels j and k, a realization is formed for the lags in the CCF. Since there are $Q_j$and $Q_k$realizations of relative times from channels j and k, respectively, there are

$$T_{jk} = Q_j Q_k \tag{3.40}$$

possible realizations of the lags in the CCF.

The realization of trial lags is selected that best fits the measured lags in the CCF. This method identifies CCF lags using

$$\delta_{jk}[i1] = t_j[1] - t_k[1] \tag{3.41}$$

as an anchor point about which other peaks are referenced. The peak in the CCF at $t_j[1] - t_k[1]$need not even appear in the CCF, because there are independent estimates of its value.

3.4 Error analysis on source localization algorithm [33,35,36]

During the numerical simulation, different types of sound signals are tested, such as human voices, truck noise, chopper sound, machine noise, etc. The positions of the sound sources are chosen arbitrarily, and the mixed signals at six microphones are generated numerically obeying the spherical spreading law.

To evaluate the accuracy of the sound source localization, error of localization result is defined as follows:

$$error_{localization} = \frac{\left|\vec{r} - \vec{r}_{benchmark}\right|^2}{\left|\vec{r}_{benchmark}\right|^2} \times 100\% \tag{3.42}$$

where r is the calculated vector result the source, and $r_{benchmark}$ is the benchmark position of the sound source.

CHAPTER 4

SOUND SOURCE SEPERATION

Any unwanted sound is noise and can be produced by many sources like a running engine, an operating machine tool, man's vocal cord and so on. Further, quickly varying pressure wave traveling through a medium is sound and when it travels through air, the atmospheric pressure varies periodically. Frequency of the sound is the number of pressure variations per second which is measured in Hertz (Hz) defined as cycles per second. Pitch of sound wave is directly proportional to the frequency of wave, high frequency wave results in high pitched sound. Sounds produced by a whistle have much higher frequency than those produced by drums.

The human ear responds to variations in frequency of sound. The audible range of human ear falls between 20 Hz to 20 kHz. The human ear is less sensitive to sounds in the low frequencies compared to the higher frequencies with peak response around 2,500 to 3,000 Hz. Sound is generally characterized by pitch, loudness and quality. The loudness of a sound depends on pressure variations. Pressure and pressure variations are expressed in Pascal (Pa). To express sound or noise in terms of Pa is quite inconvenient because we have to deal with numbers from as small as 20 to as big as 2,000,000,000. A simpler way is to use a logarithmic scale. The unit of measurement for loudness is the decibel (dB). As mentioned earlier, the human ear responds to sound is dependent on the frequency of the sound and this has led to the concept of weighting scales. The sound pressure levels for the lower frequencies and higher frequencies are reduced by certain amounts before they are being combined together to give one single sound pressure level value in a weighting **scale**. This value is designated as dB(A) and is often used as it reflects more accurately the frequency response of the human ear. A perceived soft noise has a

low dB or dB (A) value and a loud noise has a high one.

4.1 Origin of sound separation problem

Much of the early work in the area of sound recognition and separation can be traced to problems faced by air traffic controllers in the early 1950's and this effect was first described (and named) by Colin Cherry in 1953 as part of psychoacoustics [26] . At that time, controllers received messages from pilots over loudspeakers in the control tower and hearing the intermixed voices of many pilots over a single loudspeaker made the controller's task of regulation of air traffic very difficult. Our ability to separate sounds from background noise is based on the characteristics of the sounds, such as the gender of the speaker, the direction from which the sound is coming, the pitch, or the speaking speed and this was revealed by Cherry, in 1953, who conducted perception experiments in which subjects were asked to listen to two different messages from a single loudspeaker at the same time and try to separate them.

Broadbent, in the 1950's, concluded that human hearing is basically like a spectrum analyzer, that is, the ear resolves the spectral content of the pressure wave with respect to the phase of the signal by conducting dichotic listening experiments where subjects were asked to hear and separate different speech signals presented to each ear simultaneously (using headphones). The difference in sound between the ears is a notable exception that provides a significant part of the directional sensation of sound and is called inter-aural phase difference.

4.2 Background Information about some of the Sound separation techniques:

Source separation has long been a topic of interest in engineering and many algorithms have been developed to perform separation of the sound sources. In 1994, the formulation of a sound separation technique known as Blind source separation (BSS) by Comon came into picture. Independent component analysis (ICA) was the name given to the algorithms that were developed to conduct the source separation. To highlight the fact that independent components were being separated from mixtures of signals the separation techniques were named ICA and also to emphasize a close link with the classical signal processing technique of Principal Component Analysis (PCA).

There was a rapid development of ICA algorithms following the Comon's seminal paper. Based on a wide variety of principles algorithms were formulated, including mutual information, maximum likelihood and higher order statistics, to name just a few of the more popular approaches. All ICA algorithms are fundamentally similar despite such wide variety. ICA algorithms invariably obtain estimates of the independent signals by adopting a numerical approach (e.g. gradient descent) of maximizing an "independence metric", i.e. a measure of the signals' independence.

There came many different approaches to solving the source separation problem with the explosion of interest of many researchers in BSS and a great deal of progress has been made in showing that seemingly unrelated approaches were, in fact, equivalent. A major contribution to this movement was made by Bell and Sejnowski, by proposing a unifying framework for BSS based on information theoretic considerations [1] . BSS researchers soon showed the equivalence of many different approaches to BSS by continuing on the work of Bell and Sejnowski and research led to a convergence onto a small set of well understood principles, as the field of Blind

Source Separation matured.

4.3 Restriction to the number of sources

Consider situations in which a number of sources emitting signals which interfere with one another occur, like a crowded room with many people speaking at the same time, interfering electromagnetic waves from mobile phones or crosstalk from brain waves originating from different areas of the brain. In each of these situations the mixed signals are often incomprehensible and it is of interest to separate the individual signals when the total number of inherent signals are not known to us. No prior information is known about the number of the source signals that are present but the Blind Source Separation can be used to separate these signals and so the algorithm for independent component analysis fails and we need to come up with a modification to the existing algorithm to separate unknown number of sources using a fixed number of sensors. A successful separation of mixed signals resulted only when the number of signals is same as the number of sensors, by using the time domain algorithms proposed by BSS. But, they become inefficient when the number of sources increases then the sensors. Thus, in this thesis by working in the frequency domain [27], we have proposed an improved source separation approach.

4.4 Short time source localization and separation

4.4.1 Basic Assumptions and Principles

As depicted in Chapter 3, a source localization technique using Auto and Cross-correlation which can only locate the most dominant sound source in a specific frequency band at a specific time instance. Since in general the sound signals are arbitrary, the most dominant

signals in different frequency bands at different time instances may be different and this offers an opportunity for us to separate individual source signals by dividing the time-domain signals into many short time segments. In general, the shorter the time segments are, the more accurately the variations in the time-domain signals can be captured, but the worse the frequency resolution in source separation becomes and this phenomenon is exactly the same as that in short-time Fourier transform (STFT). To ensure an optimal resolution for both time and frequency in sources localization and separation, a compromise must be made. However, in this study, STFT is performed on each time segment, and the resultant spectrum is expressed in the standard octave bands where by the time-domain signals are divided into a uniform segment of $\Delta t = 0.1$ (sec).

4.4.2 Fourier Transform

The Fourier transform is used to convert data from the time domain to the frequency domain and the Fourier transform of a signal x (t) can be thought of as a representation of a signal in the "frequency domain"; i.e. how much each frequency contributes to the signal. Once in the frequency domain, the frequency components can be used to generate the frequency spectrum of the signal, which shows the magnitude of each of the frequency components calculated by the transformation and indicates the "amount" of each frequency that exists in the original waveform. A "spike" in the frequency spectrum corresponds to a dominant presence of that frequency in the waveform, while a low value indicates that there is little or none of that frequency in the signal.

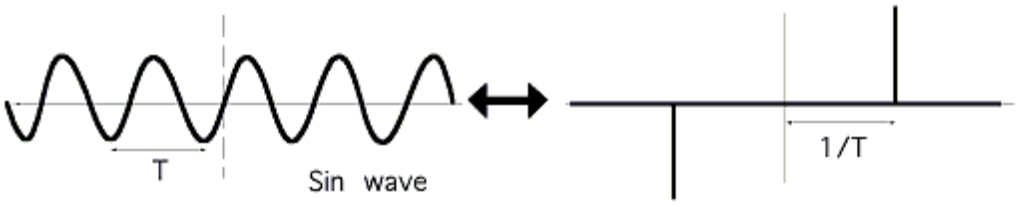


Figure 4.1: Fourier Transform for sine wave

4.4.3 Short Term Fourier Transform

A Fourier-related transform used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time is called the short-time Fourier transform (STFT), or alternatively short-term Fourier transform. This is simply described, in the continuous-time case, that the function to be transformed is multiplied by a window function which is nonzero for only a short period of time. The Fourier transform (a one-dimensional function) of the resulting signal is taken as the window is slid along the time axis, resulting in a two-dimensional representation of the signal. Mathematically, this is written as:

$$STFT\{x(\,)\} = X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)\, \omega(t-\tau) e^{-j\omega t} dt \qquad (4.1)$$

where w(t) is the window function centered around zero, and x(t) is the signal to be transformed. X(τ,ω) is essentially the Fourier Transform of x(t)w(t-τ), a complex function representing the phase and magnitude of the signal over time and frequency. The data to be transformed could be broken up into chunks or frames (which usually overlap each other) in the discrete time case and each chunk is Fourier transformed [29], and the complex result is added to a matrix, which records magnitude and phase for each point in time and frequency. This can be expressed as:

$$STFT\{x(\,)\} = X(m, \omega) = \int_{n=-\infty}^{\infty} x[n]\, w(n-m) e^{-j\omega n} \qquad (4.2)$$

In this case, m is discrete and ω is continuous. Again, the discrete-time index m is normally considered to be "slow" time and usually not expressed in as high resolution as time n.

4.4.4 Window Function

In signal processing, a window function is a function that is zero-valued outside of some chosen interval. For instance, a function that is constant inside the interval and zero elsewhere is called a rectangular window, which describes the shape of its graphical representation. When another function or a signal (data) is multiplied by a window function, the product is also zero-valued outside the interval: all that is left is the "view" through the window if we want to analyze a long signal in overlapping short sections called “windows”. For example we may want to calculate an average spectrum, or to calculate a spectrogram. Unfortunately we cannot simply chop the signal into short pieces because this will cause sharp discontinuities at the edges of each section. Instead it is preferable to have smooth joins between sections. Example are Hanning, Hamming, Gaussian, Rectangular etc.

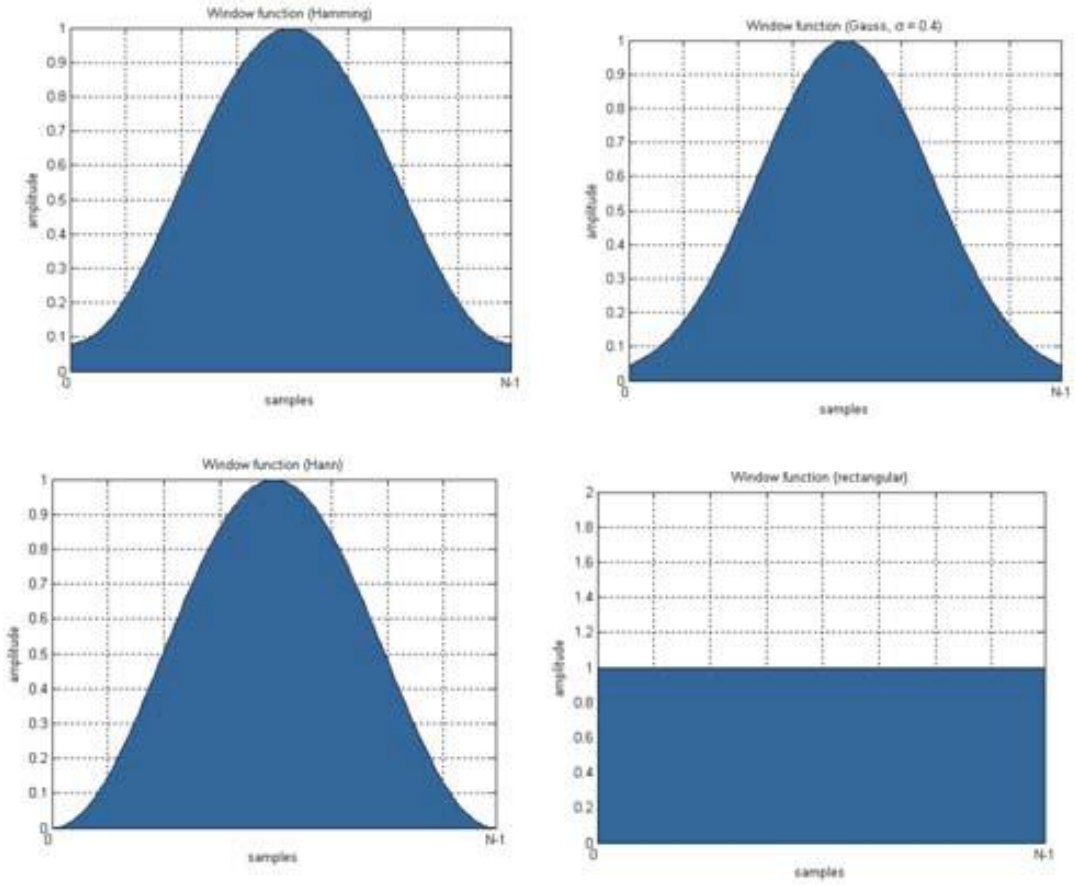


Figure 4.2: Windowing Functions a) Hamming b) Gaussian c) Hanning d) Rectangular Window

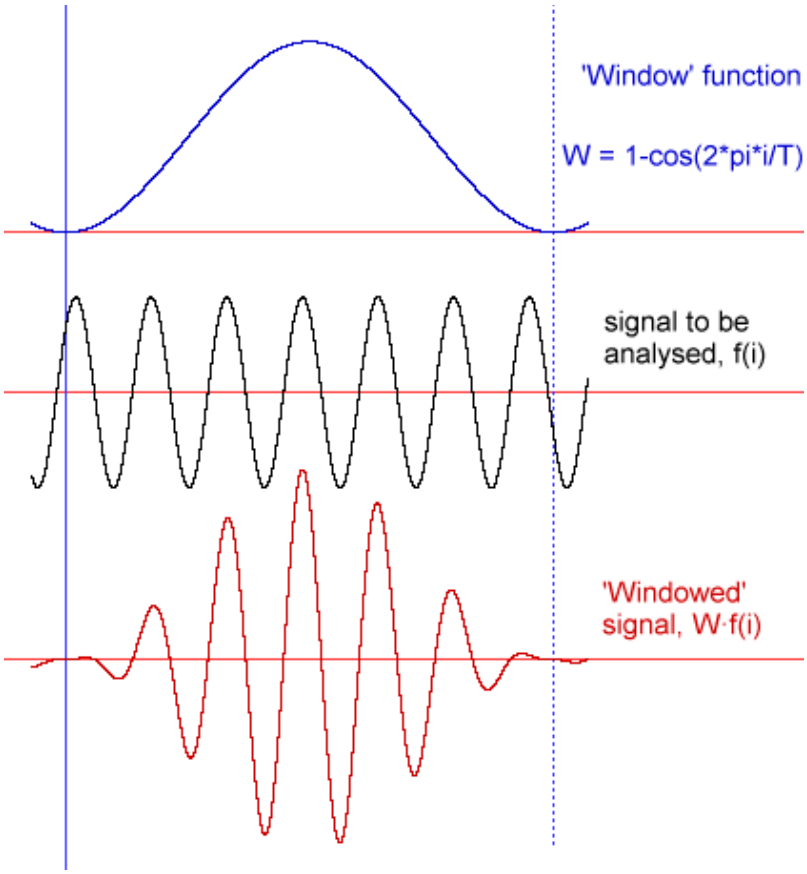


Figure 4.3: Example showing the working of a window function

4.4.5 Spectrogram

The spectrogram is the result of calculating the frequency spectrum or the Fourier transform of windowed frames of a compound signal. It is a three dimensional plot of the energy of the frequency content of a signal as it changes over time. Spectrograms are used to identify phonetic sounds, to analyze the cries of animals, and in the fields of music, sonar, radar, speech processing, etc. In the most usual format, the horizontal axis represents time, the vertical axis is frequency, and the intensity of each point in the image represents amplitude of a particular frequency at a particular time. This function divides a long signal into windows and performs a fourier transform on each window, storing complex amplitudes in a table in which the columns

represent time and the rows represent frequency.

4.5 Algorithm for Short time source localization and separation [34]

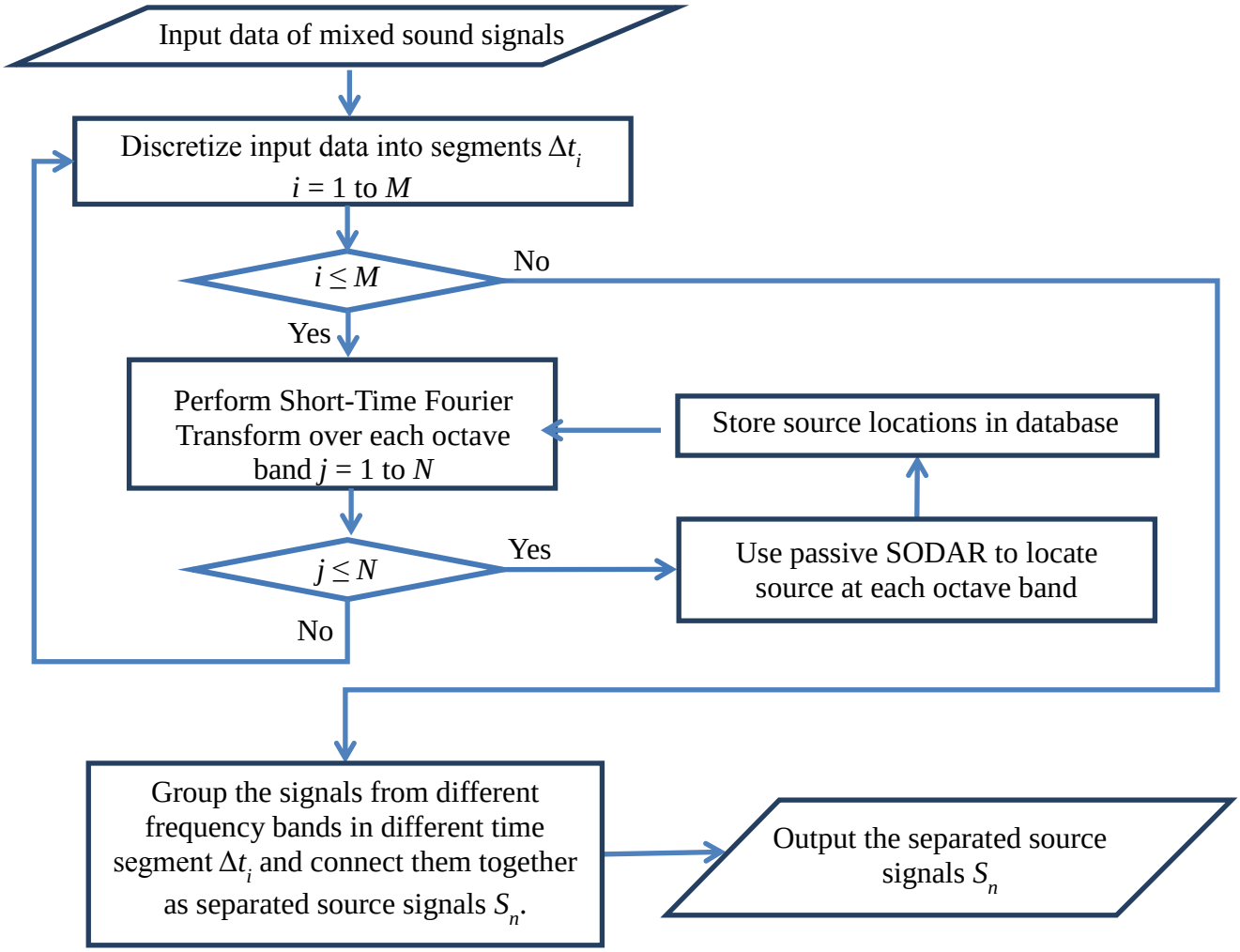


Figure 4.4: Flow chart for the short-time SLAS algorithm.

Figure 4.4 shows the flow chart of this short-time SLAS algorithm. The input data are discretized into a uniform short time segment Δt and the STFT is carried out for each Δt. The resultant spectrum is expressed in the standard octave bands and passive SODAR is used to

determine the locations of the dominant source in each band. These steps are repeated until source localizations in all frequency bands for all time segments are completed. Next, all signals in various frequency bands at different time segments that correspond to the same source are strung together, which represent the separated signals. These separated signals may be played back in which the interfering signals including background noise are minimized.

Theoretically, one may use a much finer resolution in frequency to locate and separate source signals. For example, for this short time segment $\Delta t = 0.1$, one can get a frequency resolution of $\Delta f \geq 1/\Delta t = 5$ Hz. However; this will substantially increase the computation time because source localization must be carried out over every 5 Hz for every 0.1 second of input data. For most applications such a fine resolution in frequency is unnecessary. Therefore in this study the standard octave bands over the frequency range of 20 – 20,000 Hz are used.

CHAPTER 5

EXPERIMENTAL VALIDATION OF SOUND SOURCE LOCALIZATION AND SEPARATION

Validation of Sound source localization using Auto-Correlation is conducted with various real world sounds in several non-ideal environments. The tests were conducted in Acoustic, Vibration, and Noise Control Laboratory (AVNC Lab), Wayne State University. Different types of sounds were used through the speakers and were located through the newly developed code. Sounds such as music, radio, people talk, clapping etc were used. The experimental validation was conducted to compare the results between Cross correlation and Auto correlation results to locate single and multiple sources.

5.1 Experimental validation for six-microphone set

A prototype based on this technology has been developed and its hardware includes six B&K ¼-in condenser microphones, Type 4935,two 4-channel data acquisition units, Type NI-9234 ,with a maximum sampling rate of 51.2 kS/sper channel one NI-cDAQ9174 chassis, a thermometer to measure the air temperature, camera to view the relative positions of located sources, and a laptop to control data acquisition and post processing.



(a) The array of six microphones used to locate sound sources emitting arbitrarily time-dependent acoustic signals.



(b) NI 9234 4-channel module



(c) NI CompactDAQ 4-Slot USB Chassis

Figure 5.1 Prototype device set model. (a) This device consists of six microphones, a web camera, a thermometer, and the data acquisition systems. (b) NI-9234 signal acquisition module. (c) NI USB chassis.

Different types of sounds were tested in the AVNC lab. Initially, only one speaker was used in the experiment. Both cross and autocorrelation algorithms were used to locate the sound. This procedure was followed by moving the speaker at different places within the camera range. The speaker was moved away from the microphones till 3m length and the location results were taken. Finally, the results obtained from the algorithms were compared to the benchmark locations that were taken prior to the experiment through 3-d digitizer shown below.

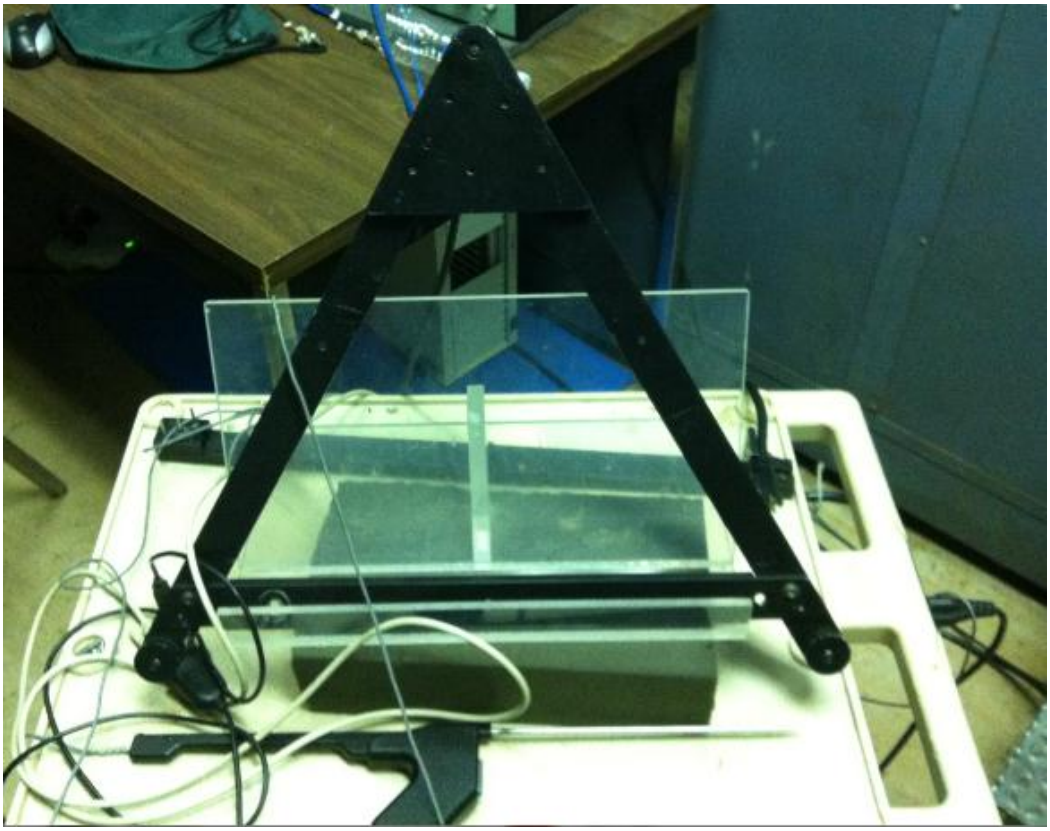


Figure 5.2: 3D sonic digitizer model 5230XL

5.2 Comparison between Cross correlation and Auto correlation:

As mentioned above, the experiments initially were carried out using one speaker.

Figure 5.3 (a), (b), (c) and (d) shows the sound source localization in the AVNC lab in the Engineering Building, which is a noisy environment. Figure 5.3 (a) illustrates the case of locating the noise from a speaker kept at a closer distance to the Microphones, Figure 5.3 (b) shows the program locating the noise from the speaker which is kept the extreme left of the picture, Figure 5.3 (c) shows the program locating the noise from the speaker which is kept the extreme right of the picture, and finally Figure 5.3 (d) shows the locating the noise from the speaker which is kept far away.



Figure 5.3 (a): Speaker kept at a closer distance to the Microphones with cross-correlation and Auto-correlation results.



Figure 5.3 (b): Speaker kept at a left to the Microphones with cross-correlation and Auto-correlation results.



Figure 5.3 (c): Speaker kept at a right to the Microphones with cross-correlation and Auto-correlation results.

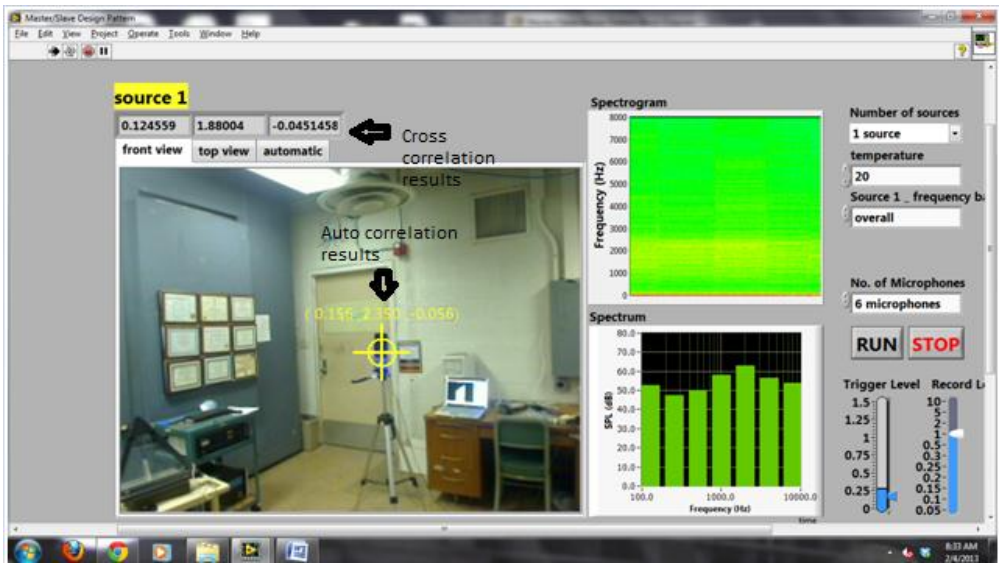


Figure 5.3 (d): Speaker kept far away to the Microphones with cross-correlation and Auto-correlation results.

5.3 Error analysis for source localization

As mentioned above, source localizations experiments were carried out to compare the results between Cross-correlation and Auto-correlation with the results that were taken from 3-d digitizer.

5.3.1 Error analysis of experimental results

Benchmark locations of the sources were measured by 3D sonic digitizer model 5230XL, which is a localization device employing the ultrasonic technologies. The 3D sonic digitizer has an ultrasonic gun and a receiver set. One can pinpoint the target with the ultrasonic gun and generate ultrasonic sound with it. The receiver recognizes the sounds generated by its producer thus can find out the geometry position in 3D space of the target. During the measurement of the benchmark location, the ultrasonic gun pinpointed at the center of the loudspeakers or other

sound sources, generated ultrasonic sound, and the position can be obtained by the 3D sonic digitizer program. For an object within a radius of 4 meters, the error margin of this 3D sonic digitizer is ±2.5mm. As the localization error of the 3D digitizer is much less than the expected error of the present approach, the location gained by 3D digitizer can be considered as benchmark position.

The error in the localization can be calculated using Equation (3.42). Table below shows the localization results and error from Cross-correlation and Auto-correlation results.

Table 5.1: Comparison between Cross and Auto-correlation

3-d Digitizer			Cross- Correlation			Error	Auto-Correlation			Error
X	Y	Z	X	Y	Z	%	X	Y	Z	%
-0.039	1.278	-0.07	0.0328	1.2554	-0.0576	**1.824352**	0.036	1.266	-0.064	**0.966952**
0.601	1.371	-0.075	0.5012	1.36	-0.054	**3.2293**	0.533	1.364	-0.065	**2.19778**
-0.455	1.7	-0.08	-0.404	1.581	-0.062	**7.304208**	-0.448	1.645	-0.069	**3.141659**
0.13	2.05	-0.09	0.095	1.9	-0.049	**7.445402**	0.122	1.983	-0.067	**3.317452**
0.19	2.601	-0.09	0.34	2.2	-0.038	**14.6788**	0.155	2.405	-0.052	**7.623439**
1.301	2.85	-0.095	0.45	2.3	-0.045	**25.21438**	0.195	2.721	-0.068	**12.93796**
0.506	3.45	-0.09	0.35	2.425	-0.026	**29.75298**	0.211	2.984	-0.039	**14.23038**

It can be observed from above table that the error reduced up to 50% when Auto-correlation algorithms were used to locate the source compared to Cross-correlation algorithms.

It is shown in the graph below:

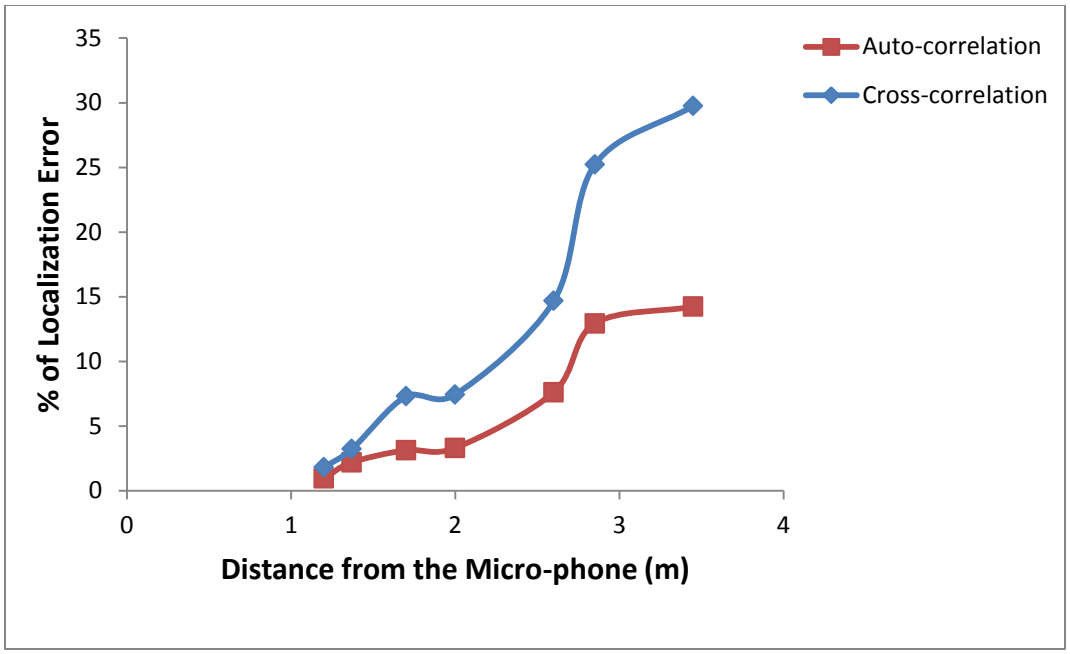


Figure 5.4: Comparison between Cross-correlation and Auto-correlation

As discussed in Chapter-3, Cross-correlation takes the maximum peak for TDOA estimation and Auto-correlation uses the exact peak for TDOA estimation. Although, cross correlation gives accurate results in many cases, but in case where there are many reflections and reverberations, Auto-correlation functions are very useful in calculation TDOA.

Once we locate the sources, next step is to separate target source from mixed signals. As discussed in Chapter-4, source separation has always been important field of research and there are many techniques that can be used for the same. In this thesis, we have developed a new technology where the sources are separated using frequency bands. The technique known as Short time source localization and separation (SLAS) uses the results from source localization. Initially, the mixed signals are divided into different frequency bands and then the localization results are used to separate the target sources which are present in different frequency bands.

5.4 Experimental validation for Source separation:

As mentioned above, sources are separated in the frequency bands using SLAS technique. In this thesis, different kinds of mixed signals were played and were separated.

Figure 5.5 (a), (b), (c) (d) shows the results that were conducted in AVNC lab, Wayne State University. The mixed signal of Man talking, Radio and White-noise was used to locate and separate all three sources. Figure 5.5 (a) shows localization results of Man and two speakers which were used to play Radio and White noise, Figure 5.5 (b) shows the time-domain and Spectrogram for the original mixed signal, Figure 5.5 (c) shows the time-domain and Spectrogram for the separated Man's Voice, Figure 5.5 (d) shows the time-domain and Spectrogram for the separated Radio Sound and finally Figure 5.5 (e) is the time-domain and spectrogram graph for separated White noise.

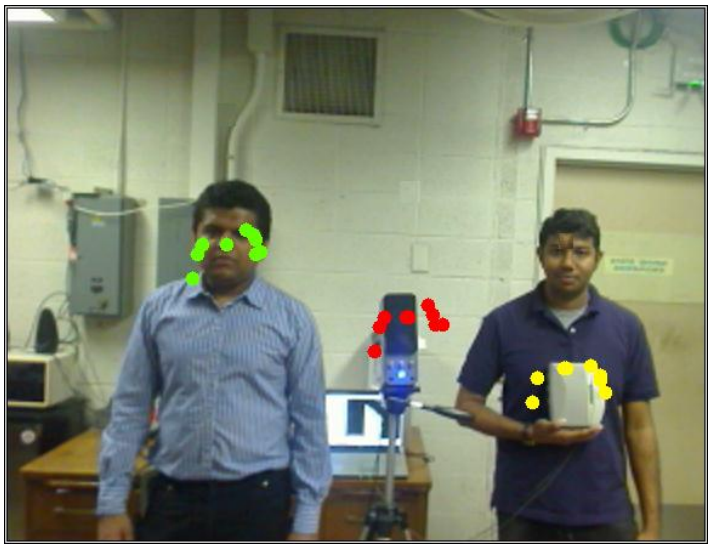


Figure 5.5(a): The dominant sound sources of a man's voice, white noise , and radio sound were captured by passive SODAR.

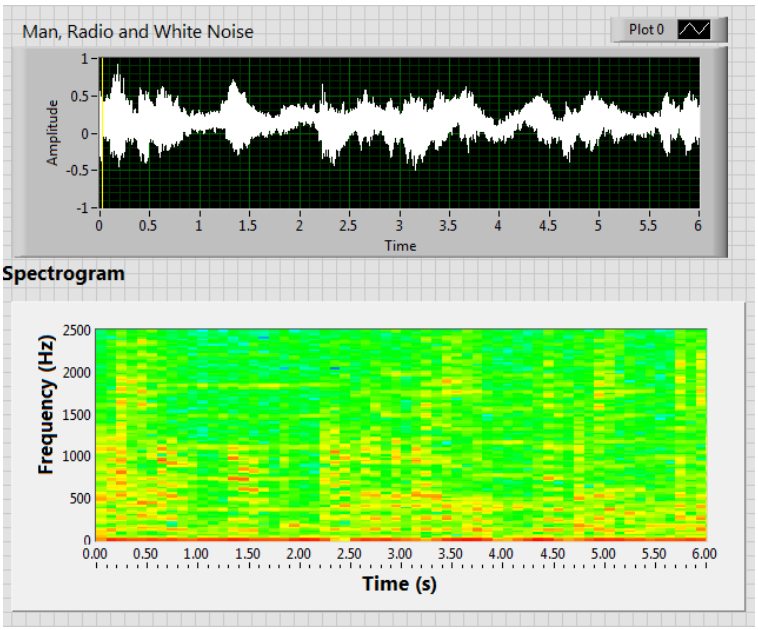


Figure 5.5 (b): The time-domain signals and corresponding spectrogram of the Mixed Signal

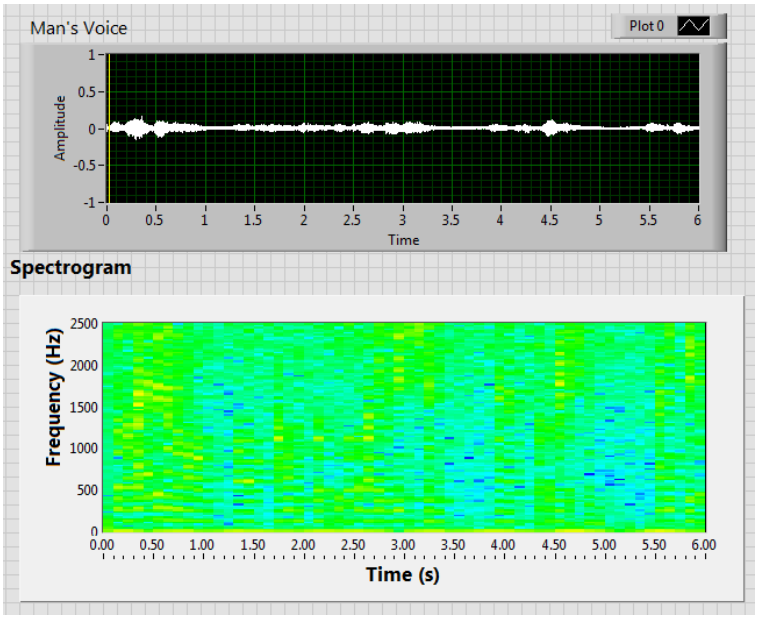


Figure 5.5 (c): The time-domain signals and corresponding spectrogram of the separated Man's Voice

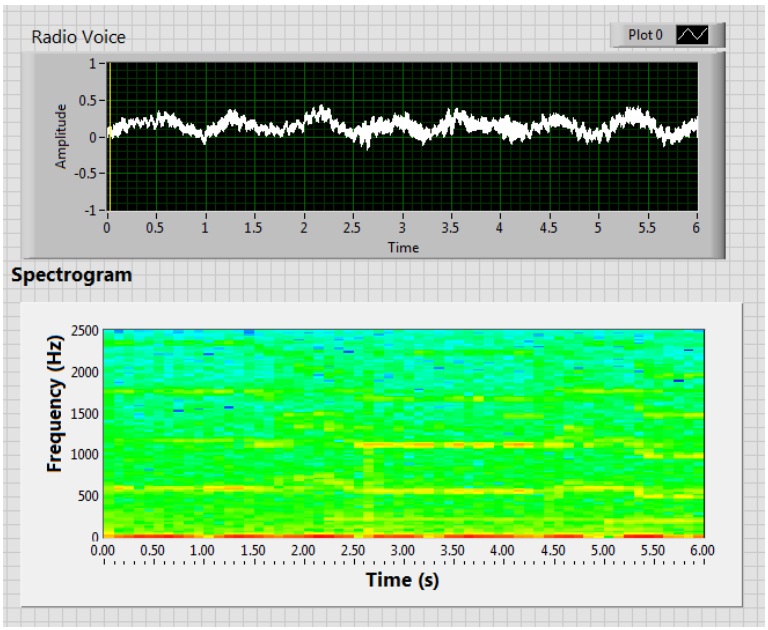


Figure 5.5 (d): The time-domain signals and corresponding spectrogram of the separated Radio Voice

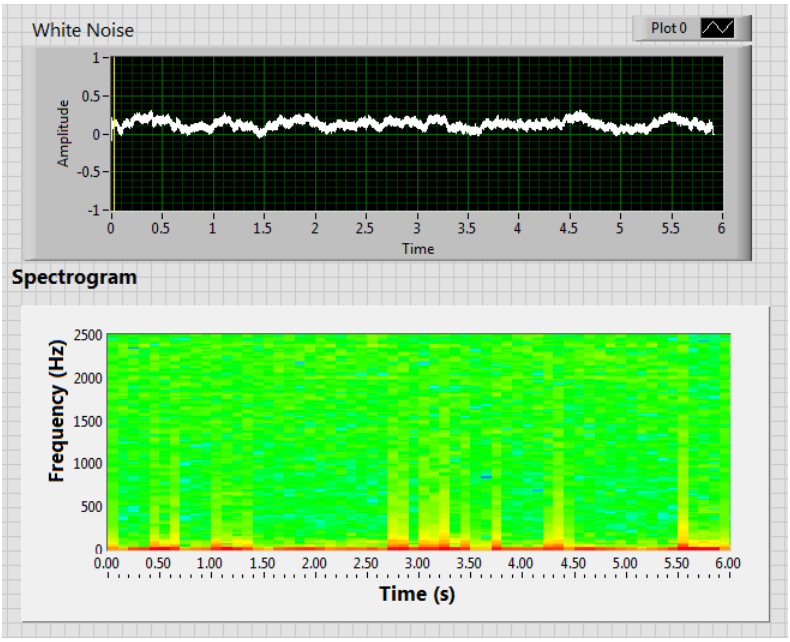


Figure 5.5 (e): The time-domain signals and corresponding spectrogram of the separated White Noise

In second case, the mixed signal of Man talking, Clapping and White-noise was used to locate and separate all three sources. Figure 5.6 (a) shows localization results of two Men and a speaker which was used for white noise, Figure 5.6 (b) shows the time-domain and Spectrogram for the original mixed signal, Figure 5.6 (c) shows the time-domain and Spectrogram for the separated Man's Voice, Figure 5.6 (d) shows the time-domain and Spectrogram for the separated Clapping sound and finally Figure 5.6 (e) is the time-domain and spectrogram graph for separated White noise.

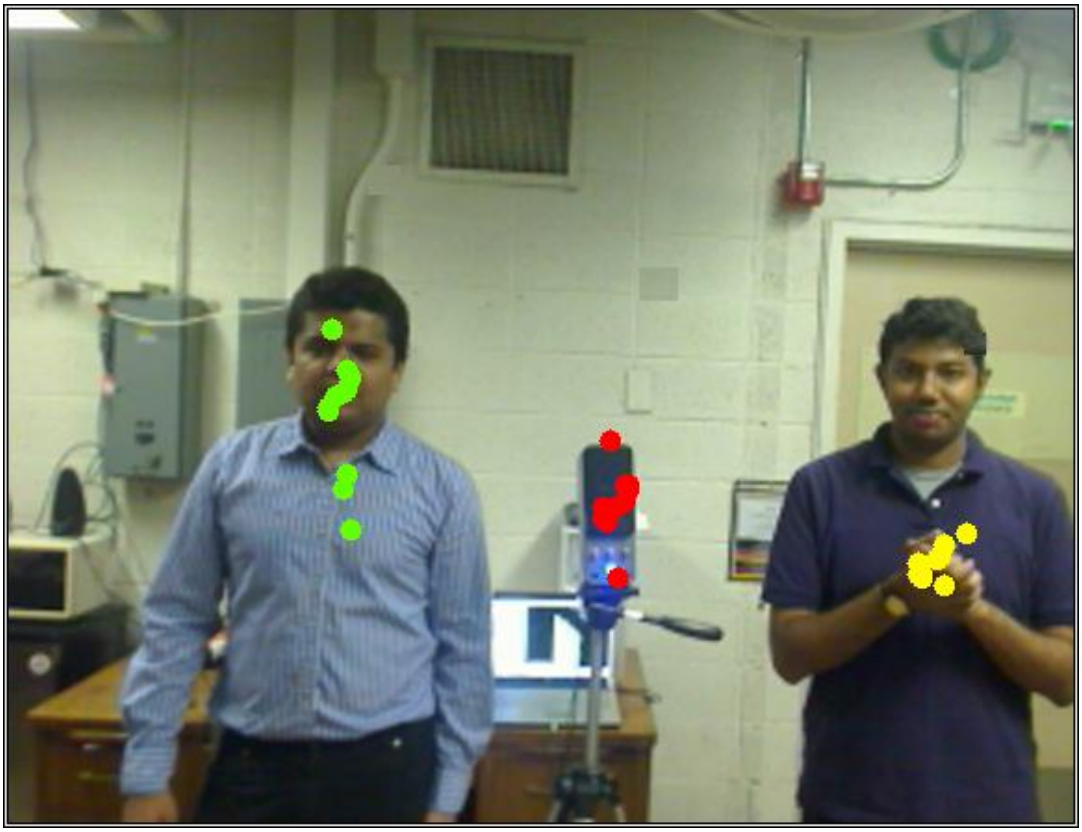


Figure 5.6(a): The dominant sound sources of a man's voice, white noise, and clapping sound were captured by passive SODAR.

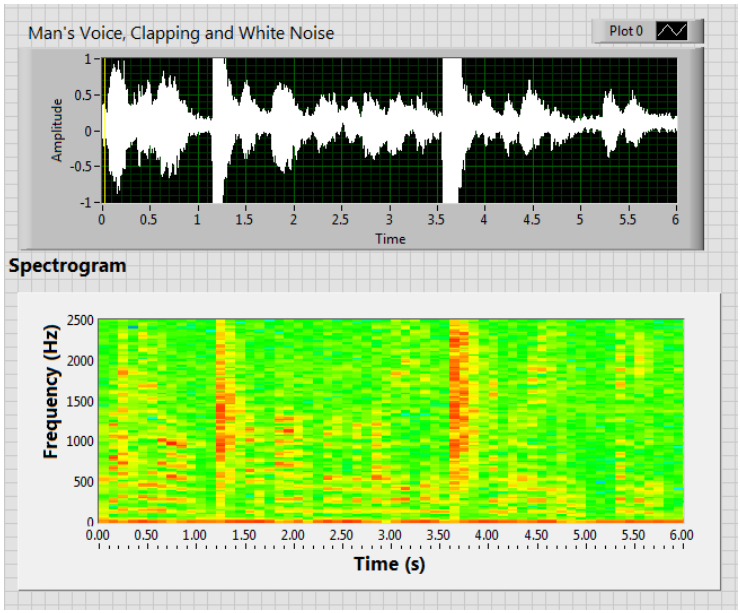


Figure 5.6 (b): The time-domain signals and corresponding spectrogram of the Mixed Signal

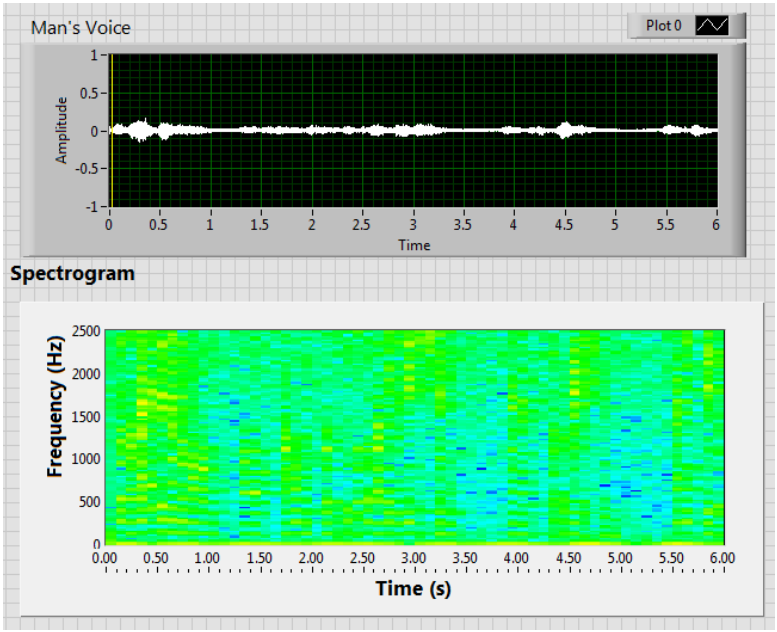


Figure 5.6 (c): The time-domain signals and corresponding spectrogram of the separated Man's Voice

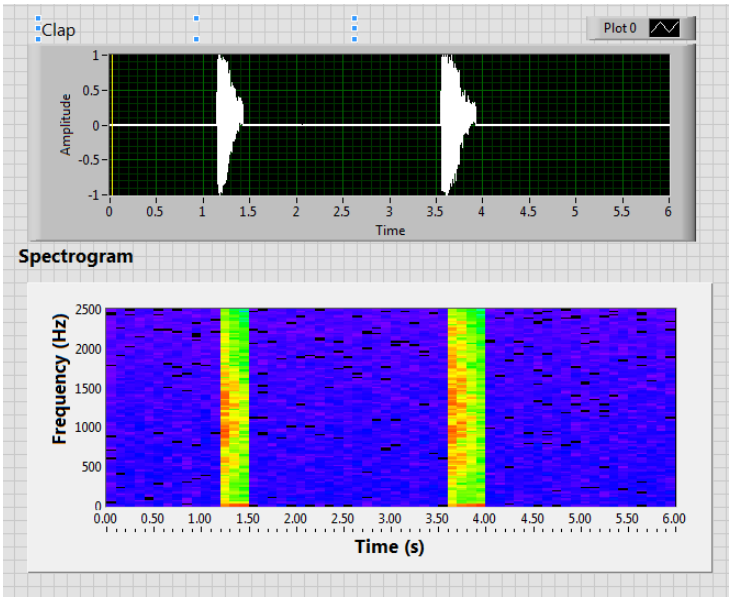


Figure 5.6 (d): The time-domain signals and corresponding spectrogram of the separated Clap sound

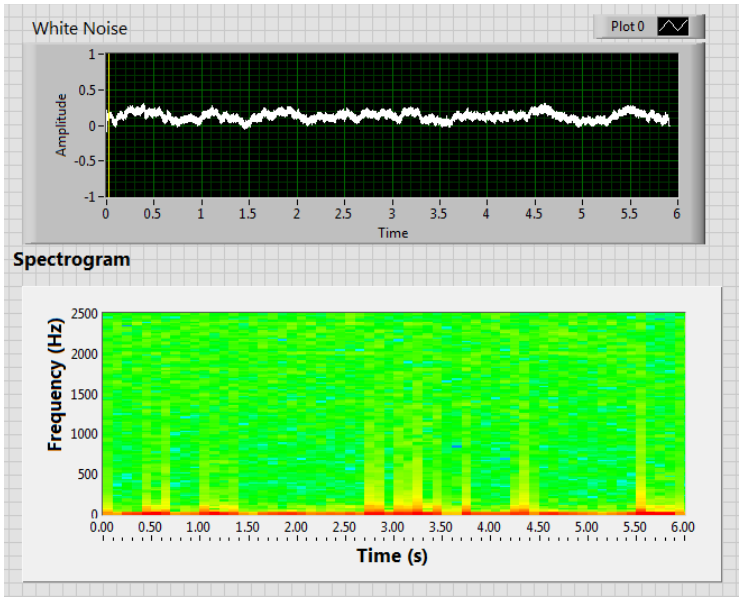


Figure 5.6 (e): The time-domain signals and corresponding spectrogram of the separated White Noise

And finally, mixed signal used for third case has Man talking, Music, Siren and White-noise was used to locate and separate all four sources. Figure 5.7 (a) shows localization results of a Man and 3 speakers used for Music, Siren and White noise, Figure 5.7 (b) shows the time-domain and Spectrogram for the original mixed signal, Figure 5.7 (c) shows the time-domain and Spectrogram for the separated Man's Voice, Figure 5.7 (d) shows the time-domain and Spectrogram for the separated Music sound ,Figure 5.7 (e) is the time-domain and spectrogram graph for separated Siren sound and finally,. Figure 5.7 (f) is the time-domain and spectrogram graph for separated White Noise.

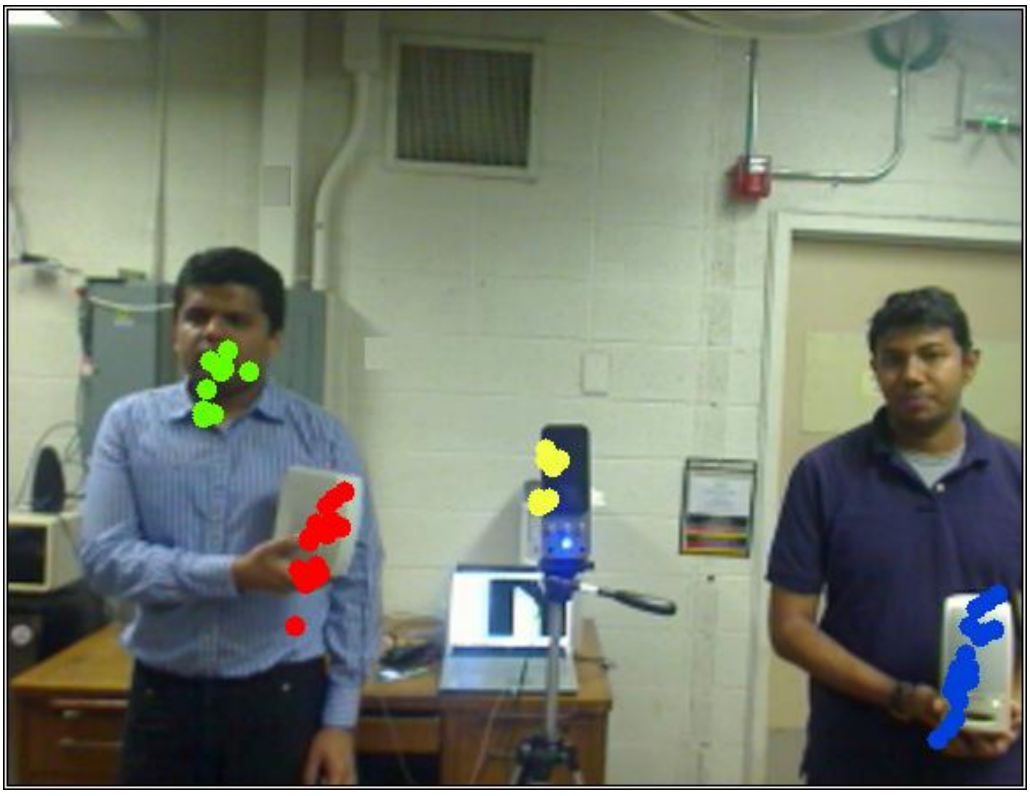


Figure 5.7(a): The dominant sound sources of a man's voice, music, white noise and siren sound were captured by passive SODAR.

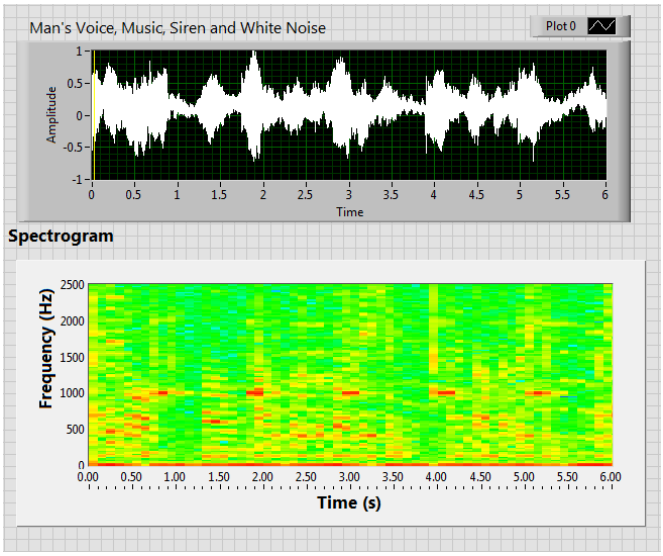


Figure 5.7 (b): The time-domain signals and corresponding spectrogram of the Mixed Signal

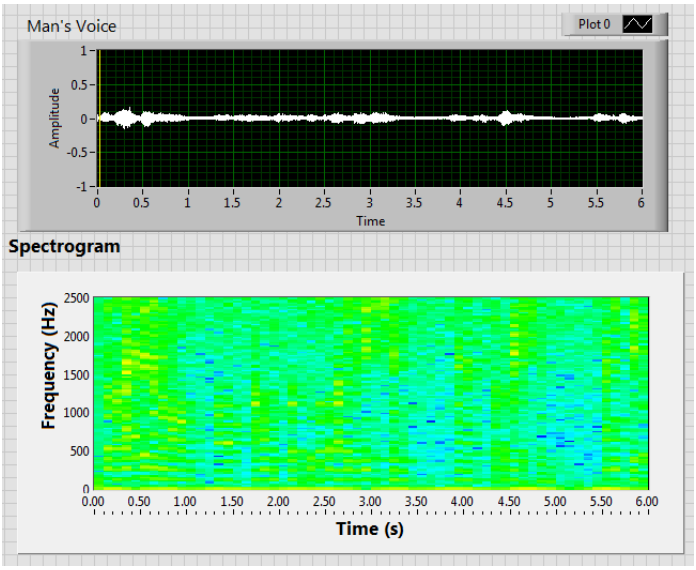


Figure 5.7 (c): The time-domain signals and corresponding spectrogram of the separated Man's Voice

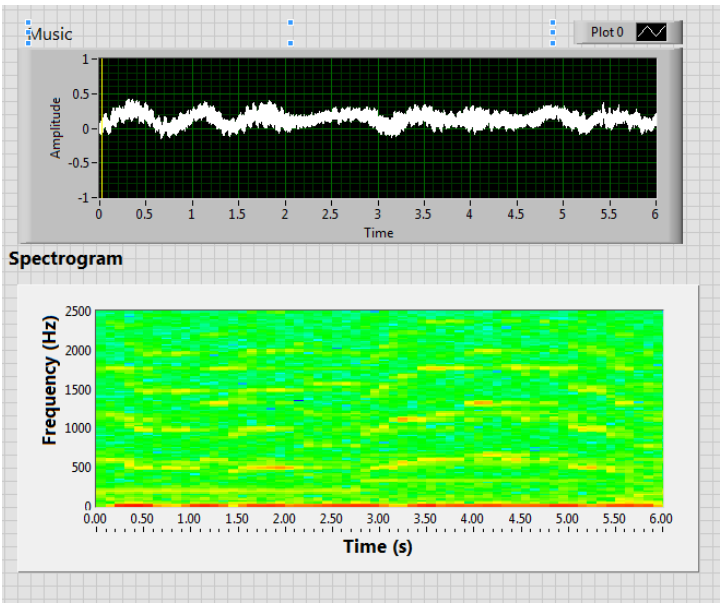


Figure 5.7 (d): The time-domain signals and corresponding spectrogram of the separated Music

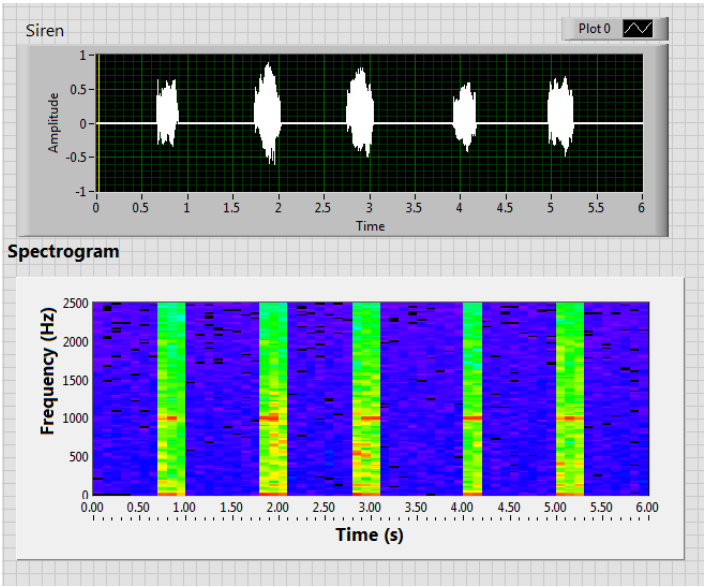


Figure 5.7 (e): The time-domain signals and corresponding spectrogram of the separated Siren sound

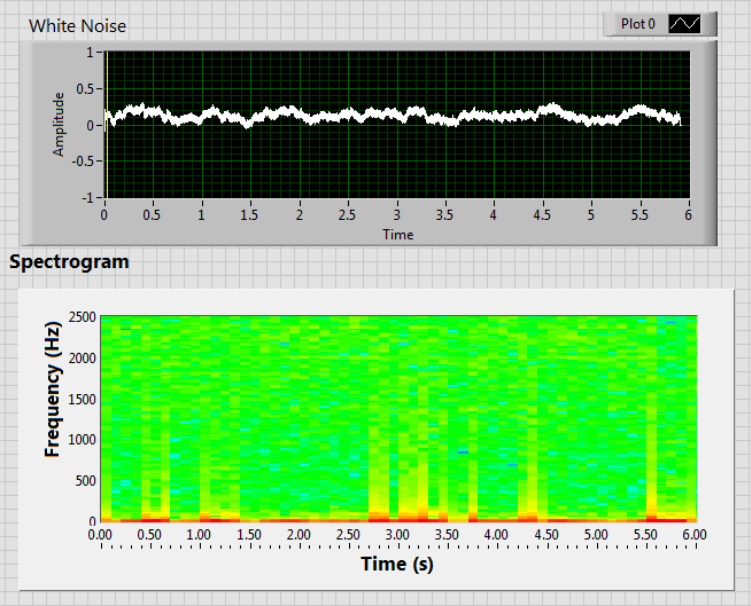


Figure 5.7 (e): The time-domain signals and corresponding spectrogram of the separated White Noise

Note that experimental results have demonstrated that the finer the discretization in time record Δt is, the better the source separation results become. Likewise, the finer the discretization in frequency bands is, the better and more complete the separated signals may be. This is because as Δt reduces, the distinctions between individual acoustic signals become more apparent, making it easier for the source separation. Likewise, further reducing the bandwidth in frequencies will greatly enhance sources separations.

CHAPTER 6

CONCLUSIONS

In this thesis, we have presented an innovative idea of Source Localization by using newly developed Auto-Correlation function. Sound separation using a Signal processing technique is also studied.

Some source localization methods were discussed in the early chapters and also various parameters involved in Time difference of arrival calculation using Cross-correlation and Auto-correlation were discussed in some detail.

We first discussed about Cross-correlation method to find TDOA and then new formulations using Auto-correlation functions were discussed. This included estimation of TDOA, counting the number of multi-paths and arrival time in both cross and auto-correlation functions.

Another innovative technology was discussed to extract the target signal from directly measured mixed signals. A new technology known as Short time source localization and separation (SLAS) was presented in this thesis. Various parameters like Fourier transform, Short time Fourier transform, Window functions were discussed.

Finally we validated all the newly developed technology by comparing the source localization results between Cross and Auto-correlation functions. Results demonstrated that the error in source localization was reduced by 50 % in case of Auto-correlation functions.

We then used SLAS technique to separate the target signals from directly measured acoustic signals. The tests were carried out in AVNC lab, Wayne state university. Three cases

were studied and the time-domain graphs and Spectrogram of both, mixed signals and separated signals were presented.

The passive SODAR [30] and short-time SLAS algorithms were used to perform completely blind sources localization and separation in a highly non-ideal environment. The accuracy in blind source separations can be further improved by decreasing the time segment Δt and using a much finer user-defined frequency band than the standard octave bands. The proposed method could potentially have a significant impact on a number of sectors, including the Homeland Security, defense industries, and manufacturing industries to identify products noise problems as well as improving the product quality issues.

CHAPTER 7

FUTURE WORK

The research performed in this thesis on source localization and separation has produced satisfactory results. However, there is much room for further improvements both theoretically and experimentally.

The auto-correlation functions have to be tested with source kept far away from the micro-phones (greater than 3m). This requires some mathematical formulations to be developed in order to achieve accurate results.

The SLAS technique has been tested to work well in case of speech signals but no concrete tests have been performed with the acoustic signals from the automobiles or the machines operating in the industry. Some testing needs to be performed at that end and parametric studies need to be taken care in case of mechanical signals.

Lastly, some of the signal processing techniques needs to be used in order to get more refined separated signals.

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ABSTRACT

DEVELOPING A SYSTEM FOR BLIND ACOUSTIC SOURCE LOCALIZATION AND SEPARATION

by

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August 2013

Advisor: Dr. Sean F. Wu

Major: Mechanical Engineering

Degree: Master of Science

This thesis presents innovate methodologies for locating, extracting, and separating multiple incoherent sound sources in three-dimensional (3D) space; and applications of the time reversal (TR) algorithm to pinpoint the hyper active neural activities inside the brain auditory structure that are correlated to the tinnitus pathology. Specifically, an acoustic modeling based method is developed for locating arbitrary and incoherent sound sources in 3D space in real time by using a minimal number of microphones, and the Point Source Separation (PSS) method is developed for extracting target signals from directly measured mixed signals. Combining these two approaches leads to a novel technology known as Blind Sources Localization and Separation (BSLS) that enables one to locate multiple incoherent sound signals in 3D space and separate original individual sources simultaneously, based on the directly measured mixed signals. These technologies have been validated through numerical simulations and experiments conducted in various non-ideal environments where there are non-negligible, unspecified sound reflections and reverberation as well as interferences from random background noise. Another innovation presented in this thesis is concerned with applications of the TR algorithm to pinpoint the exact

locations of hyper-active neurons in the brain auditory structure that are directly correlated to the tinnitus perception. Benchmark tests conducted on normal rats have confirmed the localization results provided by the TR algorithm. Results demonstrate that the spatial resolution of this source localization can be as high as the micrometer level. This high precision localization may lead to a paradigm shift in tinnitus diagnosis, which may in turn produce a more cost-effective treatment for tinnitus than any of the existing ones.

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