A study of sound filtering

Development of a filtering system

Darius Chira,Razvan Bucur,Titas Lasickas, Paulius Riauka
Electronics and Computer Engineering, ED5-1-F18, 2018-12

Bachelor Project

STUDENT REPORT

AALBORG UNIVERSITY

This document was created using LaTeX. Illustrations were created using MATLAB plotting, signal analyzer tools and Microsoft Visio. Data processing was performed using MATLAB and

What programs were used for NN stuff?

Electronics and Computer Engineering
Aalborg University
http://www.aau.dk

AALBORG UNIVERSITY
STUDENT REPORT

Title:
Project Title

Theme:
Digital Filtering

Project Period:
Fall Semester 2018

Project Group:
ED5-1-E18

Participant(s):
Darius Chira
Razvan Bucur
Titas Lasickas
Paulius Riauka

Supervisor(s):
Daniel Ortiz-Arroyo

Copies: 1

Page Numbers: 41

Date of Completion:
December 10, 2018

Abstract:

This report will cover the development and research of a noise filtering system using multiple methods.
Development and usage of a directional filtering technique for eliminating directional noise and a Neural Network algorithm for eliminating general noise. All the samples used in the report have been either recorded using a setup presented or synthetically made. Specific samples have been used to train the neural network. Different scenarios are described in order to test the filtering method and observe its behavior.

Contents

Todo list

Preface

Titas Lasickas
tlasic16@student.aau.dk

Razvan-Vlad Bucur
rbucur16@student.aau.dk

Darius Chira
dchira16@student.aau.dk

Paulius Riauka
priauk16@student.aau.dk

Aalborg University, December 10, 2018

Chapter 1

Introduction

One problem affecting 5% of world population and approximately 15% of adults aged 18 and over with and increasing rate with age which grows to almost 50% for persons aged 75 and older is hearing loss. This is quite an important impairment as it effects the quality of day to day life being harder for the individual to take part in social events and different daily activities. Besides the obvious problem of hearing loss is that about 16% of adults aged between 20 and 69 years who could benefit from a hearing aid have never used one. This is partially because of the stigma that comes from using a hearing apparatus.

Figure 1.1: Bruckhoff Hearing Aid Glasses with Bone Conduction Technology

By using a glasses frame with bone conduction technology this can be greatly improved, as glasses are more socially acceptable. Besides the social aspect, a glass frame can fit bigger batteries, more powerful electronics for digital filtering processing time and two microphones with which more complex filtering and speech recognition algorithms can be applied.

add references

With all these being said, the project will involve two filtering methods using both microphones to achieve, theoretically, a better speech perception and understanding.

The first, involves using two microphones in order to record a two or more sound sources, from different angles. With the sound samples recorded, the next step involves handling them in such a manner that allows to filter one source out, and keep the other.

Once one source has been filtered out, the next step is a neural network algorithm to filter the remaining noise from that direction and return a speech as clean and as clear as possible, in this way taking care of any noise that was happening in front or behind the person we want to hear more clearly.

Reading Guide

Chapter 2 deals with problem description and delimitation. Chapter 3 describes the setup, components and methods used for recording samples. Chapters 4 and 5 focus on the two filtering methods tested. The results for both methods are presented in Chapter 6. Chapter 7 and 8 present a summary of the work done, suggest possible future uses of the research presented and draw a conclusion of the work carried out.

wite something about machine learning too

references

Chapter 2

Problem Analysis

2.1 Problem Description

Humans have the ability to identify the source of a sound around them. In the field of neuroscience, this capability is called sound localization. The brain can determine the location of a sound with very high precision, up to 2 degrees of space. This comes from the brain's capacity to interpret information received from both ears.

Over the years, neuroscientists, have been trying to understand the mechanisms within our brains that are able to determine the location of a sound. They have identified two cues that are essential and sufficient for horizontal sound localization.

In the 1790s, Giovanni Battista Venturi conducted experiments where he played a flute around blindfolded people and asked them to point in his direction. He concluded that the sound amplitude difference between the two ears was the indicator used for determining the direction.

Much later, Malloch proposed that the difference in time between the two ears was the sign used for determining the direction of a sound.

Years later, scientists found neurons in the auditory center of the brain specially adjusted for each indicator: time and intensity differences between the two ears.

Figure 2.1 shows a circle, and a person in the middle. The person is meant to be the listener, while the circle represents a perfectly flat plane around the listeners head.

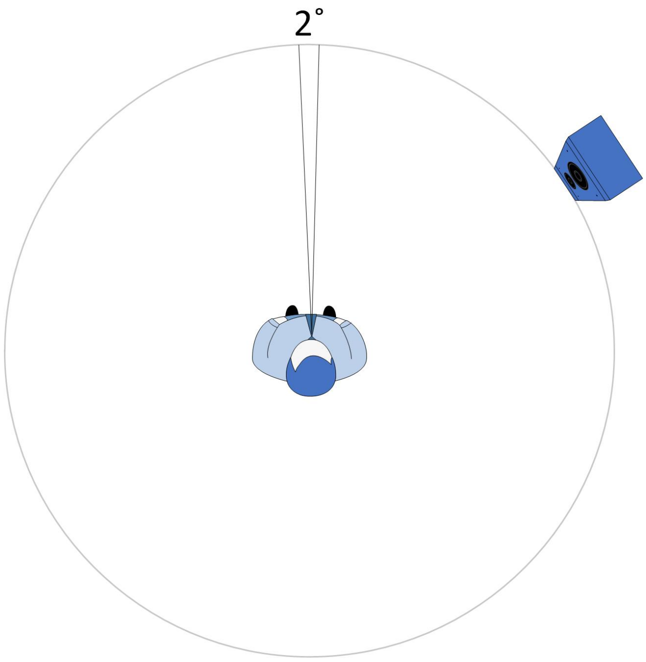

Figure 2.1: Human Hearing Accuracy

Sound coming from the speaker, would reach the right year faster and be louder than the sound that reaches the left year. The brain is able to compare the differences and tell where the sound is coming from.

Vertical sound localization behaves differently. Humans are able to determine the source in the vertical dimension, by making use of the frequency profile of the sound, determined by the size of a persons external ear, called the auricle.

The external ear is able to enhance different frequencies, based on the origin in the vertical plane. Figure XX better showcases the phenomenon.

seems more like project description, fits in abstract

2.2 Problem Delimitation

Vertical Sound Filtering

2.3 Tools

The following list contains tools and softwares used for the development of the filters:

- Python 3.6
- Anaconda 1.7.2
- Jupyter Notebook
- TensorFlow 1.13
- Keras 2.2.4
- cuDNN 8.0
- CUDA 9.0
- Matlab R2018a

ADD more shit that we used

Chapter 3

Development

This chapter describes the setup and the methods used for recording samples that have been later used in testing the filtering method.

3.1 Microphones

Out of all the possible choices, omnidirectional microphones were used. Some advantages of this type of microphones are represented by the face that they have a flat frequency response, meaning they deliver the same electrical output no matter what the angle of incidence. This was crucial to us since different angles were used in recording the samples.

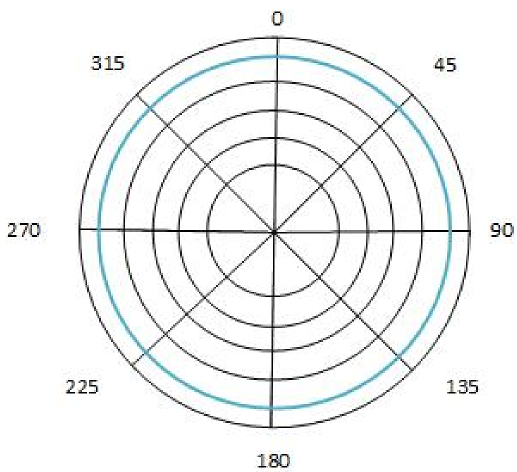

Figure 3.1: Omnidirectional Microphone Electrical Output

Figure 3.1 represents the electrical output of the microphone, in relation to the angle of incidence.

3.2 Distancing

In order to detect a delay between the sound signals, a certain distance between the microphones was necessary. Different distances between the microphones were used in different recording sessions. This poses advantages and disadvantages. For once, a higher distance between the microphones, would result in higher delay, thus giving a better accuracy. However, by increasing the distance, the gain of one of the signals reaching one microphone, would significantly increase over the other. This poses a problem when trying to separate the signals.

3.3 Environment

As an anechoic room was unavailable, the recordings were taken in one of the rooms available at the university. The sound sources around the room were dampened as much as possible, in an attempt to get clear and accurate recordings.

3.4 Sampling

A high enough sampling frequency was needed, due to two reasons. Firstly, a higher sampling frequency gives a higher accuracy in delay samples. Secondly, in order to avoid aliasing. 48kHz was used as sampling frequency. This gives the highest accuracy that the microphones can provied, and is also high enough to avoid aliasing.

3.5 Setup

Figure 3.2 represents the setup used. The microphones have been put up at a approximate height as the speakers mouth, in order to more accurately capture the delay.

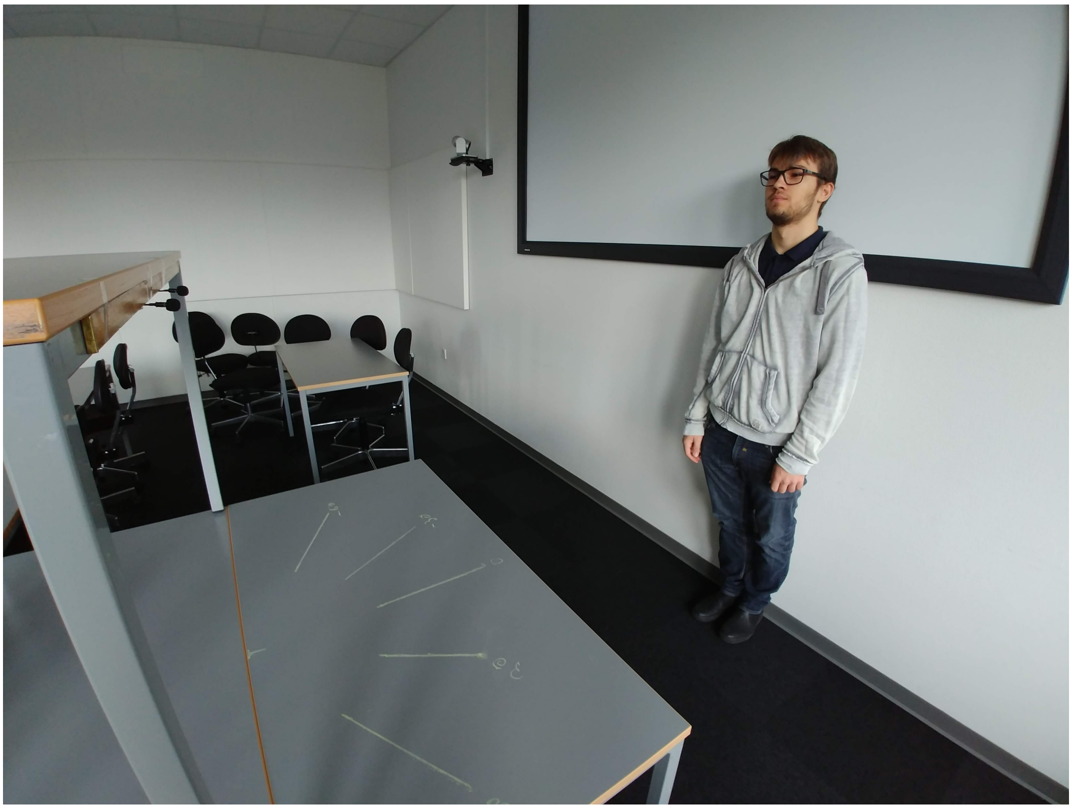

Figure 3.2: Microphone Setup

Although this height might vary in real life scenarios, the same height was used throughout multiple recording sessions due to simplicity.

Different recording scenarios were considered, involving one, two or three persons, acting as sound sources, coming from different angles.

Filtering was attempted on all of them, with different results obtained.

Figure 3.3 shows the approximate angles at which different recording were taken. Knowing the angles was important for us to be able to test the filtering method.

This wasn't used in NN part. Move to Directional filtering?

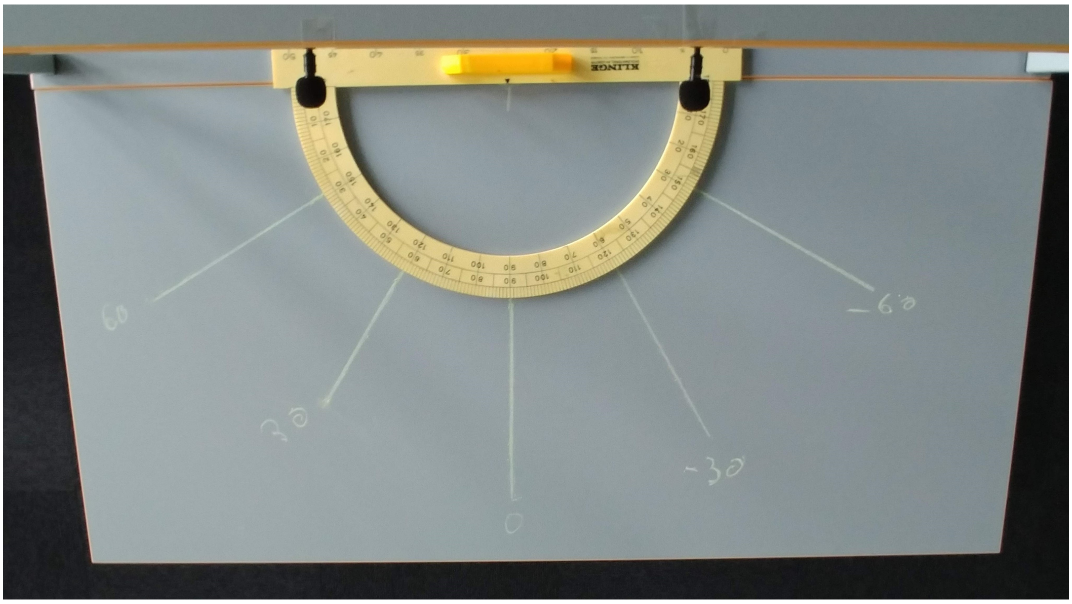

Figure 3.3: Setup for Recording

Chapter 4

Directional Sound Separation

This chapter deals with directional filtering. In the beginning, the prerequisites for the filtering idea are presented. Afterwards, the actual filtering idea is shown and explained. In the end, the results are presented, and a conclusion is drawn.

4.1 Concept

Figure 4.1 shows a scenario where directional filtering could be used. Source 1 and Source 2 are both talking simultaneously. At the origin, two microphones, left (L) and right (R) are fixed and recording.

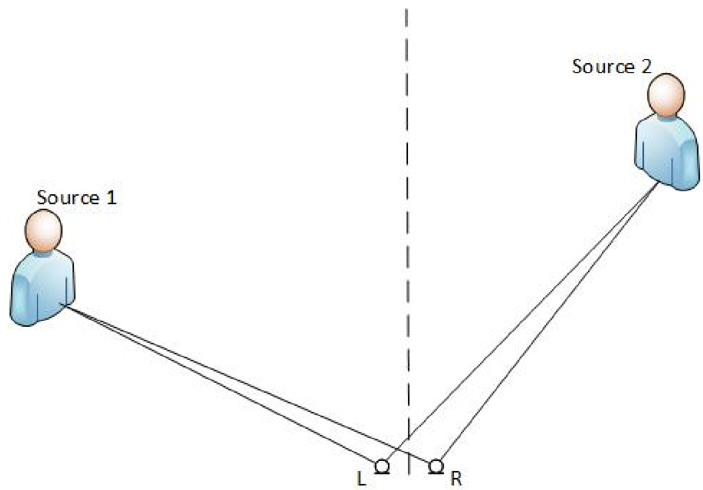

Figure 4.1: Two Persons Talking

Due to the nature of the setup, the microphones will record both the speakers. However, both microphones record two persons talking. As a consequence, each microphone returns a soundwave containing two signals. The aim is to filter out one of them by only using the two soundwaves available.

In order to be able to do this, one assumption needs to be made. That is, that the angle at which each source is located, is known.

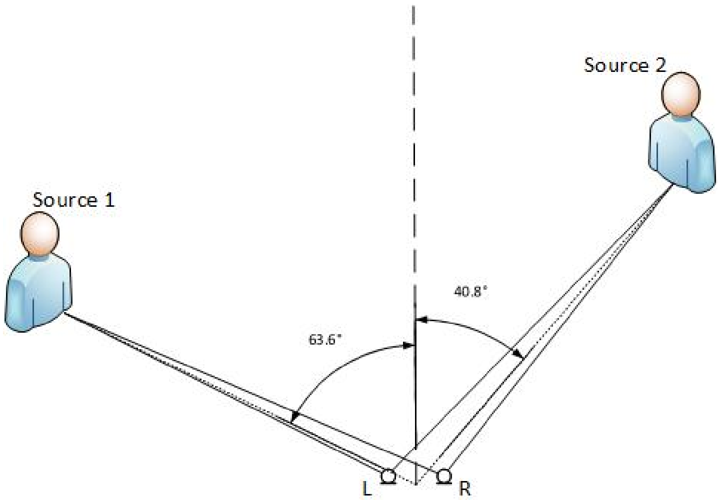

Figure 4.2: Two Persons Talking With Known Angles

Figure 4.2 represents the same scenario. However this time, the angles of the sound sources are known. The Sources and the Origin are represented with coordinates. This helps in determining the formulas that are needed in order to obtain the delay in samples.

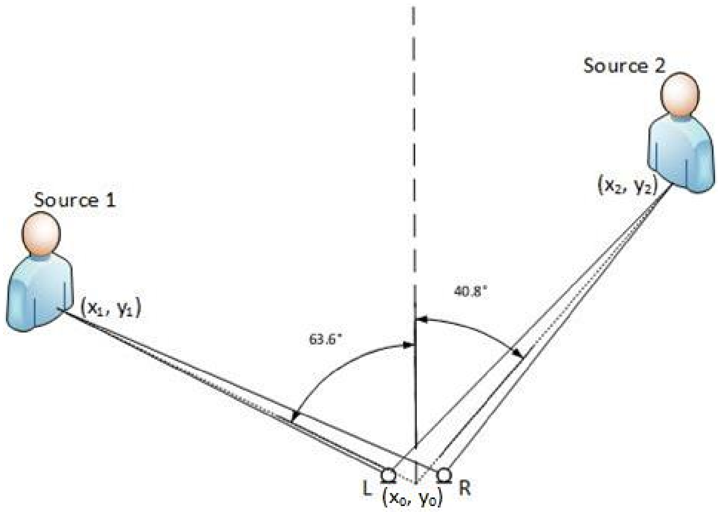

Figure 4.3: Two Persons Talking With Known Angles

Figure 4.4 represents the delay between the two signals. One advantage is represented by the fact that, no matter the distance of the source, the delay between the signals is always the same. The delay in samples is only dependent on the distance between the mics. By knowing the angle, the sampling frequnecy and the travelling speed of sound, the delay in samples can be determined. By increasing the distance between the microphones, greater accuracy could be obtained. However this would also result in a bigger difference in terms of signal gain. One signal would be significantly louder than the other to the point where filtering would not work.

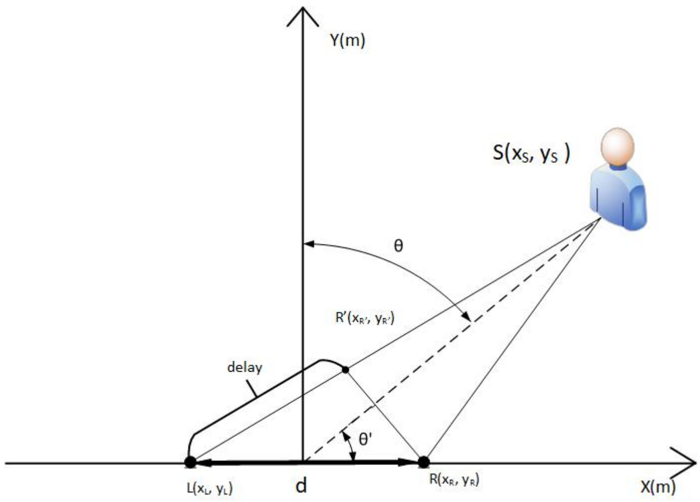

Figure 4.4: Delay

4.2 Mathematical Solution

Figure 4.5 is a simplified version of Figure 4.4 in order to better understand the mathematical proof of finding the delay in number of samples.

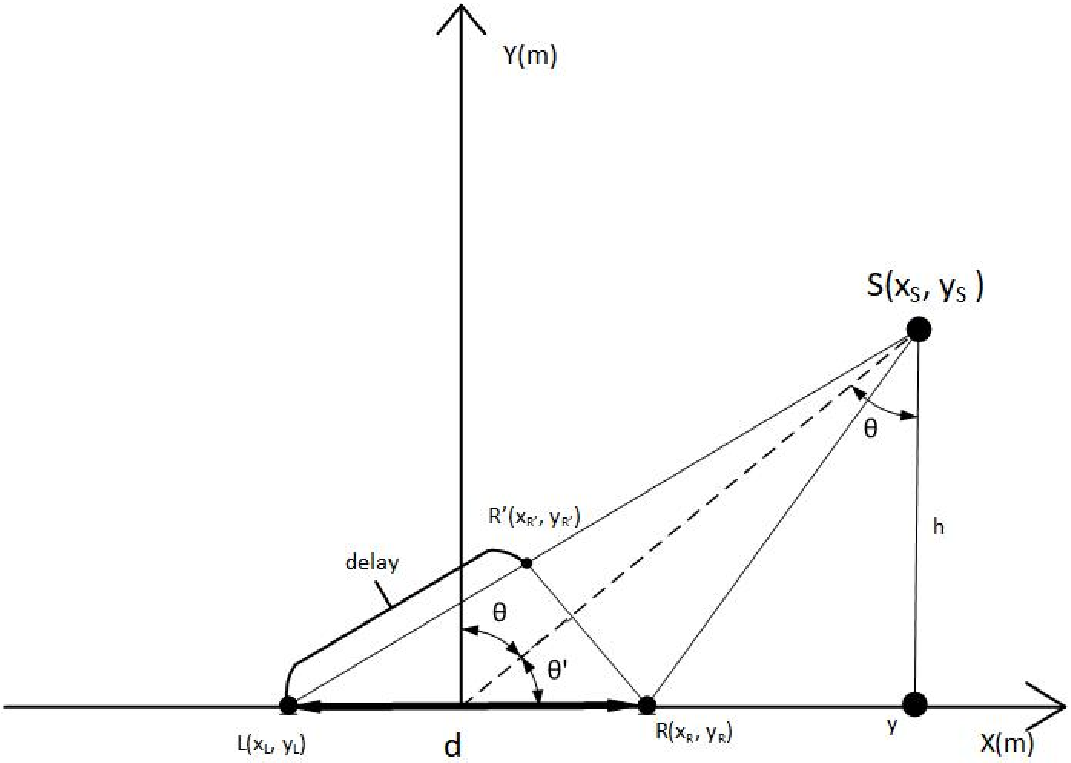

Figure 4.5: Mathematical Interpretation

Firstly, the distances SR and SL must be determined. This can be found by employing basic trigonometry. This is done by independently finding out the sides of the triangles SyL and SyR.

$$yR = sin(\theta) - \frac{d}{2} \tag{4.1}$$

$$yL = sin(\theta) + \frac{d}{2} \tag{4.2}$$

After the x-coordinates are determined, h is needed in order to calculate the y-coordinates.

$$h = cos(\theta) \tag{4.3}$$

Lastly, the sides SR and SL are determined.

$$SR = \sqrt{h^2 + yR^2} \tag{4.4}$$

$$SL = \sqrt{h^2 + yL^2} \tag{4.5}$$

Once the distances are known, the difference in distance between the signals can be found.

$$delay = SL - SR \tag{4.6}$$

At this moment, the delay is expressed in distance. By knowing the speed of sound, the amount of time it takes to travel that distance can be found.

$$delayInTime = \frac{delay}{speedofsound} \tag{4.7}$$

The time, can be converted in amount of samples by multiplying it by the sampling frequency.

$$delayInSamples = delayInTime * SamplingFrequncy \tag{4.8}$$

4.3 Filtering Idea

With the angles of both sources known, one or the other source can be isolated. The only sound source considered in this project was human voice. Therefore, the aim is to separate the two voices, by only using the sound samples recorded by both microphones. The data recorded by each microphone, contains two separate human speeches. Figure 4.6 explains the process. Afterwards, a more visual example will be discussed, aimed at better describing the procedure.

Figure 4.6: Idea diagram

Both microphones record the same data. The only two differences, are the delay in time, and the gain difference. By shifting one recorded sample in order to match the other, and subtracting the signals, the matched data is eliminated. This means that by aligning one speech, and then subtracting, the other speech is separated and obtained.

4.4 Visual Example

A visual example is explained below. Actual differences can even be seen on the waveforms themselves. The example is ideal, meaning there is no noise applied to the signals, and their purpose is to prove the idea.

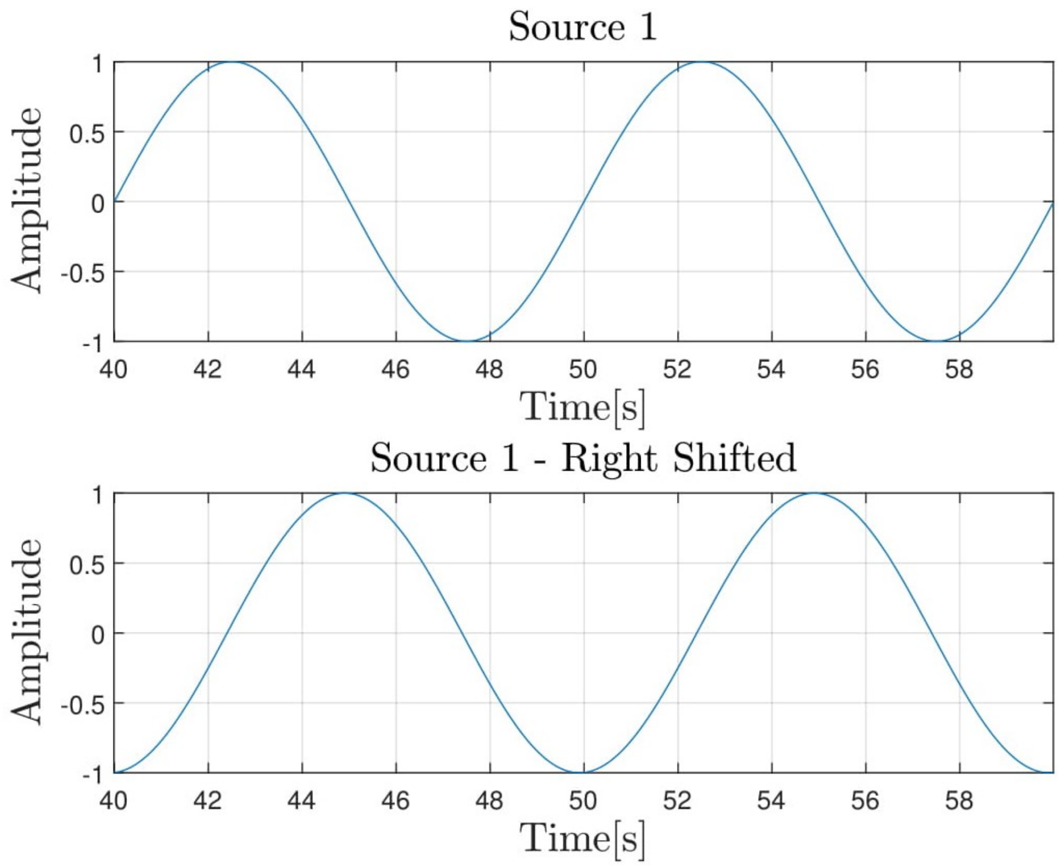

Figure 4.7: First Source

Figure 4.7 shows a simple sine wave. Source 1 is the original signal. Source 1-Right Shifted is the same signal just shifted to the right by 240 samples.

Figure 4.8 shows another sine wave, with a higher frequency and a lower amplitude. This represents the second source. Source 2 is the original signal. Source 2 - Left Shifted is the same signal shifted to the left by 377 samples.

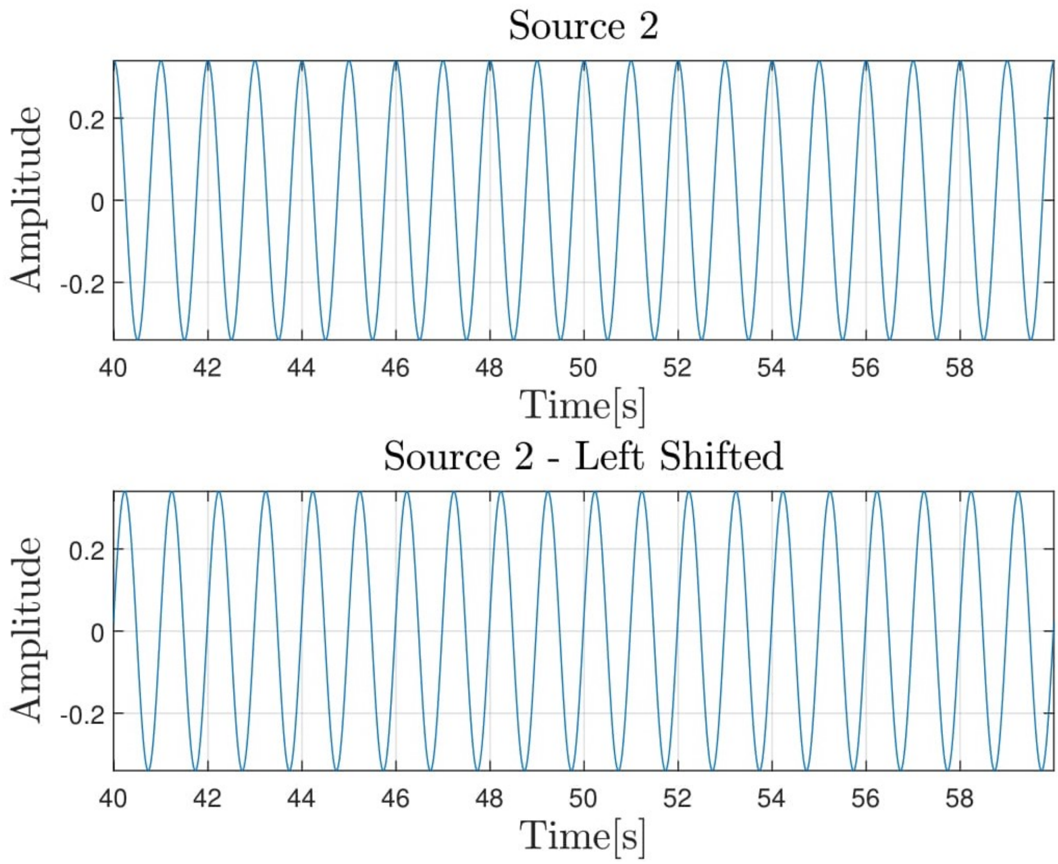

Figure 4.8: Second Source

Next step involves adding the signals.

$$Source1 + Source2LeftShifted = LeftMicrophone \tag{4.9}$$

$$Source1RightShifted + Source2 = RightMicrophone \tag{4.10}$$

Equations 4.9 and 4.10 now have both signals from both sources.

$LeftMicrophone$ contains $Source1$ and $Source2LeftShifted$. $RightMicrophone$ contains $Source2$ and $Source1RightShifted$.

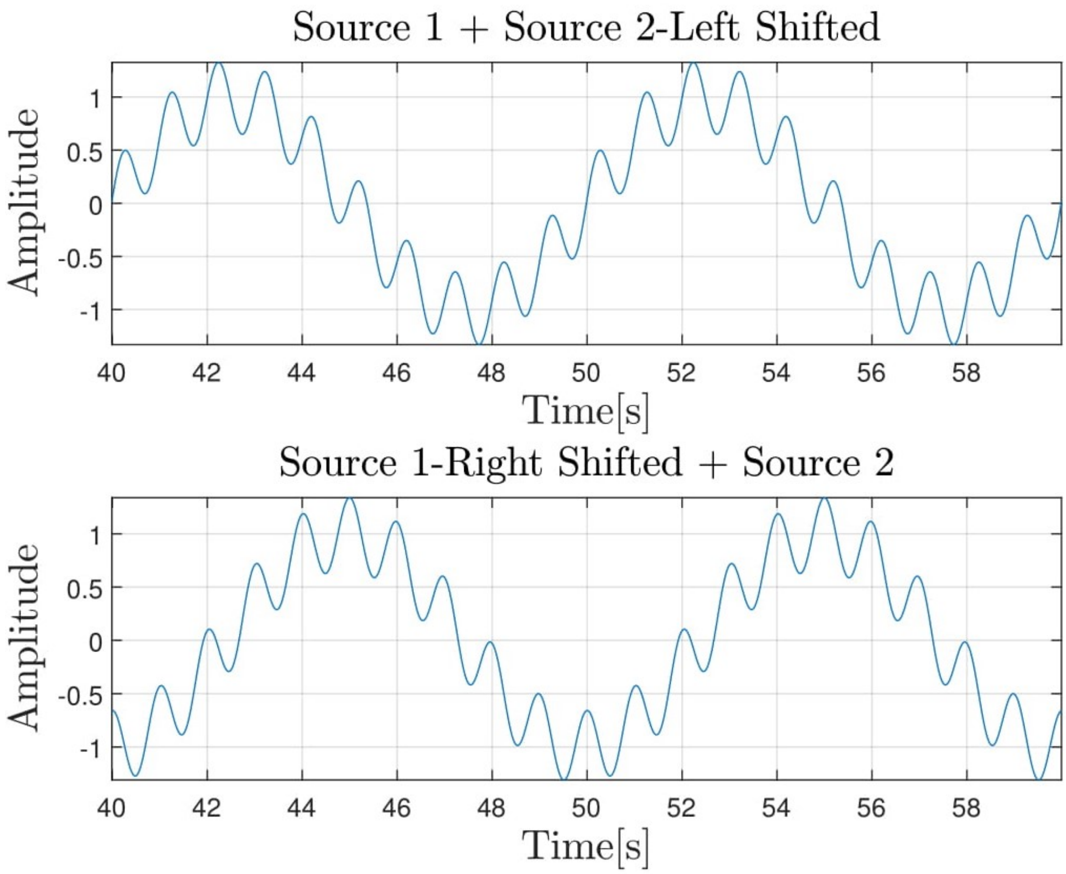

Figure 4.9: Added Signals

They are represented in Figure 4.9. The summation of both signals can clearly be seen above.

Sound Separation

We aim at separating the sounds by only using the previous signals seen in Figure 4.9. Knowing the angles and the amount of delay in samples, the separation of the two signals reduces to a matter of matching and subtracting them.

Important to notice. The matched signal is the one filtered out.

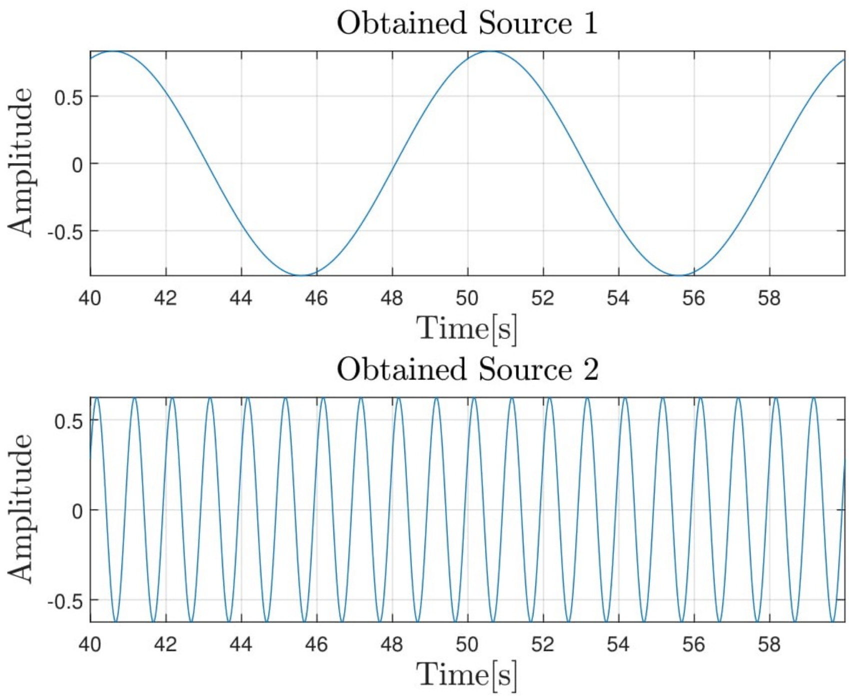

Figure 4.10: Obtained Signals

Figure 4.10 represents the obtained signals after matching and subtracting the signals in figure 4.9.

The signals seem to have a slight phase shift. Additionally, they have higher amplitudes, than the original signals. As of right now, we are not able to determine why. However the waveforms are very similar. All figure can be seen in Appendix X.

remember to put stuff in appendix

4.5 Filtering

All of the directional filtering is done by applying the logic discussed before. Prior to shifting signals and do the actual filtering, we had to remove any other delays, introduced by hardware and software.

We attempted to resolve this issue by introducing a loud sound, such as a finger snap, or a clap at the start of every recording session. Using that, we matched the highest peaks, and eliminated a big part of the delay caused by anything else besides the distance between the microphones.

4.5.1 One Source

Initially, a recording by only one person sitting in the center, meaning 0°, was recorded, to observe if after all the other delays were eliminated, the data would match.

Figure 4.11 represents the data collected. As can be observed on the figure, the two signals match in phase, and have fairly similar amplitudes.

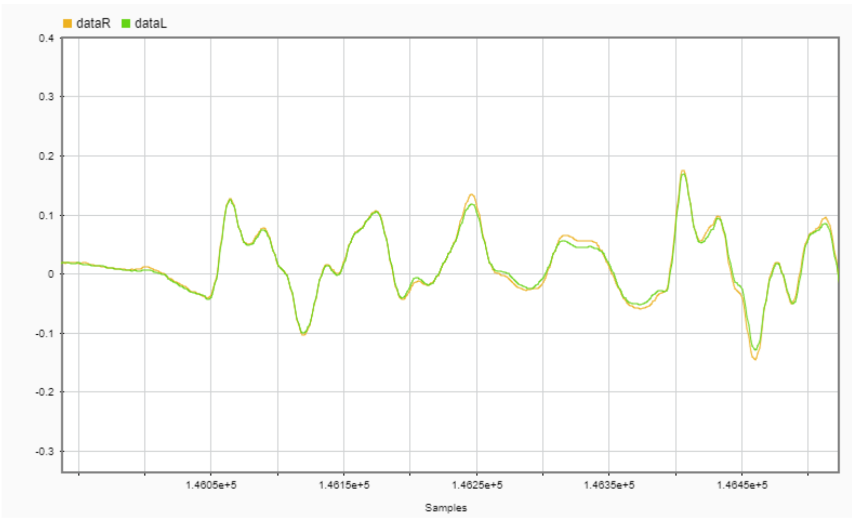

Figure 4.11: Center Sound Source

When recording with the sound source coming from the right of the setup, the right microphone has slightly higher amplitude and its' data leads the left microphone data as seen in Figure 4.12.

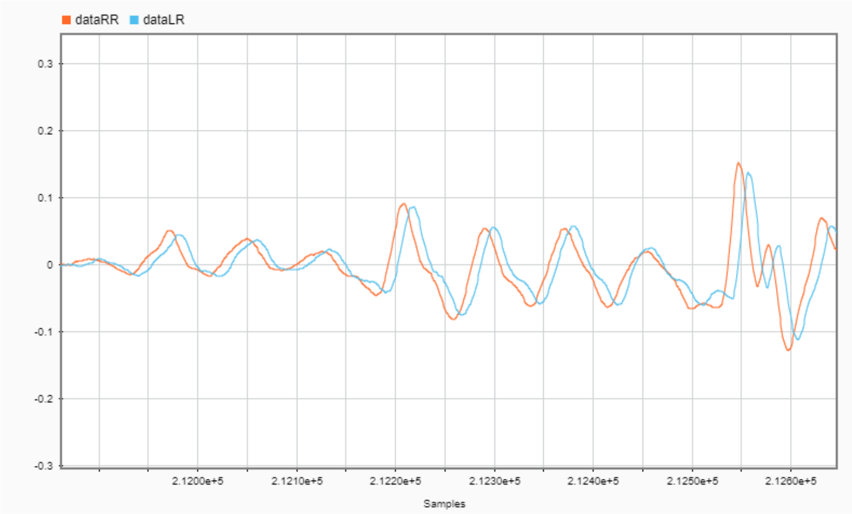

Figure 4.12: Right Sound Source

Another recording was taken, this time with a sound source coming from the left. The results can be seen in Figure 4.13.

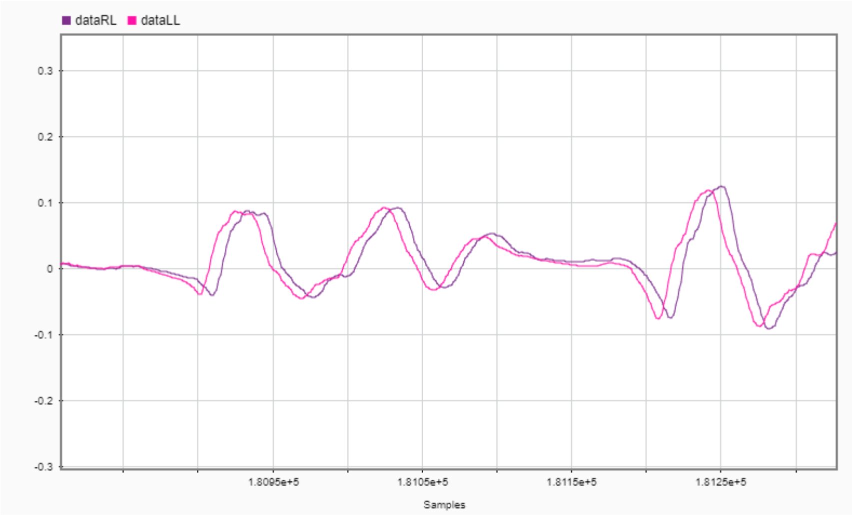

Figure 4.13: Left Sound Source

Results

An early attempt at filtering speech, was done on only one person. The data was firstly matched, and then subtracted. The result of it, can be seen in Figure 4.14. The green data represents the original recorded signal, while the blue data represents the filtered data. Ideally, the blue data would have very low amplitude, and should be inaudible.

However, after listening to the signal, it still contained enough data to hear what the person that should be filtered out, is saying. Even though the goal was relative silence, the sound level dropped significantly.

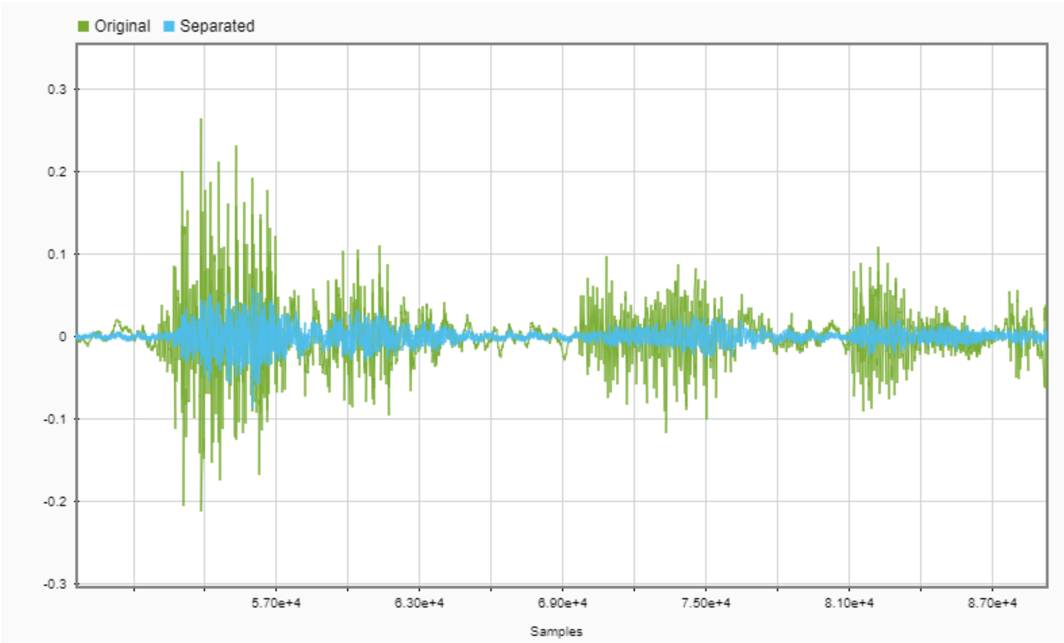

Figure 4.14: Data Comparison One Source

4.5.2 Two Sources

The same separation method was applied for two sources. Due to no other sounds being present, we assumed that this might be one of the reasons we were able to still hear some of the original speech that was intended to be filtered out. If other sound would be present, maybe their strength would overcome the signal that was intended to be filtered out.

After shifting the left microphone data, some data lines up with the right microphone data in Figure 4.15, which suggests it could work and it would separate the unwanted sounds from the samples.

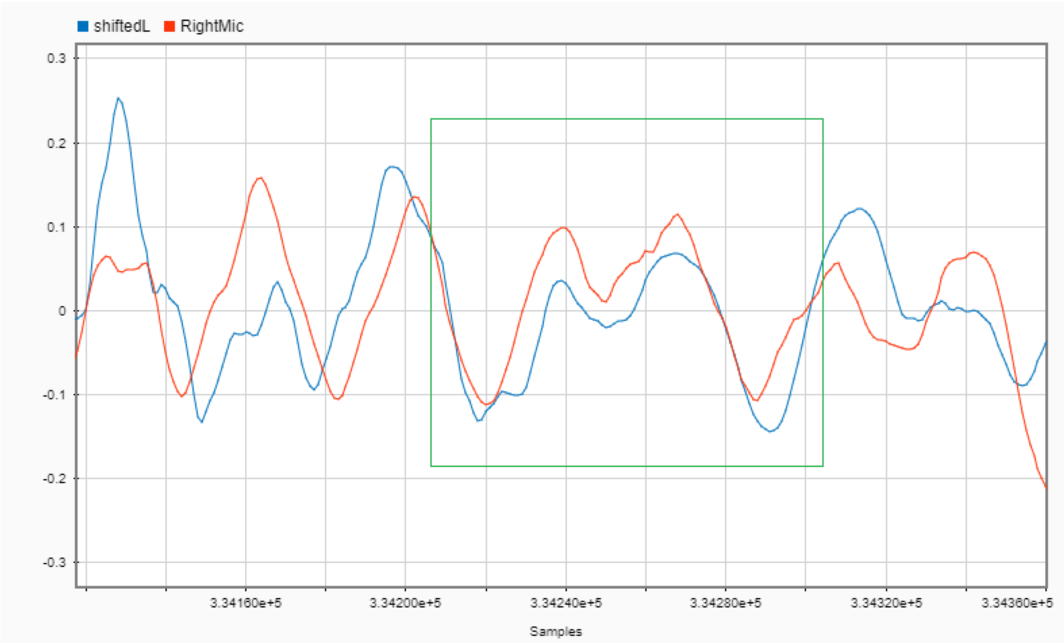

Figure 4.15: Two Sources, Aligned Data

The separated data was compared to the original data. The comparison can be seen in figure 4.16.

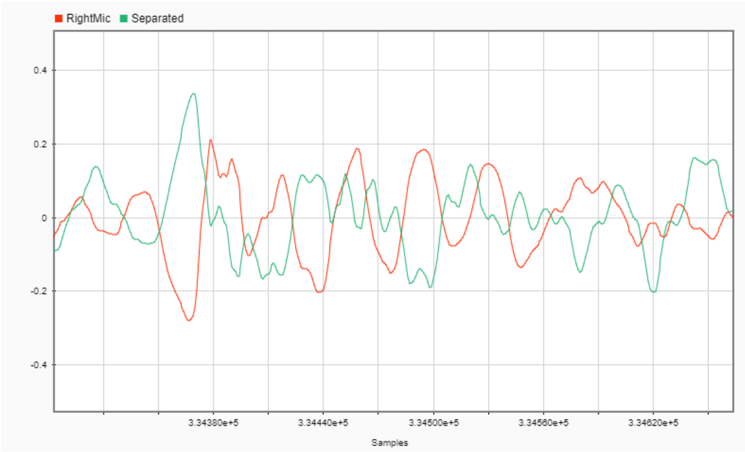

Figure 4.16: Separated Signal And Original Signal

Results

This was deemed as a failed attempt. However not necessarily because of the method, but rather because of the, equipment used and environment to record the samples, which were not ideal. Neither of the microphones captured the sound waves identically. This can be seen in Figure 4.17. The clap at the beginning of the recordings can be represented. Ideally, microphones would register identical waveform, but in the figure they are clearly different.

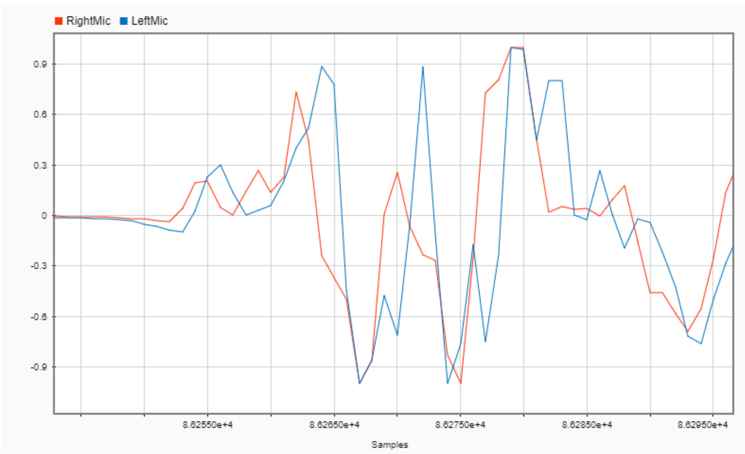

Figure 4.17: Clap in the beginning of recording

4.6 Synthetic Samples

Failing to observe any noticeable separation when using real samples, we have decided to attempt the same separation method using synthetic samples. This was done in order to find out if the method was in itself wrong, or something else had a bigger impact, due to which we were unable to see any differences.

Synthetic samples were made, by recording one person talking, and then articulating the data to take delay and gain into account, in an attempt to make them sound as real as possible.

Using synthetic samples also allowed for more flexibility when testing the code, by being able to adjust the angle of the source.

Gain ratio

A gain need to be multiplied with one of the signals, to account for the distance difference. If one source is closer to one microphone than the other, the signal from that source needs to have a higher strength, to mimic real behavior of the scenario.

Sound strength falls by a ratio of 0.5 when the distance is doubled. Meaning that sound strength follows distance inverse-proportionally.

By giving one of the microphones gain ratio of 1, the ratio for the other signal can be determined. Figure 4.18 illustrates the variables used in the equations.

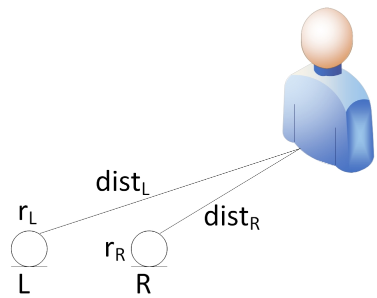

Figure 4.18: Gain Ratio

$$\frac{r_L}{r_R} = \frac{dist_R}{dist_L} \tag{4.11}$$

Using this proportion and keeping r_L as 1, the gain r_R will be multiplied with right microphone data to get realistic gain loss. Distances $dist_L$ and $dist_R$ here are the same distances, which are calculate in the delay code. This means that in order to get the gain ratio for right microphone, the distance to the left microphone ($dist_L$) needs to be divided by distance to the right microphone ($dist_R$).

Adding recordings

Firstly, each recording is shifted by an amount of samples, corresponding to the angle we want. Afterwards, they are multiplied by their respective gains. Lastly, they are cut down to the same size to make the adding easier. Right Microphone corresponding to each source will be multiplied by the gain, while Left Microphone corresponding to each source will be shifted.

Results

The speech separation was attempted successfully with synthetic samples. Either of the sources can be separated and clearly heard. The filtering method however, has some limitations. If the angle between the sources is too big, the gains of each signals are significant enough to not be able to filter them out completely, just by subtracting. We are hoping that by using machine learning, this issue could be solved as well.

Chapter 5

Neural Network Noise Suppression

In this section the Machine learning approach will be explained together with the signal processing needed for it. This method will be used to suppress the noise from the signal, keeping the speech as clean as possible.

5.1 Signal Processing

A sound wave at its most basic form is described as a vibration that propagates in a medium as gas, liquid or solid as an audible fluctuation in pressure. A transducer, as a microphone has a diaphragm that vibrates according to those fluctuations. In this way the amplitude, the power of pressure, can be recorded. Another property of of sound wave is the frequency, which is the variation of the amplitude over time, which can be easily calculated from a two dimensional plot, with the two axis being the amplitude and the time, looking at the number of occurrences of a cycle in a unit of time.

5.1.1 signal preprocessing

As sound is an analog signal, for recording that signal it will have to be sampled. Depending on the sampling rate, the sound signal can have varying degree of quality, human ears are most the most sensitive in the range of 100 to 3000 Hz which are also called the fundamental frequencies. But human voice also has harmonics which are in the range of 900 Hz to 17 KHz. According to the Nyquist rate of signal processing, the sample rate should be at least double the frequency of the signal in order to avoid aliasing.

Fits in development or introduction?

link the nr of picture in text

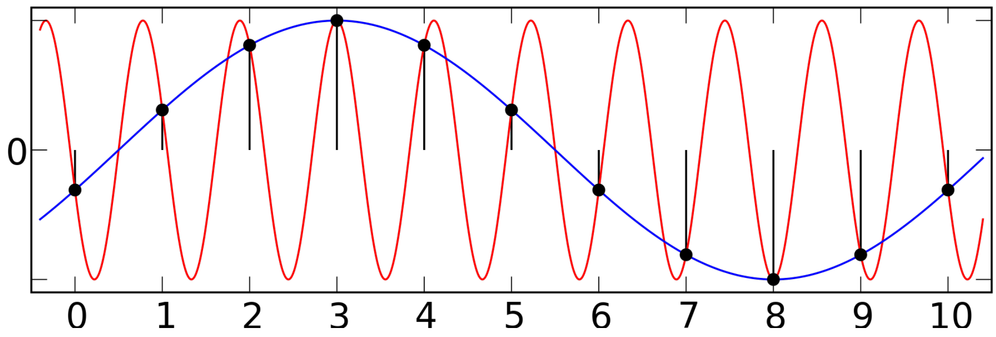

Figure 5.1: Consequences of different sampling rates

add here nr

As we can see in figure if the sampling rate is too small, the signal will be aliased and will get a wrong representation of the signal.

5.1.2 Fourier Transform

As useful as the amplitude might be, for a closer inspection of a signal it is not enough to differentiate human speech from different sound sources. Any sound signal can be recreated from a combination of sinusoidal signals at different frequencies. For that reason the Fourier Transform can be used to decompose the sound in multiple frequencies. By transforming the signal from the time domain to the frequency domain we can get a lot more information about a specific signal. By plotting these, we will get the amplitude of each frequency over the whole signal.

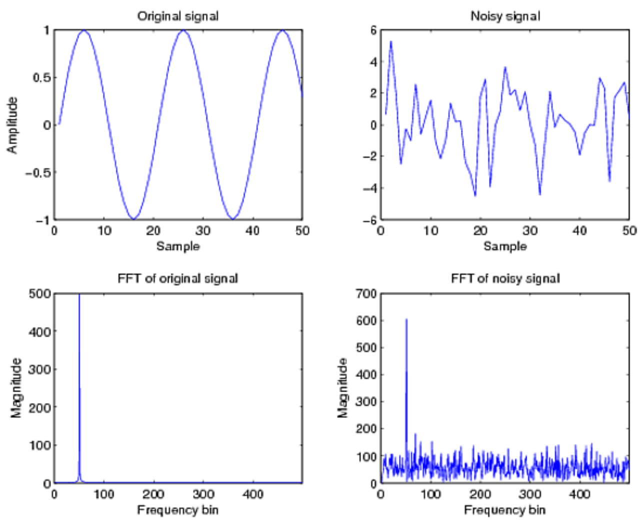

Figure 5.2: FFT representation of a sine wave and a noisy one

As we can see in figure besides being able to differentiate between different sound sources, especially clean speech, as it was said in a different sections, we know the frequencies in which human voice is so we can see it easier in a frequency domain representation , we can identify noise easier too.

add nr for picture

5.1.3 Spectrogram of a signal

Except for perfect examples, just a Fourier transform plot will not be that useful as some sound sources can be only in a part of the full sample and by viewing the plot over the whole sample it will not be accurate enough for filtering. For this reason a spectrogram can be used, which instead of taking the Fourier transform over the whole sound sample, it will make multiple ones over 0.25 second frames. By doing this we can get 3D plot, where we can have the X axis for time or samples, Y axis for the frequencies and color for the amplitude. By doing this a really clear representation of the signal can be made from which multiple aspects of the signal can be seen and used.

ADD picture of spectrogram with speech from matlab

5.1.4 Mel-frequency cepstrum

A Mel-frequency cepstrum is made out of a multitude of Mel-Frequency cepstral coefficients(MFCCs). Those are taken from a cepstral representation of the audio sample(or a spectrum of a spectrum). This can be really useful especially for speech identification as the frequency bands are spaced equally on the Mel scale instead of linearly spaced frequency used in a normal cepstrum. The mel scale is more useful for this case as it better approximates how humans actually perceive sound.

maybe photo, most probably photo

Besides this, instead of using the full cepstrum, only 24 bands can be used, by using the Bark scale instead. The bark scale is psychoacoustical scale that represents the first 24 critical bands of hearing. This can easily be made as mel scale and Bark scale are proportional to each other as 1 Bark is approximately equal to 100 mels. By doing this, memory and processing power can be saved by using only 24 bands instead of thousands.

add reference

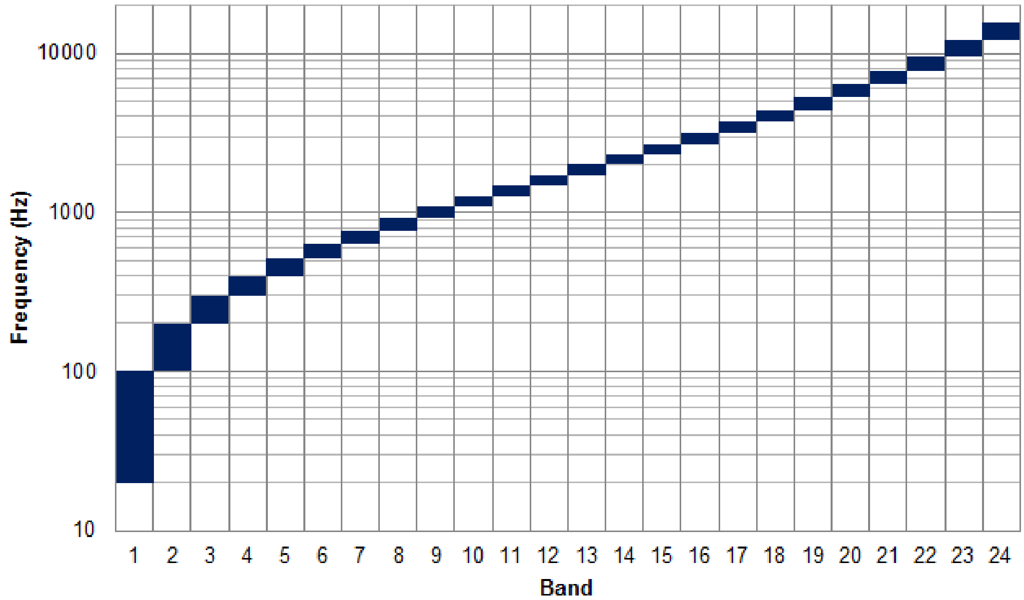

Figure 5.3: The 24 bands of the Bark Scale

5.2 Artificial Neural Network Theory

An Artificial Neural Network is a a machine learning technique or computing system that slightly resembles a brain and its neuronal connections. Being programmed without specific rules, an ANN system has one or more layers of artificial neurons with specific weights associated to each one of them. By giving the system multiple input sequences, it will ̈trainïtself by adjusting the weights to have an output prediction that will resemble the wanted output as much as possible.

5.2.1 Artificial Neurons

An artificial neuron is an elementary unit in an artificial neural network. As being inspired by biological neurons, their purpose is to simulate the different function that they have:

- Gathering all the inputs
- Multiplying with their each individual weight
- Adding all the weighted inputs
- The sum will be passed to the activation function
- Outputting the result

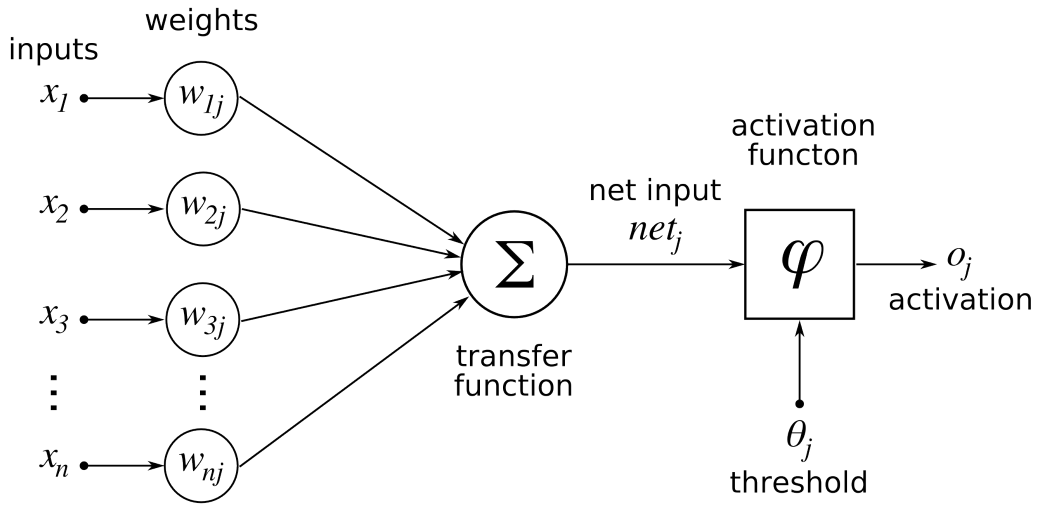

Figure 5.4: Example of an Artificial Neuron

In figure , representing an artificial neuron, all those functions can be seen. The neurons will be received, multiplied by a vector of weights, added together and sent to the activation function which will then give the output of the artificial neuron.

add nr of figure

5.2.2 Activation Functions

As stated in the last section, each neuron will have an activation function. Being biological inspired, it usually represents the rate of action potential in the cell, depending on the range and the case, this can be from 0 to 1 or from -1 to 1. In the range of 0 to 1, which resemble the biological neuron more, this can be seen as the neuron firing or not.

Two of the most used activation function are: The sigmoid Function: Which maps the input from 0 to 1.This can be really useful where neurons have to predict the probability as the output.

- The sigmoid Logistic Function: Which maps the input from 0 to 1.This can be really useful where neurons have to predict the probability as the output.

$$\phi(z) = \frac{1}{1 + e^{-z}} \tag{5.1}$$

- Hyperbolic tangent function: Which maps the input from -1 to 1. This can be used when the classification between two classes is needed.

$$\phi(z) = tanh(z) = \frac{2}{1 + e^{-2x}} - 1 \tag{5.2}$$

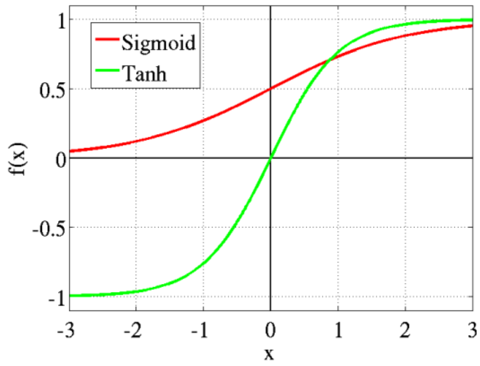

Figure 5.5: Both sigmoid and tangent functions exemplified

5.2.3 Types of Artificial Neural Network Layers

dik

Chapter 6

Discussion

This chapter seeks to understand and explain why the speech separation method worked in theory, however failed in real life scenarios. It also talks about future perspectives of the research done and presented in this report.

6.1 Observations

We believe, some of the factors presented below, might have had a high enough influence for the speech separation method to not fully function in real life scenarios.

Microphones

One of the factors that probably had the biggest impact was the quality of the microphones. As more performant microphones were not available, we resorted on using a pair of very low price microphones purchased online.

Measurements

Whenever recording samples, the angles of the recordings might not have been exact, leading to improper matching between the microphones. Additionally, even though a ruler was used to try and keep a fixed distance between the microphones, slight misalignment might have happened, thus giving the wrong amount of delay samples.

Software

Software induced delay was another issue we tried to make up for as much as possible. Having used two USB microphones, the samples have included any latency caused by the microphones, which is different from recording to recording.

6.2 Future Work

Hearing aid technologies have never been improving as fast as they do now. Ever since major smartphone manufacturer companies started investing into wireless wearable technology research, price of PSAP (personal sound amplification products) has decreased while the amount of features has increased. Throughout recent years wireless earphones became predominant in the global market due to new generation of Bluetooth technology. This improvement even further reduces power consumption of wireless technology. The only three differences between hearing aids and PSAPs were:

•The battery life. Due to a far higher number of features and consistent audio stream PSAPs consume a much higher amount of power.

•Hardware design differences. PSAPs are not oriented around sound localization to inform the user about where the sound is coming from regarding natural sources. PSAPs are often not oriented to be invisible to others, they are more often purposely made to stand out and be recognized among its competitors. Fit customization is also often minimal on PSAPs.

•Regulation requirements to produce the hearing aid and license requirements to sell it.

Most other differences lay in software and could be eliminated through a software update.

It is believed that legislative issues could be solved if manufacturers would put effort to reach for an agreement with legislators although it would require a lot of changes since current hearing aid selling process consists of far more than just taking the product off the shelf and swiping it through the register - it is normally performed at hearing clinics, hearing aid is thoroughly adjusted to fit the consumer's ear for long periods of time, warranty for these devices also is taken in a far more serious manner: it comes with included follow-up office visits, checks and cleaning procedures to maintain the highest level of performance. Some companies do express interest to merge the two markets. According to "The State of Hearing Healthcare 2017" by Lindsey Banks, "If Apple Air Pods or Samsung Gear IconX could add in hearing aid functions, that's instant access to over half of the U.S. over night."

`https://www.everydayhearing.com/hearing-loss/articles/state-of-hearing-healthcare-2017/ ((puthashhere))tech`

The value of argument regarding battery life of these two hearables should also heavily decrease in the coming years. At the end of October 2017 Samsung has announced that a considerably new generation of battery has been developed. Currently used lithium-ion batteries seem to have been pushed to it's limit and yet it still takes a fairly long time time to charge in a fast-paced society. This problem has pushed electronics manufacturers to develop energy efficient processors. A new graphene-based battery technology should enable 45 percent more capacity and 5 times faster charging speeds.

https://news.samsung.com/global/samsung-develops-battery-material-with-5x-faster-charging-speed

These reasons should lead to a breakthrough in battery life factor of next year's electronics. If not at 2019, by 2020 hearing aids should receive this battery update. Combined with improvements in Bluetooth technology, these reasons should encourage both hearing aid and consumer audio manufacturers to increase number of features in coming year's hearing aids as well as PSAPs and might bring the markets closer together.

Chapter 7

Conclusion

Appendix A

Appendix A name

Here is the first appendix