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Acoustic Detection of Rear Approaching Vehicles for Cyclists

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Preface

It is really great to achieve something after having a long time of study. I am glad that I have experienced such project and gained knowledge both in theoretical and practical field.

I would like to thank my supervisor Tony Larsson for his perceptiveness and guiding me through out this project.

I also would like to thank Kenneth Nilsson for his feedbacks on my work and Cristofer Englund who has offered me this project from the Company Swedish ICT Viktoria.

Finally, I would like to dedicate my work to my supportive parents who have done everything they could do for me to be successful.

Ahmet Tansu BAKKAL

Halmstad University, April 2014

Abstract

The project is given as a proposal for increasing the safety of cyclists riding on the country roads. It can be sometimes hazardous for bike riders to ride either on the same road with the cars or on the suburban road. Thus, an alerting system which will be mounted on the bicycle is required.

The aim of the project is to find most suitable sensor which can generate the alert early enough that cyclist can take an action before the vehicle reaches up. Since the sensor will be used for bicycles, power consumption and the size of the sensor should be rather small.

Audio detection was chosen from among all the possible detection types. In order to distinguish the sound from an approaching vehicle among all environmental noises, many samples were collected and analysed. Classifying and comparing the sounds; the most interesting features of the vehicle approaches were found out as; frequency shifts and amplitude increment in power spectrum, regularity/irregularity changes within the sound, mass point shifts and loudness level increment.

Four different methods were used regarding correlations. Samples were filtered to obtain better results. Considering all the cases, there is a threshold was set for all methods in order not to confuse them with environmental noises or riskless cases. Specifying a threshold value has also its disadvantages, because making alert generation more reliable is inversely proportional with success ratio. The most of the methods given in this report have the approximate success ratio of % 70.

Having approximately %70 of success ratio for each method is quite sufficient, considering those methods can be fused together to have more accurate sensor.

My work is a proof that many different types of sound correlations can be used to determine if there is a vehicle approaching or not. Methods that pointed out in this report can be used to build up a fine alerting system to increase the awareness of cyclists.

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Chapter 1

1. Introduction

1.1. The Problem Description

Cycling is one of the most common preferred transportations in today's World, especially in Europe. Cycling is not only an easy, cheap and nature-friendly activity but also healthy for short way trips. In addition to the fact that cycling is used for transportation, cycling is also used for sport and recreation.

As being an alternative way of transportation besides vehicles, cycling brings its own disadvantages. Bicycles don't have a discernible shape in traffic comparing to motorized vehicles which makes it harder for drivers to realise cyclists easily. Having low equipment on the bicycle by the means of security and discernibility is another disadvantage of cycling. These factors strengthen the possibility for a cyclist to have an accident with a motorized vehicle; especially during bad weathers, dark times and on winding roads.

Another tragic concern about this kind of accident is its causalities. Either it can be predicted by common sense or looking into statistics; it can be seen that causalities are not tending to be equal when a motor vehicle and a bicycle have an accident. Cyclists are exposed to higher risk of injury or even death when compared to motor vehicle drivers. In Sweden, 3000 cyclists are injured so badly each year that they are permanently crippled or needed to be taken to hospital [1].

It is more obvious how widespread is the cyclist accidents happening in Sweden, if we look into statistics. According to Swedish newspaper Dagens Nyheter (DN) [1], only 28 percent of accidents involve solely cars in Sweden. Meanwhile, 48 percent of accidents involve bikes. Bike helmets and security equipment may partly protect the cyclist, though cannot avoid accidents. While cyclists face with higher risk of injury and have majority in accidental case percentage; it is paramount to have an alerting system. The system should warn the cyclist in danger cases to avoid accidents and injuries.

1.2. Hypothetical Approach

The most important part of starting a project is to know how to interpret the main problem. There are so many different circumstances for a cyclist to face up with. In addition to the environmental cases, the type of bicycle and cyclist's purpose of cycling are also things to be taken into account. If the factors are listed up; the speed of approaching vehicle, vehicle type and the vehicle size are the variables of vehicles. The road type and the things around the road are the variables of environment that can change for each case.

As the cyclist is busy with cycling and may be having wind sound or headphones in his/her ears, our sensor should generate an alert early enough to make it possible for cyclist to take an action in the case of danger. In order to make it possible for any case, collected samples are sorted according to their main features. At least 10 different samples were analysed for each case to see which correlations are more effective. The correlations are chosen so that when a method is weak at detecting a case or has latency, another method will reinforce the case and generate the alert on time.

The direction of approaching vehicle was another concern that thought to be deceptive at the beginning. During the researches, it is found out that front approaching vehicles have low effects on frequency shifts and loudness increment since the microphone is mounted on the rear of the bicycle. It is also possible to use directed microphone to lower these effects from front approaching vehicles even more.

After analysing over 300 samples of sound and getting the results, it is now possible to detect dangerously rear approaching vehicles, at the latest, in 1.5 seconds before the vehicle reaches up. If it is necessary to talk about distance, it is possible to detect a vehicle when the vehicle is approximately 40 meters far away, though the distance is strictly dependent on vehicles' speed. This is going to be studied in details in results chapter.

1.3. Objectives

The objective of my project is to find a sensor that can detect dangerously rear approaching motorized vehicles accurately. Since the sensor is going to be for bicycle, there are some size and power limitations. Sensor can be mounted either on helmet of the cyclist or on the rear of the bike. Chosen sensor also needs to generate alert early enough to give the cyclist time for taking action.

- The sensor should warn the cyclist as early as possible for the cyclist to take an action. The most acceptable lower limit for time is settled to be 1.5 seconds. Considering the highest speed of a vehicle on a road with bicycles to be 80 km/h, the minimum distance between cyclist and vehicle should be around 35 meters before warning the cyclist in 1.5 seconds.

- Size should not be larger than the rear carrier, if it is going to be mounted on the bike. The main point is here to mount sensor as tight as possible to avoid mechanical impacts since the sensor will be greatly affected. The receiver of the sensor should be at the end of rear carrier to minimize pedaling sound effects.

- There are some limitations about weight because it will be harder to mount sensor on the bike if the sensor is so bulky. Limitation for weight is predicted to be less than 1 kg, considering there can be some hardware equipment for the software with the sensor itself for alert generation.

- Power consumption is going to be low for the sensor type I have chosen since there are no high power consuming elements. The required CPU is much lower, since acoustic sensor uses less data comparing to other detector possibilities. Though there will not be numerical limitation since it is not the focusing point of this project.

- The sensor to be chosen should be able to identify approaching vehicle.

1.4. Thesis Outline

This rest of this thesis report is split into chapters. Chapter 2 includes the theoretical background knowledge regarding the project. Chapter 3 is about the methods I have used. Chapter 4 serves to the result achieved at the end of analysis. Chapter 5 is for conclusion and discussion parts.

Chapter 2

2. Background

In this chapter vehicle detection types that used for similar purposes are going to be presented. As I personally did while starting the thesis, different type of sensor is going to be compared by the means of their technical advantages and disadvantages.

After studying and reading articles of many detection methods, acoustic detection is found to be most convenient method for my project. The technical backgrounds of correlations that I have used for detecting vehicles are going to be presented.

2.1. Doppler Radar Vehicle Detection (DRVD)

2.1.1. Operating Principle

Doppler radar detector is a specialized radar type that was created by using frequency shifts. Doppler radar transmits microwave beams with a certain frequency and receives reflected waves. Sent beams are shifted by hitting a moving vehicle and it is possible to calculate target's speed, approaching direction and road lane using this alteration, though using this method without having proper configurations is generally erroneous. The aim of these configurations is to alter the properties of the radar to have the best result. Doppler radar in down-the-road (DTR) configuration uses single antenna and the sent beams are towards the target [3]. DTR configuration is found to be proper for rear approaching vehicle detection.

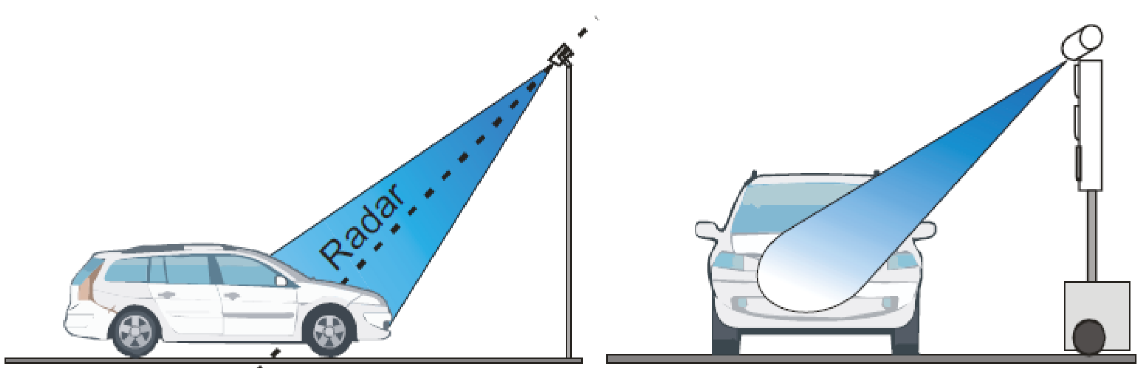


Figure 2-1: Representative Figure of Doppler Radar Application

2.1.2. Related Applications

There are some applications of Doppler radar to count vehicles, vehicle detection and speed detection. Doppler radar in DTR configuration is widely used by police department in speed enforcement and is capable of detecting a moving vehicle in a certain operation area which is generally a lane. Doppler radar in across-the-road configuration's operation area is reduced and is widely used for counting vehicles but the detection angle is relatively more sensitive and is proper for stationary cases [3].

2.1.3. Power Consumption and Range

The problematical part of DRVD is its range limitations due to the high power consumptions. Power consumption formula of radar is given as below [4];

$$P_t = \frac{P_r \times (4\pi)^2 \times R^4}{G_t \times A_r \times \sigma} \qquad (1)$$

In the formula (1), transmitted power is represented with P_t and the variables in the denominator are given as; gain of transmit antenna (G_t), effective area of receive antenna (A_r), the cross-section area of radar (σ). Pr stands for the power of received waves. Considering the distances as the beam is sending towards and the distance as the beam returns are the same; R here stands for the distance between the radar and the target. Required transmission power becomes 16 times more when we want to double the range.

According to the datasheet of ASIM Doppler Radar Vehicle Detector MW334 [13], power output could be up to 60 Watts for 40 meters range operations. 60 Watt power is considered to be extreme for our operation since low power consumption is one of our priorities.

2.2. Video Based Vehicle Detection

2.2.1. Operating Principle

Video based detection is based on a camera receiver, used as a sensor. There is no transmission power required for this kind of application. Camera captures the data using the direct sun light reflections into camera lenses. Generally low definition cameras are used for such operations since the correlations generally do not require high definition details. Video based vehicle detection makes it possible to track the vehicles once they were detected. It is even possible to identify licence plates.

Algorithms aim to look for correlating features of vehicles, remove background image and the noises such as shadow. Camera monitors the detection area and has a threshold value specified for detection range [6].

Figure 2-2: Representative Figure of Camera Receiver

2.2.2. Related Applications

Video based vehicle detection, in other words; image sensing detection, is used for all the purposes radar is used for and additionally vehicle detection. Video based detection systems are also capable to distinguish between vehicles and lanes of the road effectively [6]. This capability makes it possible to decide whether approaching vehicle is dangerous or not relatively better. Since the video is capable of recognising license plates, it is quite often used by police department.

2.2.3. Power Consumption and Range

Video based detection requires more energy than acoustic detection. CPU requirements are higher for video based detection comparing to acoustic detection since the captured data is larger and is harder to analyse [2]. Algorithms for video detection are more complex than audio detection algorithms. Another concern is the sensor type; even the cameras with low definition have more power consumption comparing to microphones.

According to my researches, the power consumption of 480 p video camera and required CPU for such detection is around 20 Watts put together. [2] There is no range specified while settling that power consumption. The range can be shorter than 35 meters for Sweden, considering the weather in Scandinavian lands is generally foggy or dusky during the most of the day.

2.3. Acoustic Sensor Vehicle Detection

In this section, microphone, in other words; acoustic sensor, is briefly presented. The main principles of operation and field of use are mentioned. The more technical details of the microphone I have used are going to be mentioned in the methods chapter.

Figure 2-3: Representative Figure of Acoustic Sensor

Microphone, in this project, is used for data capturing acoustic sensor. There are two main reasons that the microphone is found to be most convenient sensor. First reason is its low energy consumption; microphone does not transmit any energy to the environment to collect data but uses the data that created solely by environment. Second reason is the range requirement; sound waves can spread up to 100 meters in ideal cases. Since our range should be around 30 meters, unideal cases can be mostly tolerated.

2.3.1. Operating Principle

There are two types of acoustic detection for vehicles used in real life which have some differences in their operation principles. One of them is called passive acoustic array sensor which finds its area of usage in over-road applications and battlefield monitoring as well as civil surveillance. Second one is acoustic detection with single passive microphone which is used for individual riders/drivers.

Passive acoustic sensor array (PASA) consists of an array/arrays of microphones. This kind of application uses the latency and angle differences between its microphones. For a PASA example of a pair of microphone, when there is no vehicle detected, the latency between upper and lower microphones is appreciable. Once the vehicle detected, latency between lower and upper microphones gets so less that sound arrives almost instantaneously at both of the microphones [7]. PASA is also capable of detecting the range of approaching vehicle but it is only possible after associating the arrival direction. PASA is widely used in battlefield monitoring because passive sensors are hard to detect by enemy forces.

Figure 2-4: Representative Figure of PAAS

Acoustic detection with single passive microphone is another type which is going to be used in this project. Basically a single microphone and CPU are used for this type of application. CPU is programmed for using signal feature correlations of the sound of dangerously approaching vehicles. Microphone captures the data and converts it to electrical signals which will be interpreted by central processing unit in real time. Features of the sound are analysed in the CPU with the help of the inner software [2]. Some of the correlations may generate an alert. According to alert generation chart, the case is decided to be dangerous or not. Alert generation chart includes correlating features of approaching vehicle where the features are organized considering their importance in alert generation.

There are some problematic parts of acoustic detection technique. One of them is their lower speed limitations; acoustic detectors are weak at detecting slow approaching/retrieving vehicles since the indicators of slow vehicles are rather weak. Both acoustic sensor types have some lower speed limitations. According to previous single passive microphone detector application, this value is settled to be 30 mph [2], though it is not impossible to detect vehicles lower than this speed but has quite low success rate. According to my studies; there can't be a speed limitation specified, though some brief statistics can be mentioned. As the success ratio for each correlating feature is around % 70, this rate greatly decreases when approaching vehicle is small and slow. This is because the environmental noises become dominant against the weak indicators of small and slow vehicles and system remains unalarmed. This decrement in success rate is going to be mentioned widely in results section.

Another disadvantage of acoustic detection is masking effect by environment. In some cases, targets' sound can be faded or masked by stronger signal from other signals, such as uncritically approaching vehicles [7].

2.3.2. Related Applications

Passive acoustic array sensors are not generally for individual use but for collecting data by over-road detection.

Passive acoustic sensor array is used for traffic counting, battlefield monitoring, vehicle detection and for occupancy counts. Passive acoustic array sensors (PASA) are generally used on the roads where slow moving vehicles in stop and go traffic flow are not present. There is some lower speed limitation for this kind of sensors as it is mentioned before, since slow vehicles have weak indicators on the feature of the sound.

PASA is not good detection type for distinguishing between lanes on the road. Since the sounds coming from another lane of the road can be deceptive while trying to measure one single lane [7].

Single passive microphone acoustic detection is used for individual drivers/riders [2]. Single microphone detector can be used for vehicle detection, vehicle counting and speed detection, though vehicle counting can be erroneous.

According to my studies; when two vehicles approach together one after another, the indicator of posterior approaching vehicle can be damped. Two cars vehicle be counted as one single vehicle since the posterior vehicle will be ignored. This effect is because the frequency is damped as the anterior vehicle passes by and posterior vehicle's frequency indicators can become inadequate for alert generation.

2.3.3. Power Consumption and Range

The cost of power array acoustic sensor with two microphone arrays is around 1000 American Dollars [8]. It uses 24 direct current volts and power can be provided by solar cells. The range of PAAS is larger than single microphone acoustic sensors.

The single passive microphone acoustic detection is the main theme of this report. The required microphone for this project can be found for 50 Swedish crowns. The required CPU can be found in a notebook for 900 Swedish crowns [2]. The cost of the CPU itself will be lower.

The approximate power consumption of single microphone vehicle detection including CPU idle and microphone itself is around 8.5 Watts put together [2]. The lowest acceptable range is considered to be 35 meters. This value is calculated considering the highest speed of a vehicle on a road with bicycles to be 80 km/h, the minimum distance between cyclist and vehicle should be around 35 meters before warning the cyclist in 1.5 seconds.

The important part here is to be careful for not to choose frequency-filtered microphones. Since the most of the correlations used in this project is regarding frequency correlations, the interesting frequency bands must remain within the data.

2.4. Correlating Features

In this section, theoretic background of correlating features is going to be presented. Correlating features are chosen to be reinforcing when a correlation is weak at detecting a case or has latency. By doing so it is more likely to get an alert early enough to warn the cyclist.

2.4.1. Root Mean Square Analysis (Loudness Level, RMS)

Root mean square, in other words quadratic mean, is a statistical measure. Root mean square takes the quadratic mean of the magnitude value of a varying signal. This method is used in electrical engineering and is useful for positively and negatively varying signals such as sinusoids.

In this project, root mean square tool is used to measure loudness level. Loudness level, so the root mean square value tends to increase as the vehicle approaches and tends to decrease as the vehicle retreats [9]. Root mean square calculates the values for each frame and the algorithm compares present value with previous values. If the increment is larger than threshold value, system generates an alert. The formula is given as below;

$$RMS = \sqrt{\frac{1}{n}\left(x_1^2 + x_2^2 + x_3^2 + \cdots + x_n^2\right)} \quad (2)$$

In the formula (2), n stands for number of elements in each frame. The variable x_i stands for i^{th} sample of frame.

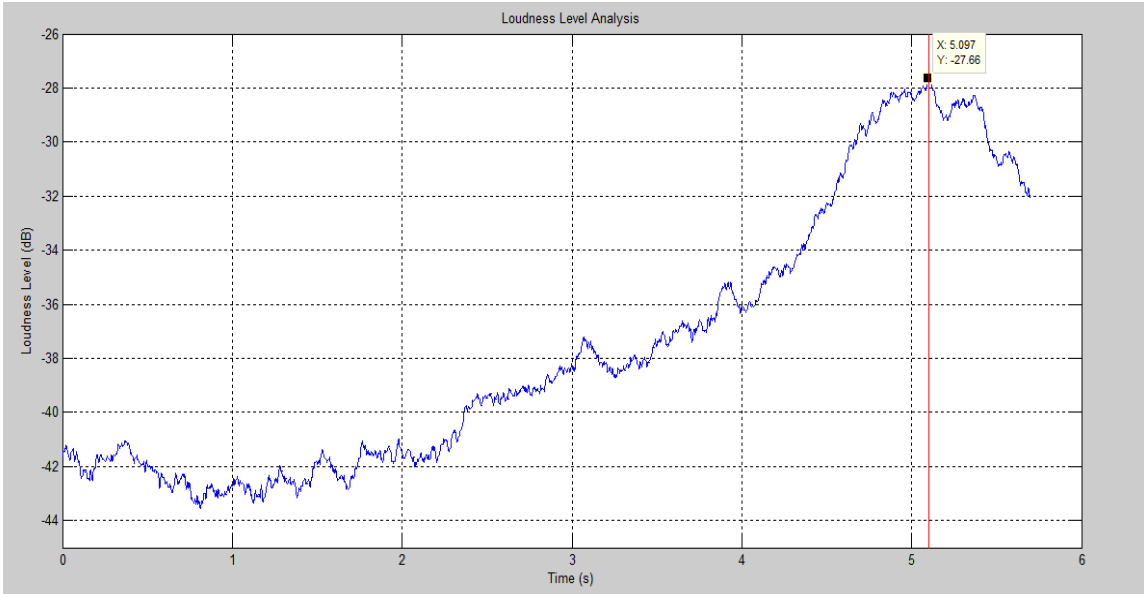


Figure 2-5: Root Mean Square Amplitude Variation vs. Time of an Approaching Vehicle

Figure 2-5 belongs to a sound sample of an approaching vehicle. Red line indicates the moment where the vehicle catches up the cyclist which is at 5.097th second for this case. The threshold value is not the RMS value itself but a comparison of present value with the previous values. In other words, having an increment, for example, from -30 dB to -25 dB will generate an alert.

2.4.2. Spectral Centroid Analysis (SCA)

Spectral centroid is a frequency domain feature which points out the central mass point within the power distribution of the spectrum. SCA is generally used as a brightness measure of the sound. When there is a vehicle approaching, the mass point tends to shift higher frequency ranges since the brightness will increase [2]. The formula is given as follows;

$$Spectral\ Centroid = \frac{\sum_1^n f(i)x(i)^2}{\sum_1^n x(i)^2} \quad (3)$$

In the formula (3), n stands for the number of elements per frame. f(i) stands for centre frequency of i^{th} bin and x(i) is weighted frequency value.

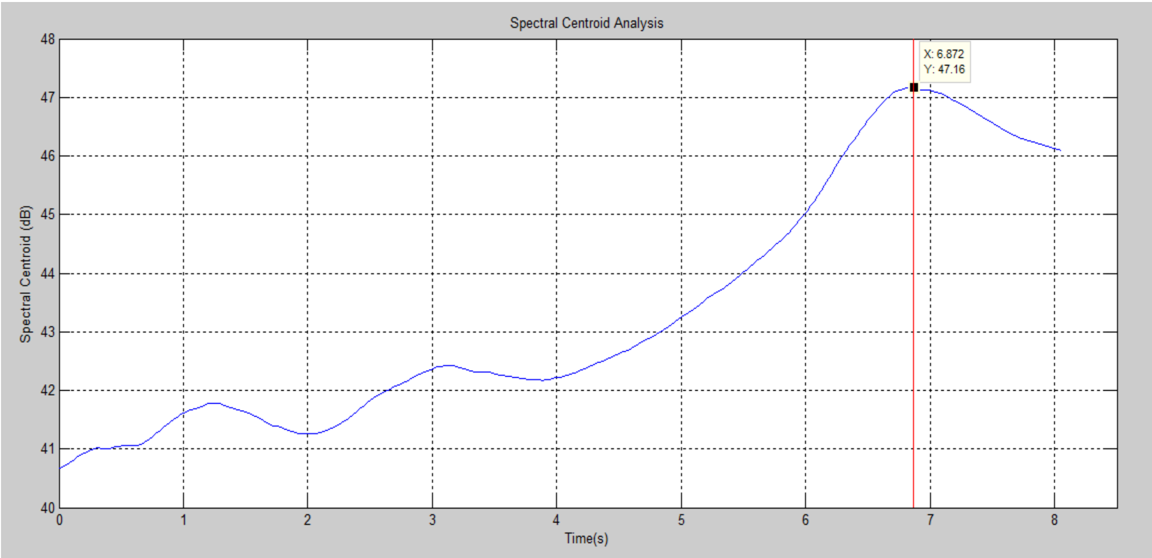


Figure 2-6: Spectral Centroid Amplitude Variation vs. Time of an Approaching Vehicle

Figure 2-6 belongs to a case where the vehicle reaches up the cyclist at 6.872^{th} second which is the peak point in the graph. Red line indicates the moment where the vehicle catches up the cyclist. Threshold here is not dependent on the Spectral Centroid value itself but the increment, as it was in the loudness level before. Threshold is specified to be 1 dB and is going to be studied more detailed in results parts of the report.

2.4.3. Spectral Entropy Analysis

Spectral entropy is a measuring tool of entropy within the sound. Since the word entropy refers to irregularity, spectral entropy analysis can said to be measuring irregularity as well. When a vehicle approaches from rear, it creates a certain pattern which will decrease irregularity. The background sound is generally not as regular as vehicle sound. Spectral entropy tends to drop when there is an approaching vehicle detected [2]. The formula is given as below;

$$Spectral\ Entropy = -\sum_{1}^{n} x(i)(\log(x(i)) - \log(\sum_{1}^{n} x(i))) \quad (4)$$

In the formula (4), x(i) stands for weighted frequency of i^{th} bin. n stands for the number of elements of each frame.

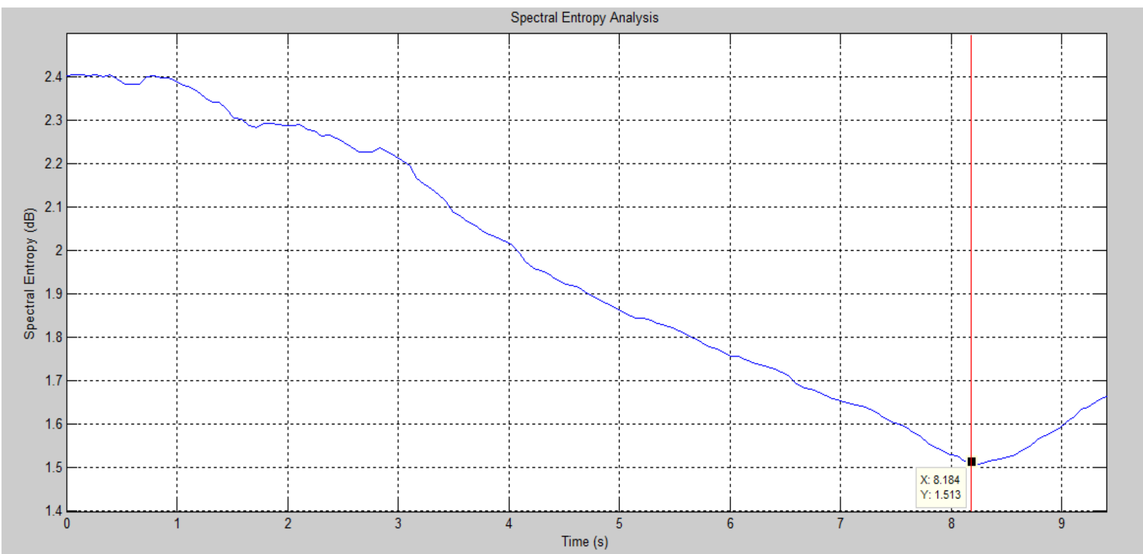


Figure 2-7: Spectral Entropy Amplitude Variation vs. Time of an Approaching Vehicle

Figure 2-7 is a characteristic figure when there is a vehicle approaching. Red line indicates the moment when the vehicle catches up the cyclist, for this case vehicle catches up the cyclist at 8.184th second which is the lowest peak point in the graph. As the vehicle passes by the cyclist, spectral entropy tends to increase and revert to its initial position as it can be seen in the graph.

2.4.4. Weighted Frequency Spectrum Analysis (WFS)

Weighted frequency spectrum analysis is the name of analysis which uses short time fast Fourier transform, additionally there is a configuration specified for alert generation in this project. One single FFT cannot characterize changes in spectral content over time, thus instant changes is visualised by short time FFT function [10].

This method tends to be used as a measurement tool of energy radiation. Every sound in the environment radiates energy in certain frequency bands which is dependent on their type of sound [10]. The work to be done for this chapter was to find out, if there is a specific frequency band created by approaching vehicles. Hopefully, there was an interesting frequency band found. Applying short-time FFT proves that as the sound source gets close to the sensing device, energy is radiated in higher values.

There is a configuration done in order to ease alert generation algorithms. This configuration is simply done by splitting up sound sample into 0.5 second parts, likewise a hamming window. Fast Fourier transform of each part of the sound sample is taken and analysed. There is some frequency bands which have frequency bins tend to significantly increase when there is a vehicle approaching. This is because the radiated energy of the related frequency bins is fed by approaching car sound. Comparing threshold value with the present value, vehicle approaching sound can be identified. Threshold value was set considering environmental sounds in order to get most reliable result. The sample graphs are given as below.

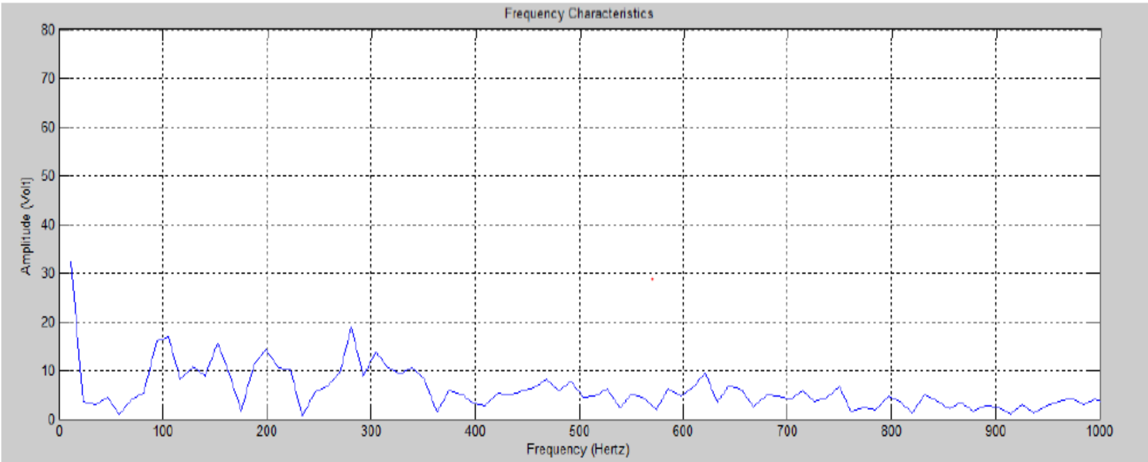


Figure 2-8: Frequency vs. Amplitude Graph of Background Sound

Figure 2-8 belongs to the interval where there is no vehicle detected yet. As it can be seen from the figure there are no significant amplitude peaks of any frequency bins. The example figures are chosen from figures of unfiltered data to point out the interesting frequency band, figures of filtered data are given results part as well.

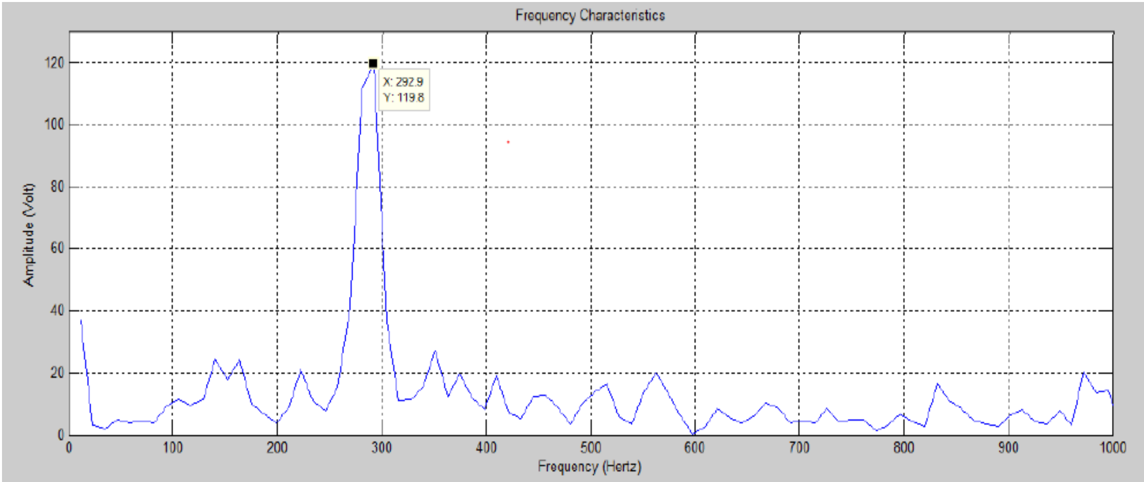


Figure 2-9: Frequency vs. Amplitude Graph of Vehicle Approaching Sound

Figure 2-9 belongs to the interval where there is a vehicle detected. In order to point out the difference between two signals distinctively, the largest amplitude increment is presented in this section. More detailed graphs are presented in results part.

As a summary, radiated energy in related bins tends to increase when there is a vehicle detected. In order to show this energy radiation spectrum in one single graph, short-time FFT is taken for each recorded sound sample. The graph is presented as below;

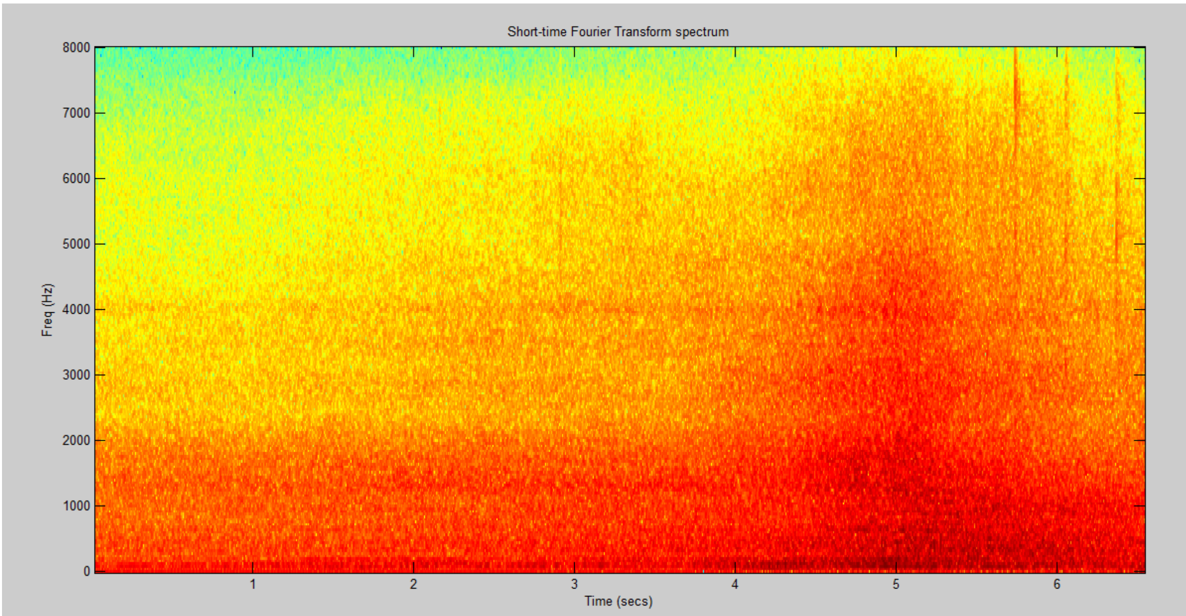


Figure 2-10: Frequency Energy Spectrum Variation vs. Time of Vehicle Approaching Sound Sample

Figure 2-10 belongs to a case where the vehicle reaches up at 5th second. This graph is summarizing the aim of the analysis given in this section. As it can be obviously seen from the graph, radiated energy is greatly increasing as the vehicle closes up. This energy increment reveals itself in amplitude increment which is useful for detection.

Chapter 3

3. Methods

In this chapter, the general theme is going to be the path I have followed for my achievements. Data capturing for this project, software and algorithms that I used are going to be presented.

After comparing the literature studies I have chosen the single microphone detection for my project. I have bought a suitable microphone that I can use with my smartphone. The frequency band of the microphone is between 30 Hz and 20 kHz. I have chosen Matlab as the software for signal processing.

The application for sound recording was installed to my smartphone. The software that I have chosen has the sampling frequency of 16 kHz and records the data in '.wav' format. The sampling frequency of 16 kHz is convenient for me because the default sampling frequency of the 'wavread' function has also 16 kHz while importing the data into Matlab. Though the 'wavread' function allows me to change it, it is easier to use it without any alterations. Another advantageous concern about the sound recording software is its recording format. Smart voice recorder saves the data in '.wav' format and Matlab only allows importing sound samples in '.wav' format since it is the only uncompressed format for the sound. This makes it possible for me to use the data directly after recording without using any other software for conversion.

I have classified sound samples in general as; environmental noise and vehicle approaching sound. I have collected the data for around 10 seconds for each sample regardless its type. For vehicle approaching sound samples, that much length of sound sample includes the parts where the vehicle is outside of detection area and the vehicle is within the detection area.

The microphone I have chosen is attachable anywhere on the bicycle. An external sponge is being used which physically immunes the microphone against wind. The microphone is attached on the rear carrier towards rear of the bike while capturing rear approaching vehicle data. The distance was kept in acceptable ranges. If an environmental noise recording, for example bird singing, is made in a very close distance, correlations may give unreal results.

I have also made a sub-classification with the approaching vehicle sound samples. There are three different criteria of classification. Vehicles were classified according to their speeds, their sizes and the roads they are moving on. Sound samples were examined in the total of 18 different groups. 10 samples were collected for each group and analysed using Matlab.

I have used speed calculation based on Doppler Effect to classify the vehicles according to their speeds. I have chosen different type of roads to see if the road type is the main factor for my analyses. Size classification is not based on technical methods but personal perception, vehicles were classified as; small, medium and large vehicles.

3.1. Data Capturing

This section includes the data capturing part before analysis. The microphone that I have used in this project is general purpose microphone. It is important to choose general purpose microphone for not to have inner frequency or distance filtering. In the market most of the microphones are filtered for some specific purposes. Frequency filtering or distance filtering would take away the useful parts of data and may spoil all the correlations.

3.1.1. Microphone Properties and Usage

Cable microphone Snopy SN-2023 used in this project for collecting data. According to its datasheet this kind of microphone is produced for all the recordings devices such as notepads, mobile phones and voice recorders. The microphone was bought for 35 Swedish crowns and has the following technical properties [11];

- Microphone has the nominal power consumption of 50 mW

- Microphone’s frequency range is between 30 Hz and 20 kHz.

- Microphone has the weight of 118 grams.

- The sensitivity of microphone is -58 dB.

- It has universal jack sockets (3,5 mm) and comes with the 1.2 meters long cable.

Usage of microphone is quite easy. As it is mentioned in technical properties part, microphone has the universal jack socket and fits my smartphone. My smart phone requires a recorder application besides microphone; this application was installed under the trade market name of Smart Voice Recorder.

Before the data capturing, all the required equipment should be set in position. When the expected scenario occurs, recording starts by pushing a single button. The most convenient recording should go on until the expected scenario ends and everything settles down as it was before the vehicle gets in detection area.

3.1.2. Use of Smart Voice Recorder

Smart voice recorder was chosen among similar android applications. One of the main reasons to choose this application is its simplicity. Smart voice recorder also visualise some technical properties and allows controlling them, such as sampling frequency. Sampling frequency is one of the main properties that is necessary for this project to be known.

Figure 3-1: Smart Voice Recorder Interface

Smart voice recorder application saves sound samples in '.wav' format which is the format I need to have for importing data into Matlab. The format '.wav' is an uncompressed format that Matlab software can extract data and import it. Using this application, recorded data can be directly transferred into Matlab without using any other converter. These are the main properties of Smart Voice recorder that should be known for my data capturing part.

3.2. Data Classification

In this section I am presenting how did I create the scenarios for data capturing and how did I classify them. As I mentioned in chapter introduction, there are two criteria for the main classification as; environmental noise and vehicle approaching noise. My first purpose was to identify vehicle approaching sound among those sounds.

I have captured human talking data without cycling sound. The most important part is here designating the distance. For some correlations that I am using, distance can be the decisive point. Considering the minimum distance between the cyclist and the microphone to be 60 centimetres, environmental noise sound samples were collected.

I have captured environmental sounds while cycling without any approaching vehicle sounds. I have placed the microphone as it normally should be placed, on the rear carrier. Since the project was offered especially for country road cyclists, I have focused on country road environmental sounds. I have captured all the noise data for at least 6 seconds long.

I made some sub-classifications before capturing vehicle approaching sounds. I have used three different criteria for making the sub-classification. These criteria are; vehicle size, vehicle speed and road type. I have used two different road types as asphalt road and country road. I have split vehicle size up to three different groups as; small, medium and large vehicles. I did not use strict norms while classifying the vehicle sizes. I simply grouped vans, busses and big vehicles into big sized vehicles; medium cars to medium sized vehicles and little vehicle into small sized vehicles. I have used Doppler Effect speed calculations to classify vehicle speeds. I have used three groups as slow, medium and fast for speed classification. In total I had 18 different groups to be analysed.

I created these groups to see if there will be any differences in correlation outputs and detection time. The results are going to be mentioned in results chapter.

After classification types were settled, vehicle approaching scenarios have started. I start recording when the vehicle is around 80 meters far away and ending the record just after vehicle passes by. In most of the data I have one or two seconds after the vehicle passing by to see how soon the correlations are settling down.

3.2.1. Speed Calculation based on Doppler Effect

This property is a speed calculation method using the Doppler Effect frequency shift. In this project, it is just used for data classification.

In simple words; Doppler Effect says that the emitted frequency is not the same as the observed frequency/frequencies if the sound source is moving respectively to the observer. The observed frequency is larger when the sound source moving towards. There will be a change as a pitch in frequency suddenly after the vehicle passes the observer. This pitch is going to be the key of our speed calculation. The formula of Doppler shift is given below [12];

$$f = \frac{c+Vr}{c+Vs} fo \quad (6)$$

In the formula (6), f stands for the observed frequency and fo for omitted frequency. Vr is the speed of the receiver relative to the air and Vs is the speed of the sound source. The the speed of approaching vehicle, two different observed frequencies are defined. Considering the fact that the speed of a cyclist is quite small comparing to speed of the sound, receiver's speed is ignored to make the calculations easier. Letting the observed frequency to be f1 as the vehicle approaches, f2 as the vehicles retreats and constant c in the equation is the speed of sound [12];

In order to calculate moves towards to be f1 and as the vehicle moves away to be f2, following equation can be written;

$$f1 = \frac{c}{c-Vs} fo \quad (7)$$

$$f2 = \frac{c}{c+Vs} fo \quad (8)$$

Since the fo is dependent on vehicle, fo cannot be known. Organizing the formulas (7) and (8), formula (9) can be obtained.

$$v = \frac{f1-f2}{f1+f2} c \quad (9)$$

Formula (9) gives the velocity in meter per second. Multiplying the obtained velocity with 3.6, the result can be change into kilometre per hour. Implementing these formulas is given in related codes part in this chapter.

3.3. Matlab Analysis

In this section, Matlab software is briefly presented. The codes used in project are going to be presented and explained.

3.3.1. Matlab Introduction

Matlab is a mathematical programming language which has a large field of usage in computational and mathematical science. Matlab offers many mathematical methods as functions in its own library. Matlab allows plotting the functions and data, creating user interfaces and interfacing with other languages such as C and C++ [14].

With the additional package, Simulink, it is possible to make model based design. Simulink is quite popular for both electrical and electronics engineers.

For my project digital signal processing toolbox is quite often used. Many complicated calculations are given in functions which can be directly used. Help section of Matlab is well organized part that is really helpful for the ones who are not familiar with this software.

3.3.2. Matlab Codes

In this part the codes that I have used is going to be presented. Since some cycle formulations are quite hard to present in the report so some abbreviations will be used. The uninteresting parts such as plotting codes are not going to be presented in order to be brief to the point.

```
%=========================================================================
% DATA READING FROM SOURCE


[a]=wavread('bbo1');
[a,fs]=wavread('bbo1');
[a,fs,nbits]=wavread('bbo1');

%=========================================================================
```

Data reading from the source is done as given above. The data to be analyzed is ‘bbo1’, fs stands for the sampling frequency and nbits stands for the number of bits per sample. The ‘wavread’ function can be used without specifying sampling frequency as well. If the sampling frequency would not be specified, Matlab would use default sampling frequency of 16 kHz.

```
%======================================================================

k=1:length(s);
f=k/length(s);
w=(2*pi/length(s));

F=f*fs;

A=abs((fft(s,length(s))));
Ar=((fft(s,length(s))));
Arf=((fft(S,length(S))));
zeit=length(s)/fs;
%======================================================================
```

The codes given above show the Fast Fourier Transform part. The constants 'f' and 'k' are the constants to obtain a frequency axis. 'w' stands for angular frequency and F stands for real frequency in Hz. The constants starting with the letter 'A' are weighted frequencies; 'A' is absolute and for unfiltered data, 'Ar' is for unfiltered data and finally 'Arf 'is for filtered data. The constant 'zeit' automatically calculates how long the input data is in seconds.

```
%======================================================================
%       SPEED CALCULATION OF PASSING CAR

    for i=1:n;
    if MS(i)==max(MS);

       v1=((x(i)-x(i+2))/(x(i)+x(i+2)))*c;
       v2=((x(i)-x(i+1))/(x(i)+x(i+1)))*c;
    end

       v=(v1+v2)/2;
       V=v*3.6;
end
%======================================================================
```

The codes above are for speed calculation of vehicles. The constant 'n' is the number of half seconds of input signal. The input signal is split up into half second pieces in order to identify passing by moment of the vehicle. MS(i) is a row amplitude vector which have maximum weighted frequency amplitudes of half second pieces. The largest amplitude within MS(i) vector belongs to the case where the vehicle is passing by. The 'for and if cycles' finds when the vehicle is passing. x(i) have the frequency values corresponding to MS(i) values. Finding where the vehicle passes by, speed can be calculated as it is presented in Doppler Effect speed calculation section. I have used to moments to approximate the speed to have more reliable results. The capital 'V' gives the result in kilometer per hour.

```
%======================================================================
 %ROOT MEAN SQUARE ANALYSIS

for i=1:length(s)-49;

R(i)=rms(abs(a(i:i+49)));

end

for i=1:length(s)-49;

Rdb(i)=20*log10(abs(R(i)));

end


for i =1:length(s)-549;

Rdbm(i)=mean(Rdb(i:i+500));

end
%======================================================================
```

The codes given above are for loudness level analysis. Cycles are used to create sliding frames. First cycle takes the root mean square of input signal. Second cycle converts RMS value into dB. Third cycle is for getting rid of small amplitude noises. Considering we sample 16000 elements per second, we take the mean value of less than 0.03 second at third cycle.

```
%===========================================================================
% SPECTRAL CENTROID ANALYSIS

laenge=length(x);

zeit=laenge/Fs;


fftlaenge=(2048);

fenster=fftlaenge;
noverlap=1638;

s=specgram(x,fftlaenge,Fs,fenster,noverlap);

C = sum((repmat((1:size(s,1))',1,size(s,2)) .* abs(s))) ./ sum(abs(s));

Csmooth=smooth(C);

CsmoothdB=20*log10(Csmooth);

for i=1:(length(CsmoothdB)-30);

   Cmean(i)=mean(CsmoothdB(i:i+29));

end



chronik=0:zeit/length(Cmean):zeit-(zeit/length(Cmean));

figure(1);plot(chronik,Cmean); grid on;
title('Spectral Centroid Analysis');
xlabel('Time(s)');
ylabel('Spectral Centroid (dB)');
%===========================================================================
```

The codes given above are for spectral centroid analysis. The constant ‘laenge’ is the length of the input signal x, ‘zeit’ calculates automatically the length of input signal, ‘fftlaenge’ and ‘fenster’ are the length of the frames for FFT calculation, ‘noverlap’ is the permitted overlap between windows. The function ‘specgram’ calculates FFT of the signal with a sliding window. The function ‘repmat’ replicates and normalizes the function and returns it in a row vector. As a result the resultant vector is converted in dB’s and plotted.

```
%==========================================================================
%SPECTRAL ENTROPY OF THE SOUND

fenster = 2048
laenge = length(x);
k=1;
zun=1;
while ( (k+fenster-1) <= laenge )
Gerahmtessignal = x(k:k+fenster-1);
v = Gerahmtessignal.* hann(length(Gerahmtessignal));
N = length(v);
A=fft(v);
P = ((sqrt(abs(A).*abs(A)) * 2 )/N);
P = P(1:fenster/2);

d=P(:);
d=P/sum(P+ 1e-12);
%Entropie Rechnung
logd = log2(d + 1e-12);
Entropy(zun) = -sum(d.*logd)/log2(length(d));
k=k+Overlap;
zun=zun+1;
end
    Entropym=smooth(Entropy);
    Entropyt=Entropy.';

    Entropydb=-20*log10(Entropyt);
    zeit=length(x)/Fs;


    for i=1:(length(Entropydb)-20);

     Edb(i)=mean(Entropydb(i:i+20));


    end


%==========================================================================
```

The codes given above are for spectral entropy analysis. The imported data is ‘x’, ‘fenster’ stands for window size, ‘laenge’ is the length of the signal. The variables for the loops are ‘k’ and ‘zun’. ‘Gerahmtessignal’ stands for the framed signal of imported data, ‘A’ is weighted frequency vector. The variables ‘d’ and ‘P’ are for entropy calculation. After obtaining entropy values in a vector, the vector is improved for a better result and plotted.

```
%=====================================================================
%FIR Equiripple Bandpass Filter

fNyquist=fs/2;
Ap=5;

Ast1=30;

Ast2=30;

fst1=30;

fp1=50;

fp2=500;

fst2=520;


d=fdesign.bandpass(fst1,fp1,fp2,fst2,Ast1,Ap,Ast2,fs);

Hfiltre=design(d,'equiripple');

s=filter(Hfiltre,S);

%=====================================================================
```

In the codes given above, fNyquist is the nyquist frequency which to be used for normalization. Ap is allowed ripple, Ast1 and Ast2 are the attenuation values. The frequencies fst1 and fst2 are the ending and starting points of stop band respectively. The frequencies fp1 and fp2 are the starting and ending points of pass band respectively. Hd is the filter itself, s is the filtered data and S is the raw data.

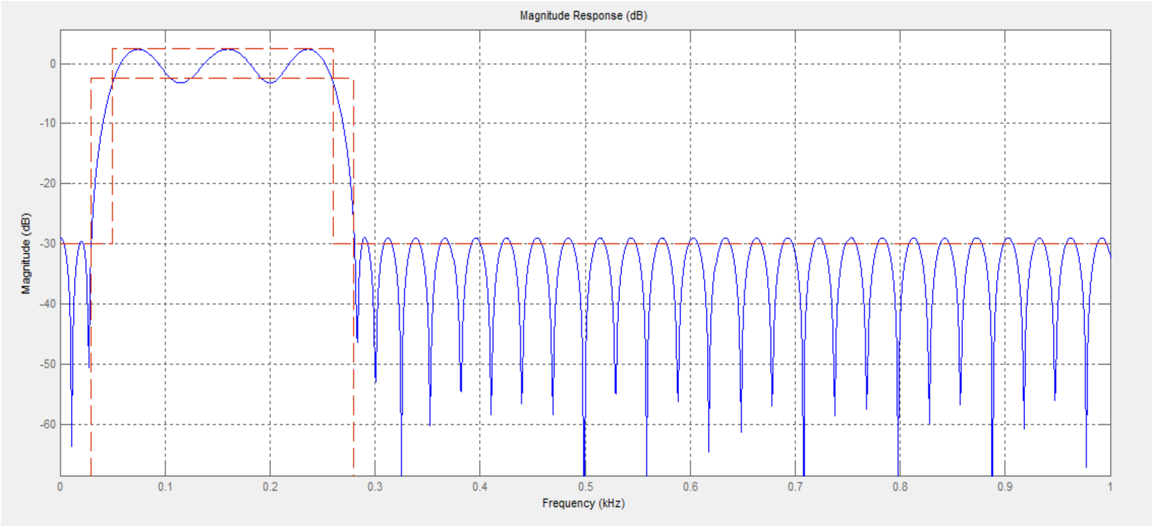


Figure 3-2: Magnitude Response of Designed Band-pass Filter

Figure 3-2 was plotted to visualize the filter designed for the project. As it can be clearly seen from the graph, uninteresting frequencies were damped. Only important frequency band is kept so that unwanted confusions can be avoided.

```
%=============================================================
if n>=1;
s1=s(1:(length(s)/n));
k1=1:length(s1);
f1=k1/length(s1);
w1=(2*pi/length(s1))*k1;
F1=f1*fs;
A1=abs((fft(s1,length(s1))));

% Dominant Amplitude and Frequency

MS(1)=max(A1(20:end));
DC(1)=max(Af1(1:20));

for i=1:500;
    if A1(i)==MS(1);
    x(1)=F1(i);
    end
end
 fh(1)=interp1(F1,A1,x(1));
end

%=============================================================
```

The codes given above are for weighted frequency spectrum analysis. This part shows only first half second piece of the input data. ‘If cycle’ ensures that the input data is larger than half second. I did not use hanning window since its shape and confliction may alter the input data. The vector s is the main input data and s1 is the first half second of s and the input data for first half second piece analysis. The constants k1 and f1 are for obtaining the frequency axis. F1 is angular frequency and A1 is weighted frequency of s1. MS(i) is a vector which collects the maximum amplitude of weighted frequency. First 20 samples were not taken into account since it is the DC value component caused by microphone itself. DC(i) is the vector that collects DC values for each piece of data. DC values are related with number of elements so that DC values are same for all half second pieces. Second cycle finds the corresponding frequency of largest amplitude component. The vector fh is a procuration vector which has the same data as MS vector has.

In order to show the energy radiation distribution in one single graph, frequency spectrum of the whole input signal is provided with following codes;

```
%======================================================================
% SHORT TIME FFT PROJECT

figure(29);
hsize=400;
fenster=hanning(hsize);
nsfft=hsize;
noverlap=windowsize-1;
[S,F,T] = spectrogram(a,window,noverlap,nsfft,fs);


imagesc(T,F,log10(abs(S)))
set(gca,'YDir','Normal')
xlabel('Time (secs)')
ylabel('Freq (Hz)')
title('Short-time Fourier Transform spectrum')

%======================================================================
```

The codes given above are the short time Fast Fourier transform of the input signal. The constant hsize is the window size for hanning window, fenster is the window created for short time FFT and nsfft is the length of the FFT's to be taken. Noverlap is the allowed overlap for hanning window.

Chapter 4

4. Results

In this chapter, results of the analysis work are presented. The results are going to be separated as the analysis work was separated. As it was mentioned previously, threshold values are specified within this chapter.

4.1. Matlab Results

In this section, the resultant figures are going to be evaluated separately according to the type of analysis. Analysis types are evaluated under the same subheading to show their efficiency with different type of sound in an obvious way. Finally two of the best analysis type is going to be fused.

4.1.1. Root Mean Square Results (RMS)

In this part, the loudness level with root mean square analysis is presented. The explanations and the type of sound can be found just under the graph. Besides presenting general characteristic of different audio type, statistical results and threshold selection are also given.

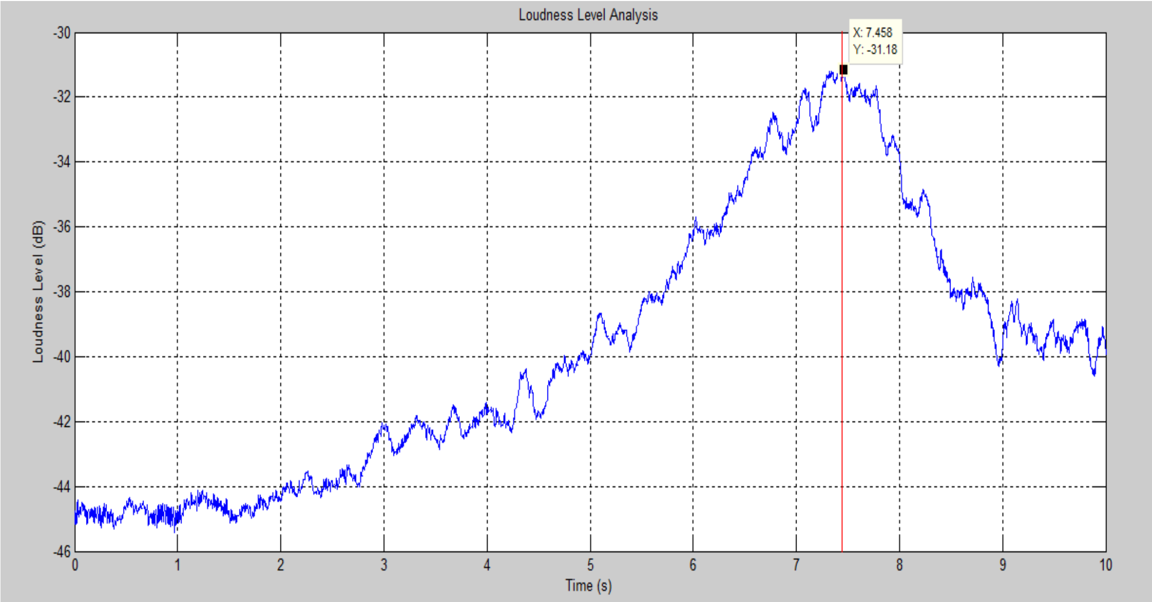


Figure 4-1: Root Mean Square Amplitude Variation vs. Time of an Approaching Van

The figure 4-1 is presented as a representative figure of general characteristics and belongs to the sound sample of an approaching van. Red line indicates the moment when the vehicle catches up the cyclist. The threshold value for generating an alert is set to be 5 dB increments in the RMS value. Threshold value is not based the loudness level value itself but the increment. Having an increment that exceeds 5 dBs will generate an alert. According to the given threshold value, the vehicle gets in the detection area roughly 2.5 seconds before the vehicle catches up the cyclist. The vans were grouped into big sized vehicles.

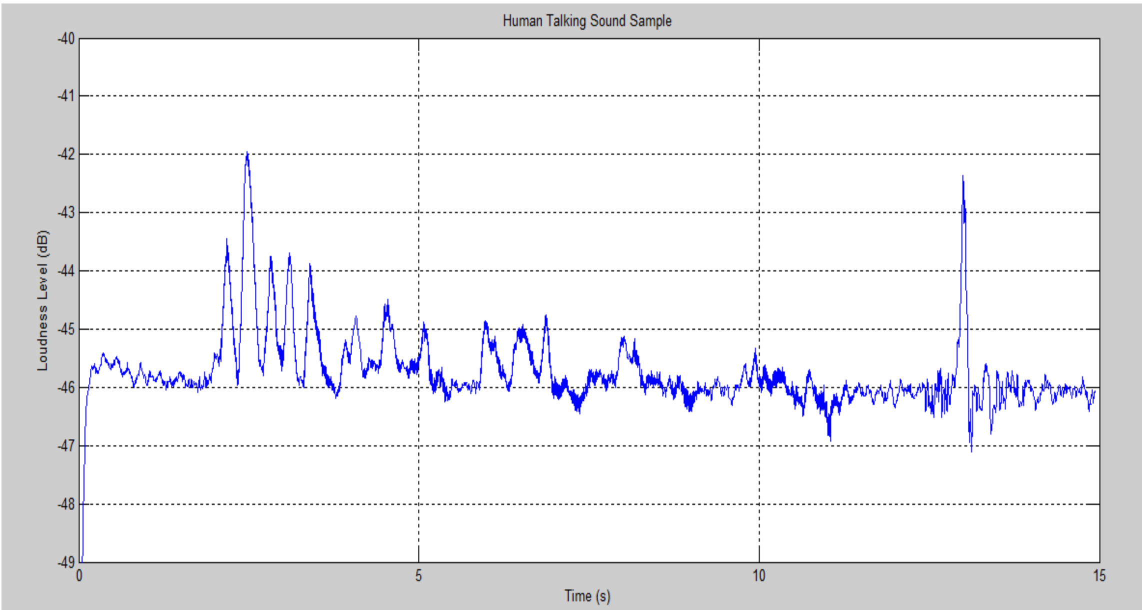


Figure 4-2: Root Mean Square Amplitude Variation vs. Time of Human Talking Voice

The figure 4-2 belongs to human talking sound sample. This sample was taken from a distance as it should be between a cyclist and the sensor. Human talking RMS variation is more oscillating than vehicle approaching sound. The increment does not exceed 5 dB since the points in the graphs are compared to the mean value of previous points.

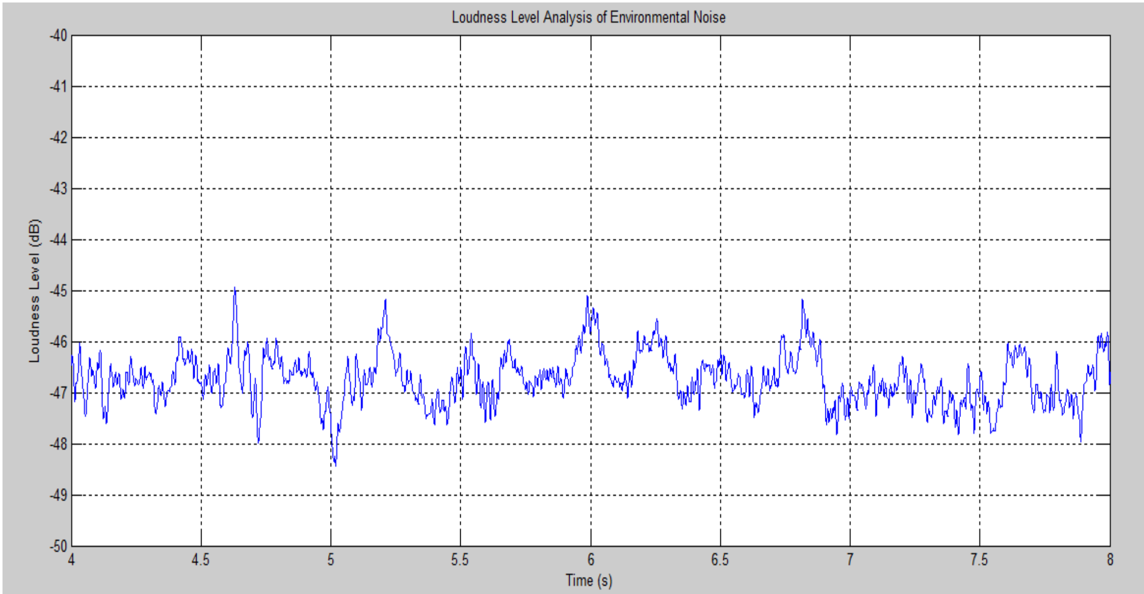


Figure 4-3: Root Mean Square Amplitude Variation vs. Time of Environmental Noise

Figure 4-3 is a representative figure for environmental noise. Environmental noise includes possible external sounds which cyclist may face in the real life. The mounting place of microphone is paramount for the level of environmental noise. For this project microphone was placed at the ending point of the carrier to minimize pedalling effects. In practical life, using a directed microphone is going to minimize pedalling noise even more.

As it was mentioned in former chapters, each method has its own success rate. Success rate is settled down for each case to minimize the unreal alerts and maximize the real detections; this is going to be shown in threshold selection part under this title. The success rate is dependent on vehicle speed, environmental circumstances and vehicle type. Statistical results aim to show general case and contain as many circumstances as possible including environmental noises.

In order to show the effect of vehicle type on loudness level analysis, different vehicle types within a certain speed band were compared. At least 100 different samples were used in total and results are as follows;

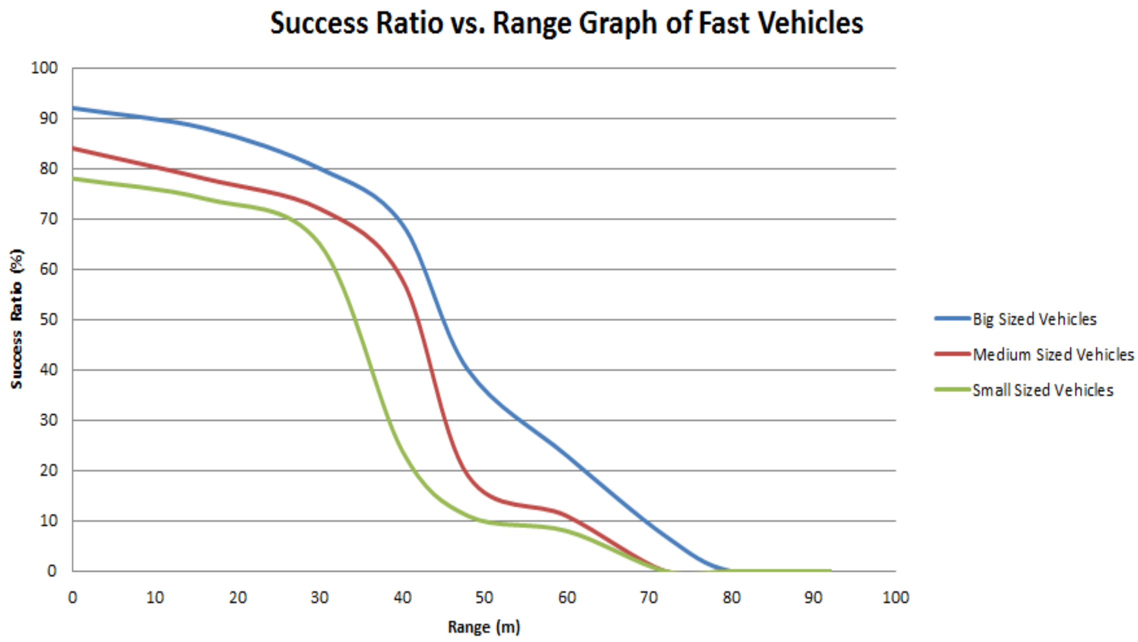


Figure 4-4: Vehicle Size based Success Rate vs. Range Graph for Fast Vehicles (RMS)

Figure 4-4 is presented to show the effect of vehicle size on loudness level analysis, thus only fast vehicles were taken into account for this graph so that the large difference in speed is avoided. In the graph, different sizes of vehicles are shown in different colours. As expected; success rate is higher for bigger vehicles since bigger vehicles are generally stronger sound sources and has stronger indicators. There are no detectors used for range specification, instead speed calculations and time were used to calculate the range for the graphs. The average speed of fast vehicles is calculated to be 76,4 km/h. Considering this speed, roughly 30 meters range is enough for detection at least 1.5 seconds in advance, though minimum range varies since some vehicles are little faster or little slower.

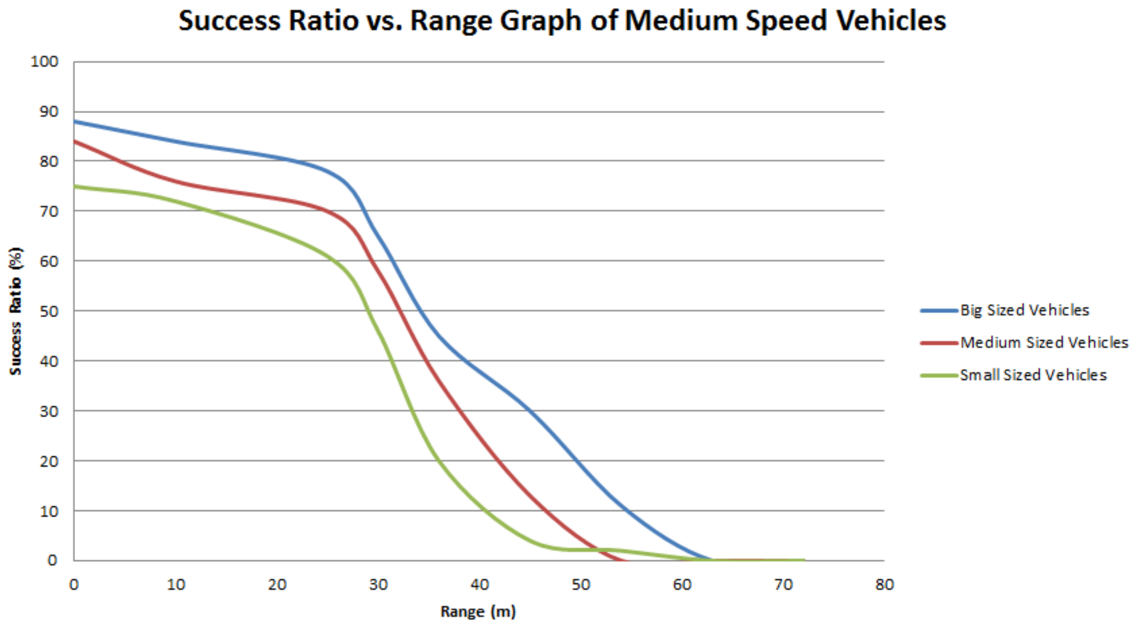


Figure 4-5: Vehicle Size based Success Rate vs. Range Graph for Medium Speed Vehicles (RMS)

Figure 4-5 is presented to show the success rate of medium speed vehicles. As it was in Figure 4-4, big vehicles are easier to detect and have relatively higher success rate. Detection range for acceptable success rates is slightly shorter than fast vehicles', but the time for the cyclist to act is does not differ much. The average speed of medium speed vehicles is calculated to be 57,6 km/h which means approximately 23 meters range is enough for 1.5 seconds detection in advance. Statistical graph for action time left for the cyclist is separately presented (See Figure 4-7).

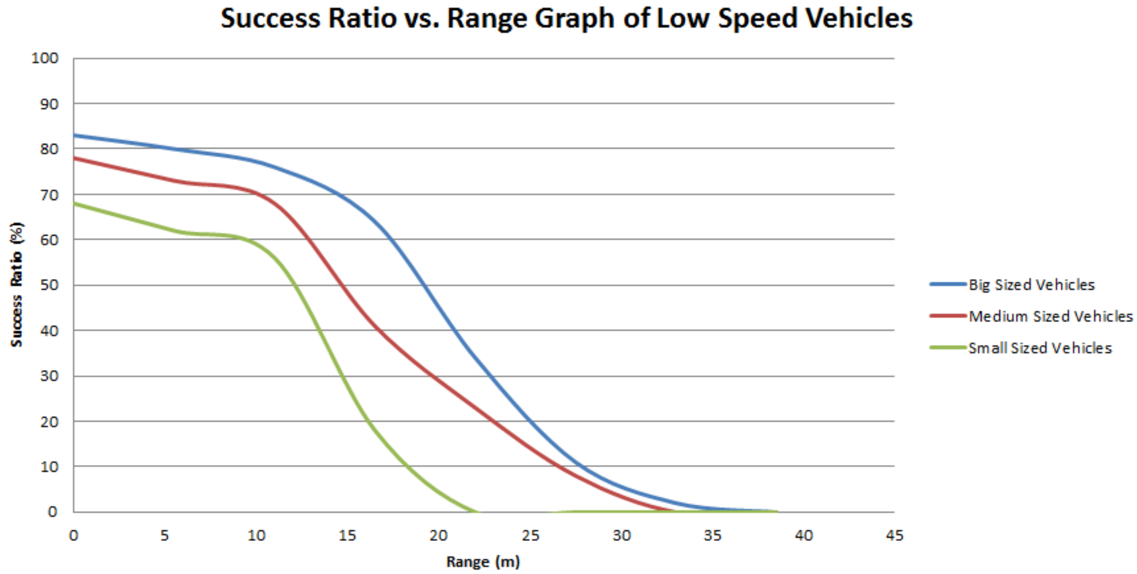


Figure 4-6: Vehicle Size based Success Rate vs. Range Graph for Low Speed Vehicles (RMS)

Figure 4-6 shows the success rate depending on detection range for low speed vehicles. As it was mentioned previously, low speed and small vehicles are the hardest type for detection since they have weak indicators in the sound sample. As it was mentioned before, the speed for each sample is calculated using speed calculation based on Doppler Effect. The average speed of low speed vehicles is calculated to be 33,8 km/h. Using this value, the minimum range can said to be around 13 meters to have the detection early enough.

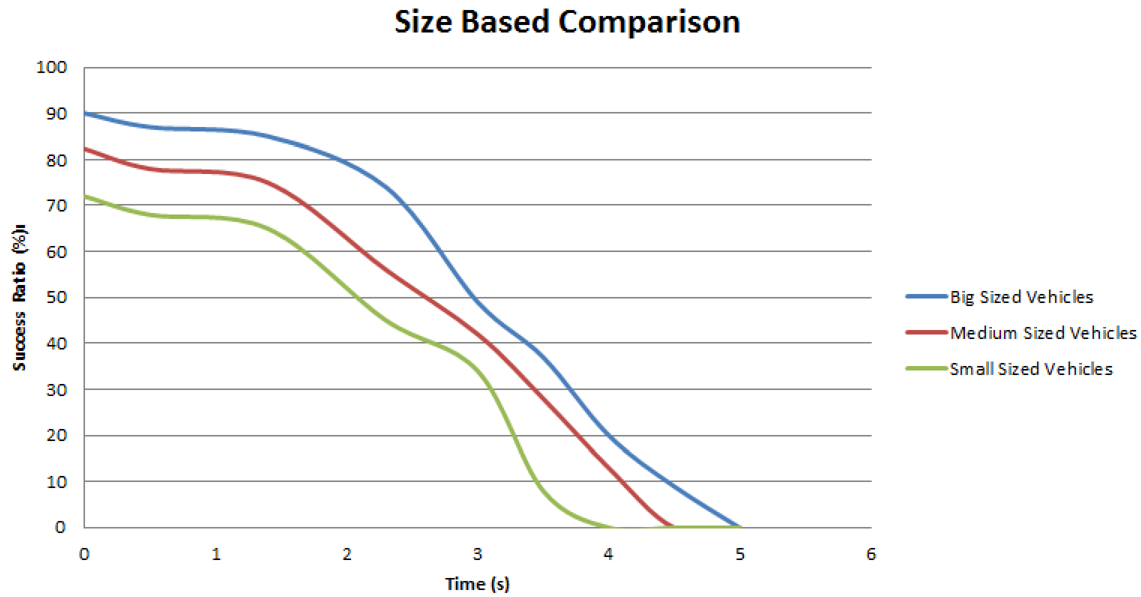


Figure 4-7: Vehicle Size based Success Ratio vs. Time Graph (RMS)

Figure 4-7 is a summary for Figures; 4-4, 4-5 and 4-6. In the figure, mean success ratio for different size of vehicles was calculated regardless their speeds. Unlikely the graphs given previously, figure 4-7 was plotted dependent on time. The null point in the graph is the moment when the vehicle catches up the cyclist and time on the x-axis is the time left for cyclist to act. The purpose of plotting the success rate versus time graph is to show time left for cyclist to take an action. It is easier in graphs to see the time left before vehicle catch up the cyclist rather than range, so the figure 4-7 can said to be more accurate. As it can be seen, bigger and faster vehicles are easier to detect since they have stronger correlating indicators in the sound sample.

Another concern about detection with loudness level analysis was deciding the threshold value. Threshold value should be chosen properly, so that device shouldn't generate much unreal alerts or be so late for alert generation. In order to show that the chosen threshold value is the optimum one, success rate is going to be calculated and plotted for some certain upper and lower threshold values. For choosing the threshold value, successful cases are considered to be the cases where the cyclist has the action time for at least 1,5 seconds. Case is considered to be unsuccessful if the system generates an unreal alert, for example; if the alert is generated for environmental noise, or be so late for alert generation.

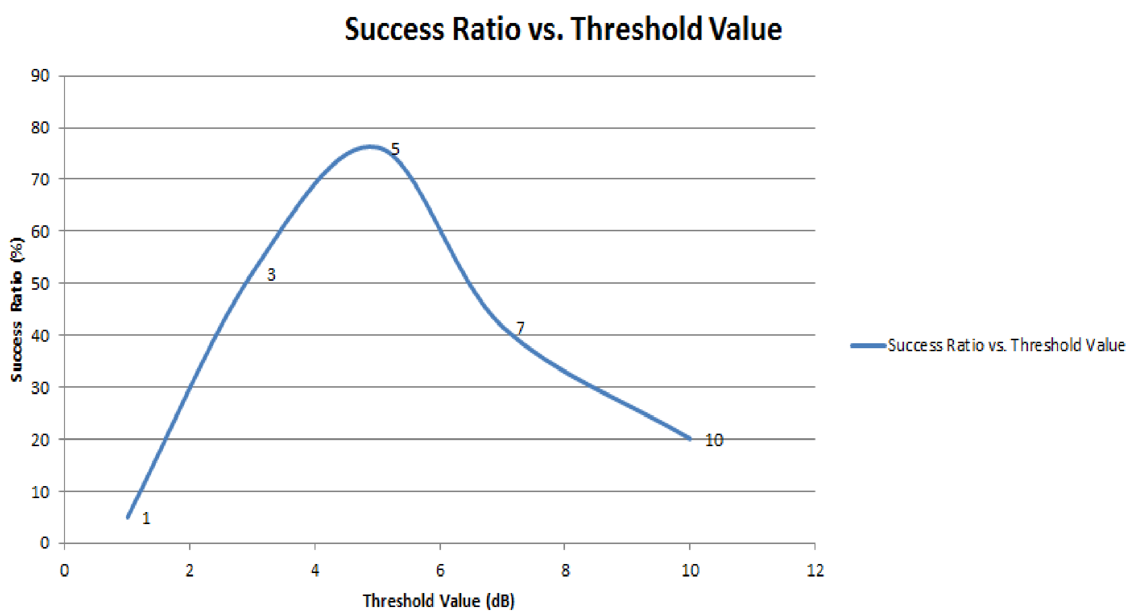


Figure 4-8: Success Ratio vs. Threshold Value (RMS)

The aim of Figure 4-8 is to show that the optimum threshold value is 5 dBs. There are 5 values used for plotting as they were tagged on the graph. If we had used a threshold of 3 dBs, background noises could mislead alert generation. On the other hand, having the threshold of 7 dBs would have great latency and sometimes even unable to detect the vehicle, especially if the vehicle is a low sound source. 1dB or 10 dBs were extreme example points to show the success rate is even lower for these values. The success ratio for 5 dB threshold is found to be %77,3 for this detection type. The pure environmental noises are also taken into account by taking their weighted averages.

4.1.2. Spectral Centroid Results (SCA)

In this section spectral centroid variations of sound samples are presented. In addition, threshold specification and statistical results are also given. Statistical results are examined using as many samples as possible including background noises. Some characteristic graphs are given as below;

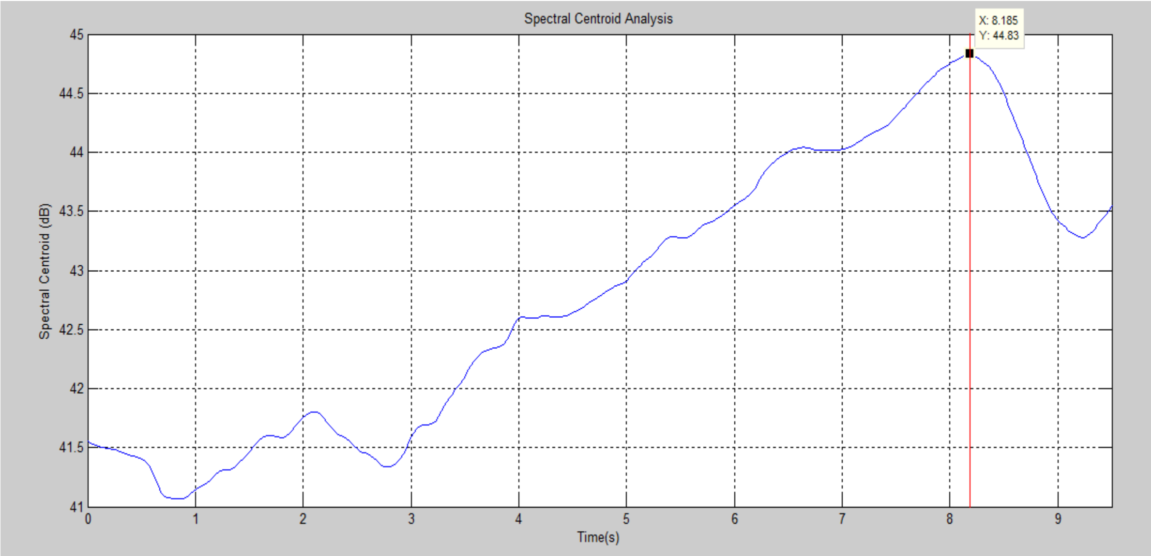


Figure 4-9: Spectral Centroid Amplitude Variation vs. Time of an Approaching Vehicle Sound

Figure 4-9 shows the characteristics of mass point value versus time, as a vehicle approaches from rear. Red line indicates the moment when the vehicle catches up the cyclist which is 8.165th second for the case given in the graph. Threshold is specified to be 1 dB for this type of analysis. Detection does not start earlier than 2.5th second, because threshold is calculated comparing present value with the mean value of previous values. It is important to do so, because when there is no vehicle present spectral centroid may have sudden decrements in which case also generally have sudden increments after this moment. If that kind of comparison wasn't made, spectral centroid would generate unreal alerts in which case the success would be damped due to the unreal alert generation.

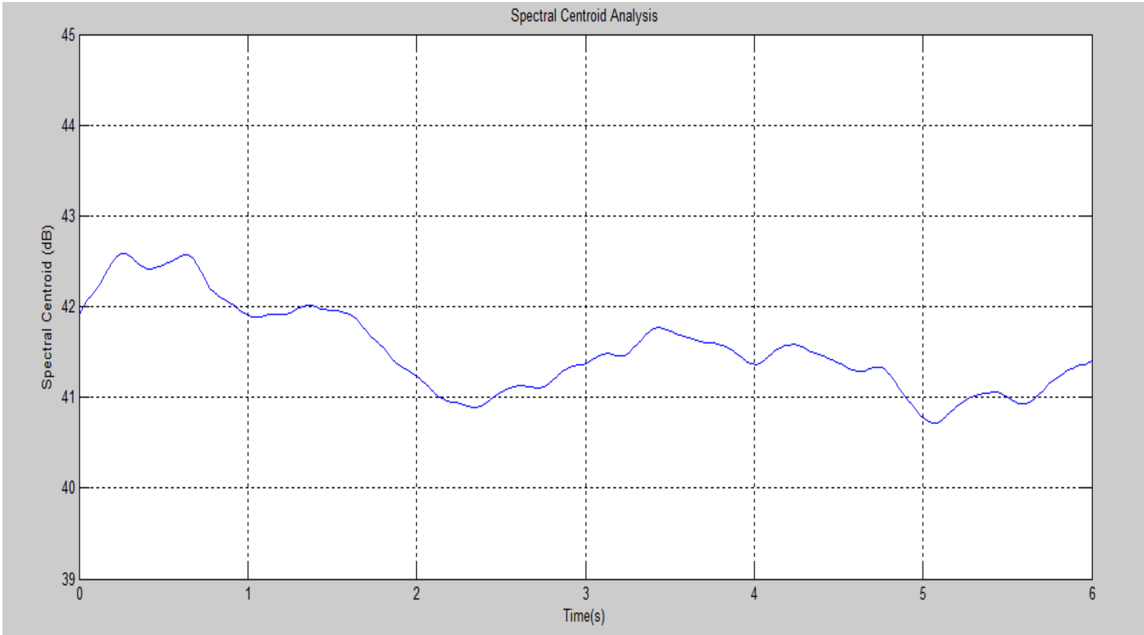


Figure 4-10: Spectral Centroid Amplitude Variation vs. Time of Environmental Noise

Figure 4-10 shows the spectral centroid characteristics when there is no vehicle presence but the environmental noise. As it can be seen there is no distinct increment, though it could increase but not as it is when there is a vehicle approaching.

In order to show the general case with few graphs, statistical results are also given as it was mentioned. The sound samples of vehicle approaches contain environmental noises, but pure environmental noises are also taken into account by taking weighted mean, as it was mentioned before. The case is considered to be successful if there is no alert generated for environmental noises. On the other hand, for the vehicle approaching sound samples; the case is considered to be successful, if there are no unreal alerts and alert is generated at the latest 1.5 seconds before the vehicles catches up the cyclist.

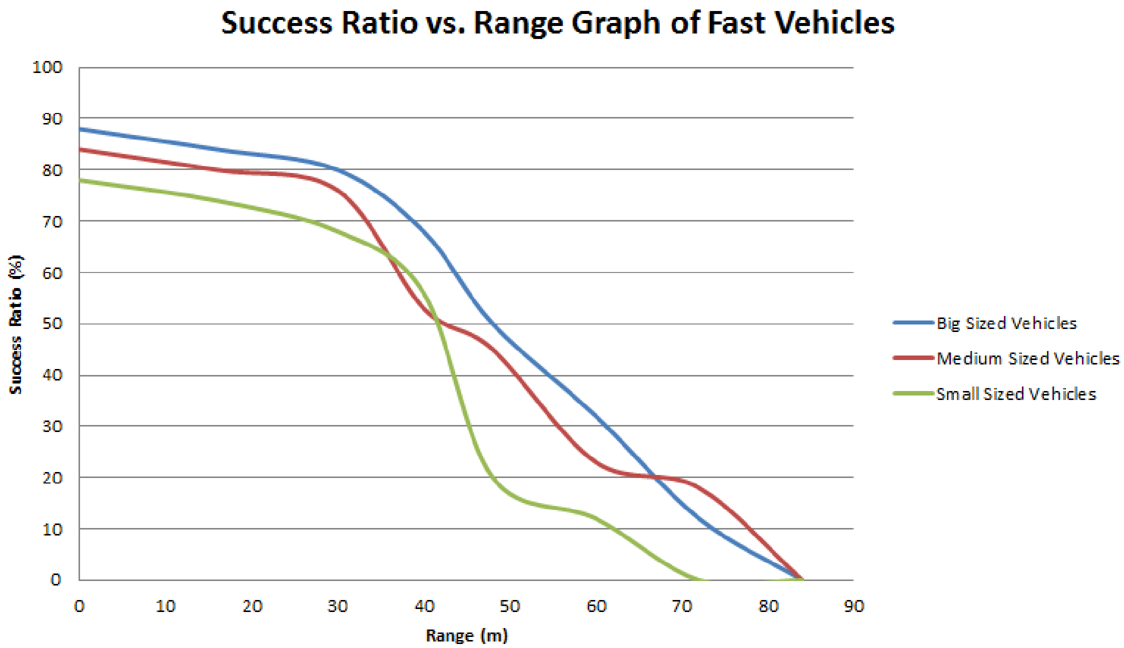


Figure 4-11: Vehicle Size based Success Rate vs. Range Graph for Fast Vehicles (SCA)

Figure 4-11 shows the success ratio versus range graph of fast vehicles for different vehicle sizes. Range is calculated using speed calculation based on Doppler Effect and time. The same sound samples were used for statistical results of every method, so the average speed is 76,4 km/h as it was in RMS analysis and the minimum required range is around 30 meters.

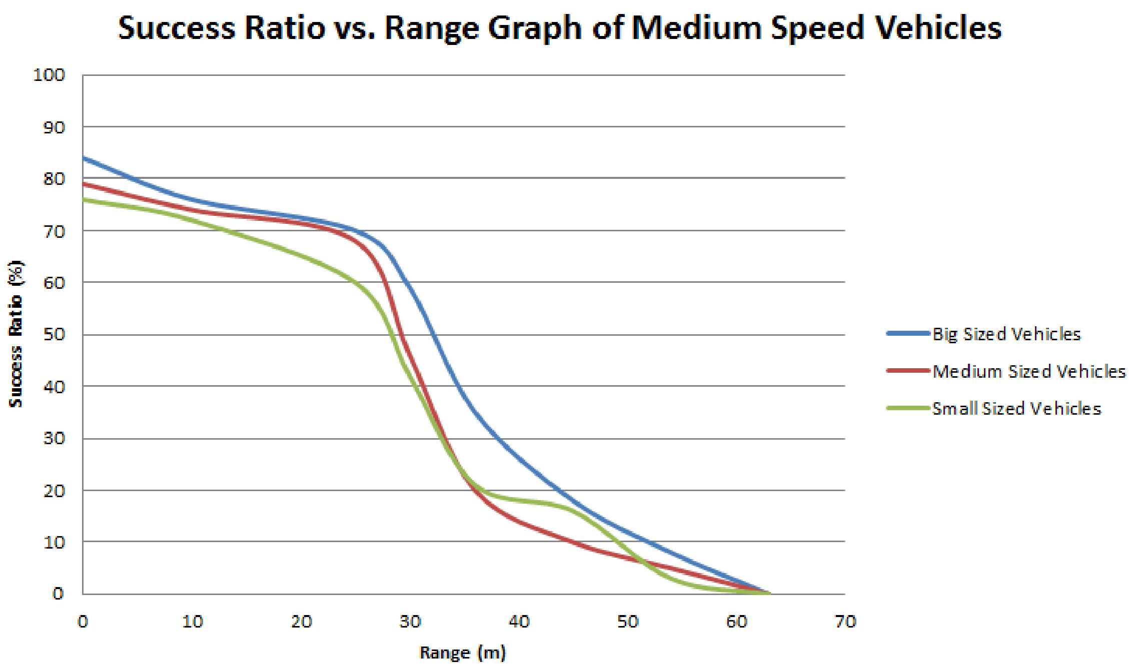


Figure 4-12: Vehicle Size based Success Rate vs. Range Graph for Medium Speed Vehicles (SCA)

Figure 4-12 is showing the success rate versus range graph of medium speed vehicles for different vehicle sizes. The average speed of medium sized vehicles is 57,6 km/h and the minimum range required is 23 meters to have a detection early enough. The detection success in general is slightly lower than fast vehicles but the time left for the cyclist to act does not differ much, this is going to be presented in time dependent graph as well.

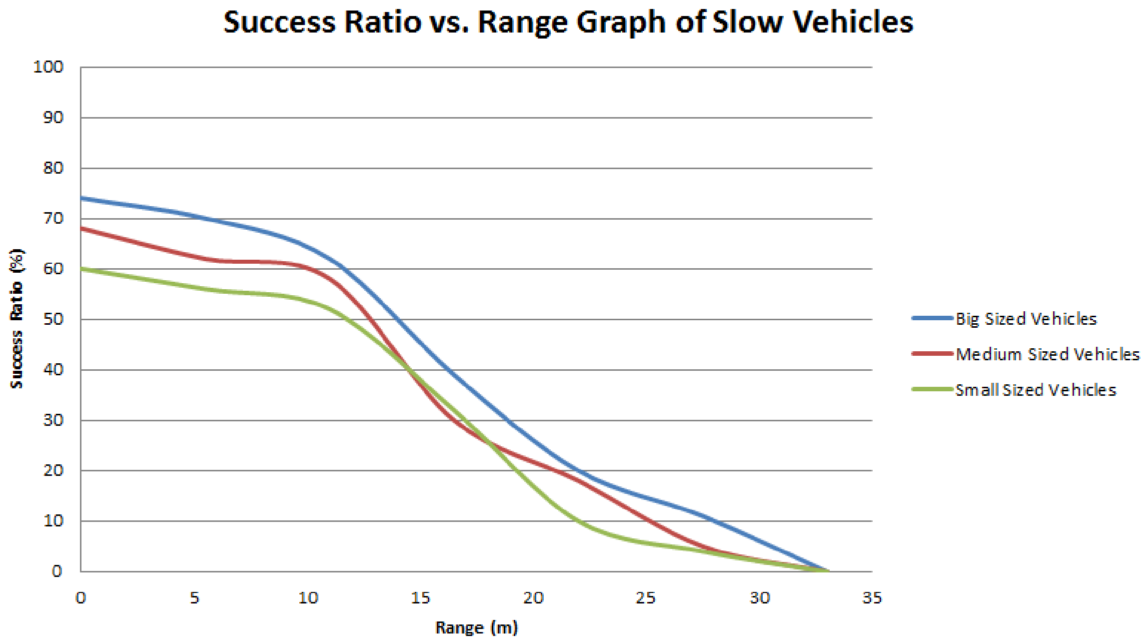


Figure 4-13: Vehicle Size based Success Rate vs. Range Graph for Slow Vehicles (SCA)

Figure 4-13 shows the success rate versus range graph of different vehicles sizes in slow speed vehicle group. As it is expected the success ratio for slow vehicles is relatively low since they cannot change the brightness level of the sound fast enough comparing to fast vehicles and medium speed vehicles. The average speed of slow vehicles is 33,8 km/h and the minimum range is around 13 meters in order to have the detection early enough.

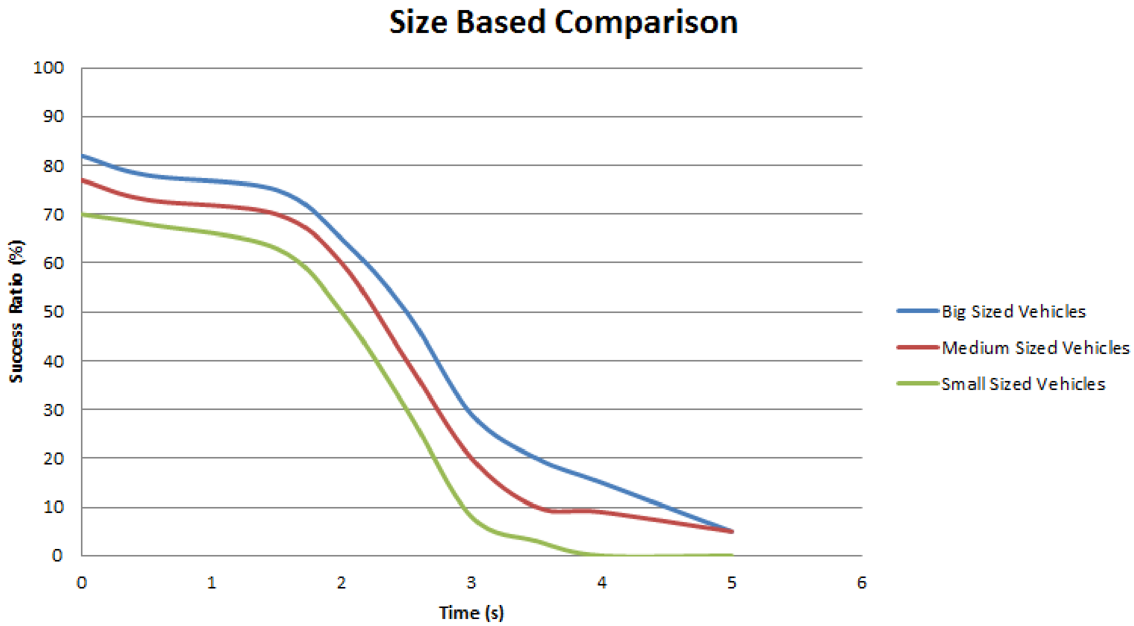


Figure 4-14: Vehicle Size based Success Rate vs. Time Graph (SCA)

Figure 4-14 shows the success rate versus time graph for different sizes of vehicles regardless of their speed types. Figure 4-14 is a summary for previous statistical results. It is more general view than previous graphs to see how early alert can be generated. Null point on the x-axis indicates when the vehicles catches up the cyclist and seconds are the time left for cyclist to act before vehicle catches up. Time is directly taken from analysis graphs and detection results, so given time is more reliable considering there may be some errors in range calculations.

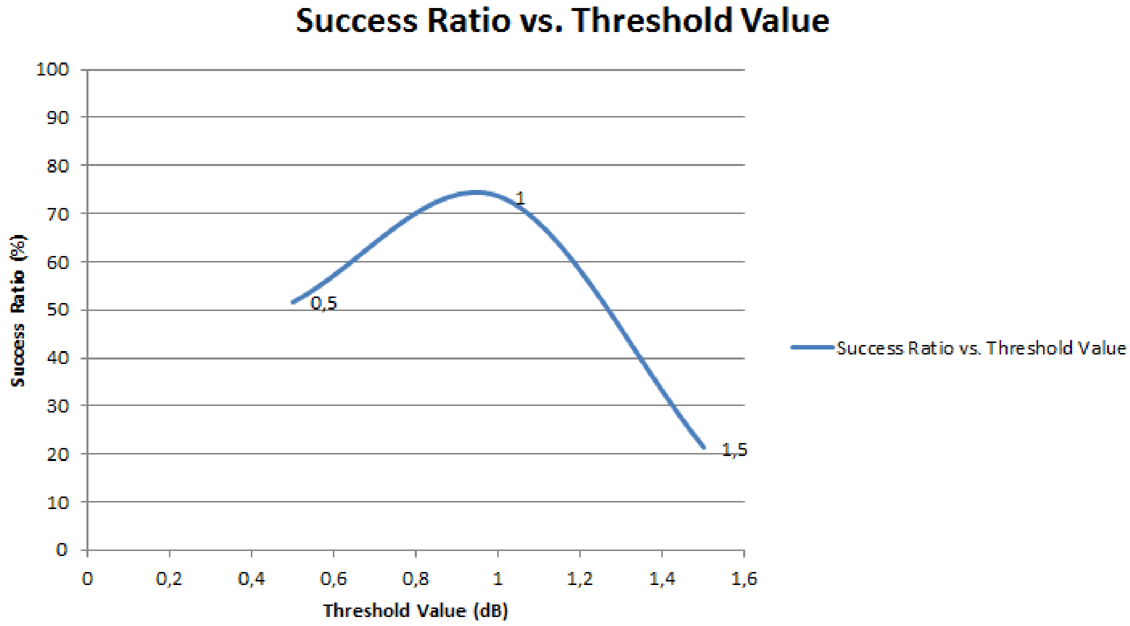


Figure 4-15: Success Rate vs. Threshold Value Graph (SCA)

Figure 4-15 justifies threshold selection. Having threshold value of 1.5 dBs is so high to detect vehicles early enough. Having 0.5 dB can detect vehicles earlier than 1 dB but it can be problematic for noises. 0.5 dB threshold is not as successful as 1 dB threshold to ignore noises and this is because the success rate of 0.5 dB is lower than 1 dB. The success ratio for 1 dB threshold value is calculated to be %73,65.

4.1.3. Spectral Entropy Analysis (SEA)

In this section spectral entropy analysis is presented. As it was mentioned before spectral entropy is a measure of irregularity, this measure tends to decrease as the vehicle approaches since vehicle approach sound will create a certain pattern. During the experiments, it is found out that environmental noises are negligible as long as they are continuous. Although transient sounds may mislead alert generation.

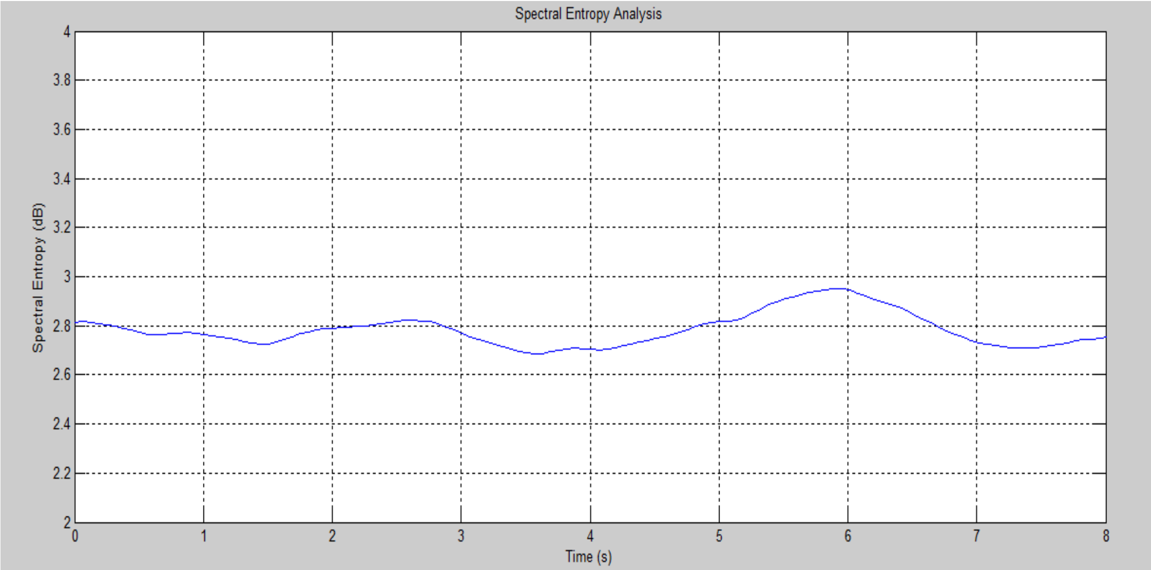


Figure 4-16: Spectral Entropy Amplitude Variation vs. Time of Environmental Noise

Figure 4-16 is the environmental noise recorded when there is no vehicle presence. Since there are no pattern changes within the sound, spectral entropy tends to oscillate around a certain value. Environmental noise includes pedalling sound and tire sounds as well. The value that the spectral entropy is oscillating around is dependent on irregularity level of environmental sound. In order to execute detection, the threshold cannot be the spectral entropy value itself but the decrement compared to approximation of previous values. The purpose of doing an approximation of previous values and comparing it with present value is to eliminate sudden changes caused by transient changes in the environment, such as stopping and starting pedalling for a moment.

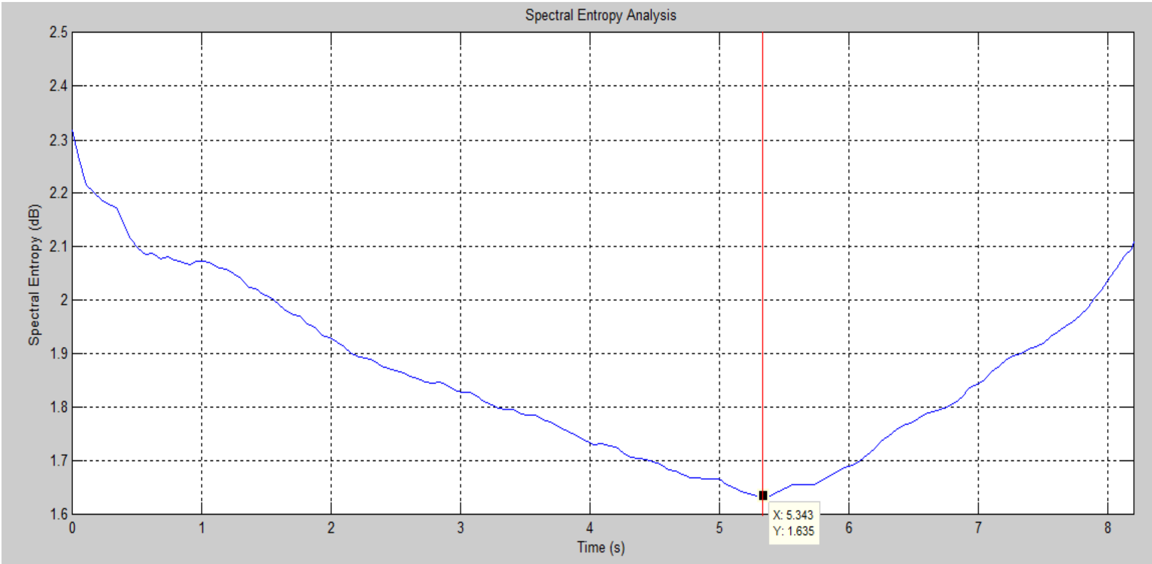


Figure 4-17: Spectral Entropy Amplitude Variation vs. Time of Vehicle Approaching Sound

Figure 4-17 shows the case where there is a vehicle approaching. Red line indicates the moment when the vehicle catches up the cyclist, for the presented graph; vehicle catches up the cyclist at 5.343th second and then passes by. The decrement is obvious comparing to environmental noise. As it was mentioned before, threshold is by the means of decrement and in dB. Threshold is decided to be 0.4 dB and is going to be compared with other threshold value possibilities by the means of success ratio under this title.

As it is done for every type of analysis, success ratio is going to be presented based on range. Range is a clue for detection quality and its effectiveness. Range is calculated using speed calculations based on Doppler Effect and time. The graphs are given as follows;

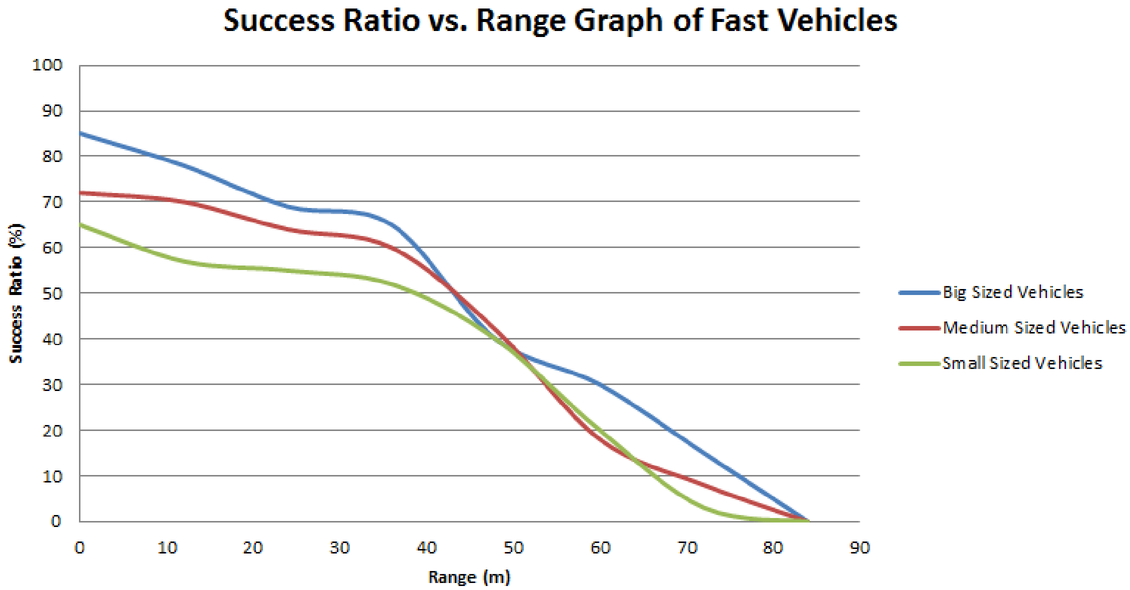


Figure 4-18: Success Ratio vs. Range Graph of Fast Vehicles (SEA)

Figure 4-18 shows the success ratio dependent on the range for fast vehicles. Range is calculated using speed and time data. Even though the success ratio of big sized vehicles is higher, the dependency on size is relatively less for this method, especially for further ranges. As long as the vehicle can create a pattern that can be sensed by microphone, presence of vehicle can be detected. The strength of the sound, so the size of the vehicle is absolutely an important factor, though is less related comparing to radiated-energy based methods, such as root-mean-square analysis. The average speed for fast vehicles is 76,4 km/h and the minimum range should be around 30 meters to have the detection 1.5 seconds in advance.

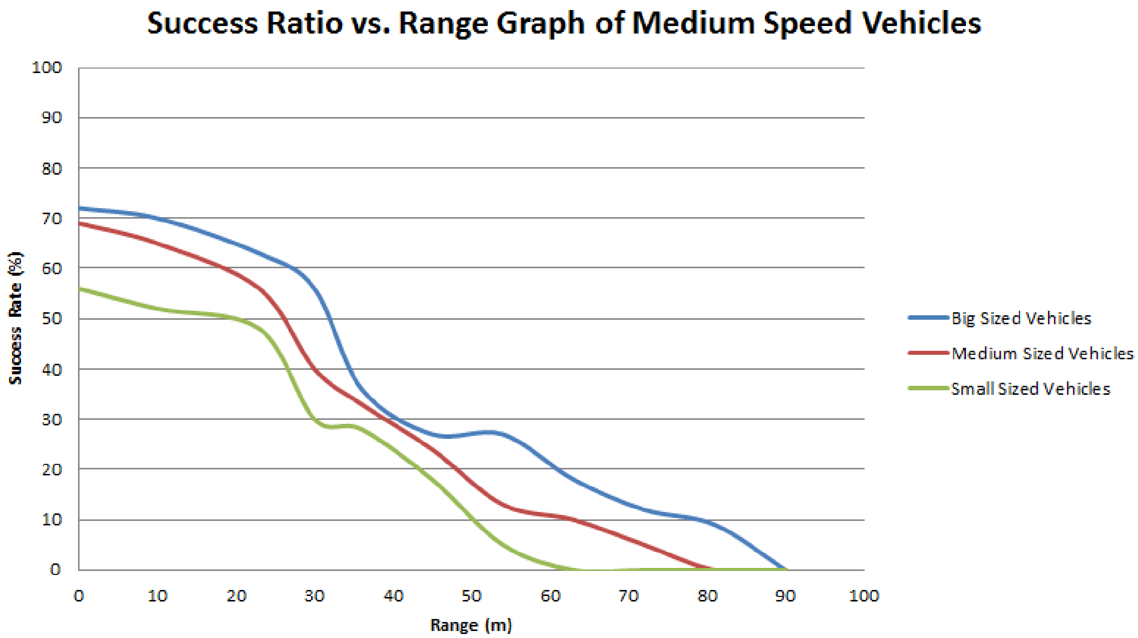


Figure 4-19: Success Ratio vs. Range Graph of Medium Speed Vehicles (SEA)

Figure 4-19 belongs to a size based comparison figure for medium speed vehicles. Speed is calculated using time and speed data for each sample. As it is expected the success rate are higher for bigger vehicles. Since same data is used for all the correlations, the minimum range should be around 23 meters for medium speed vehicles.

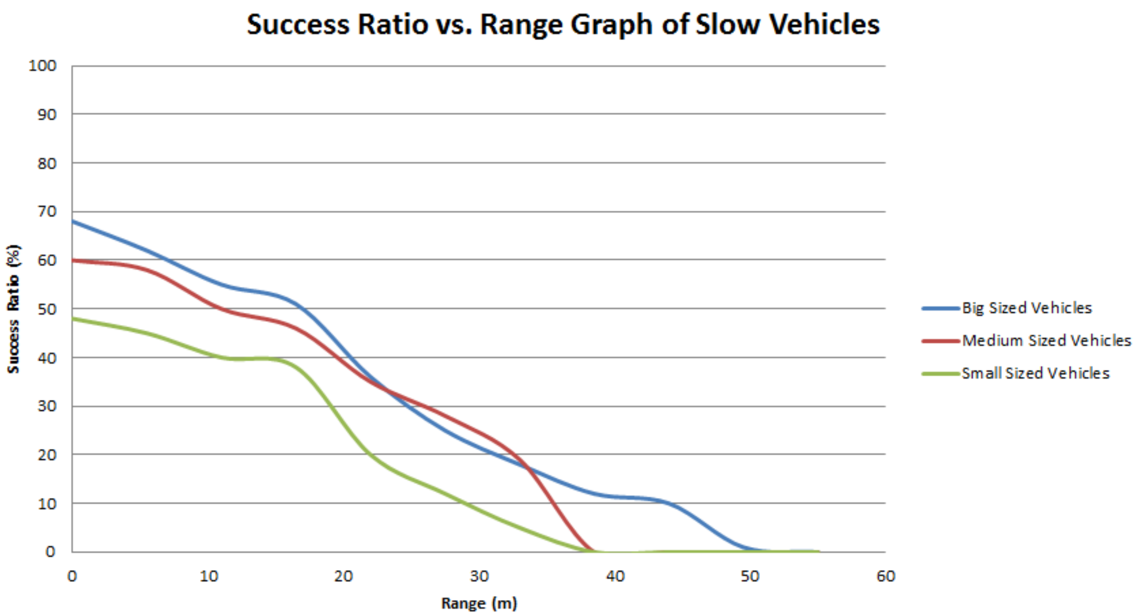


Figure 4-20: Success Ratio vs. Range Graph of Slow Vehicles (SEA)

Figure 4-20 belongs to the size based comparison of slowly approaching vehicles. The approximate speed for slow vehicles is 33,8 km/h which means cyclist have 1 second to react when vehicle is 13 meters far away.

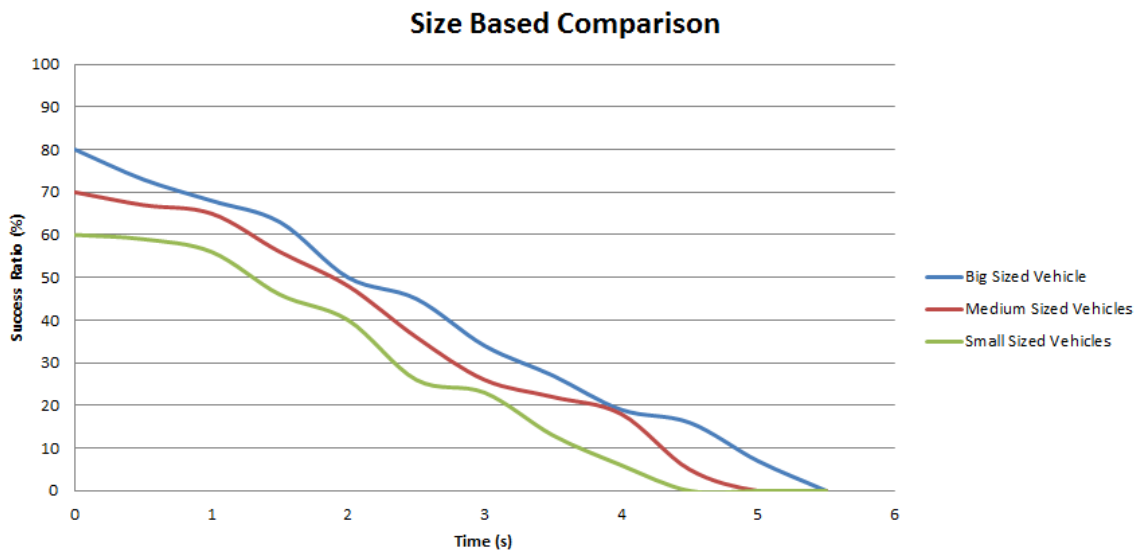


Figure 4-21: Vehicle Size Based Success Ratio vs. Time Graph (SEA)

Figure 4-21 shows the success rate versus time based on vehicles' size. The null point is the moment when the vehicle catches up the cyclist and the time on the x-axis is the time left for the cyclist to act. The moment after the vehicle catches up the cyclist would be quite uninteresting since it is the success ratio diagram of a pre-warning detection. Weighted mean success rate of same sized vehicles are examined together regardless their speeds. Seconds on the time axis indicate the time left before the vehicle catches up the cyclist and null point is the moment when vehicle catches up.

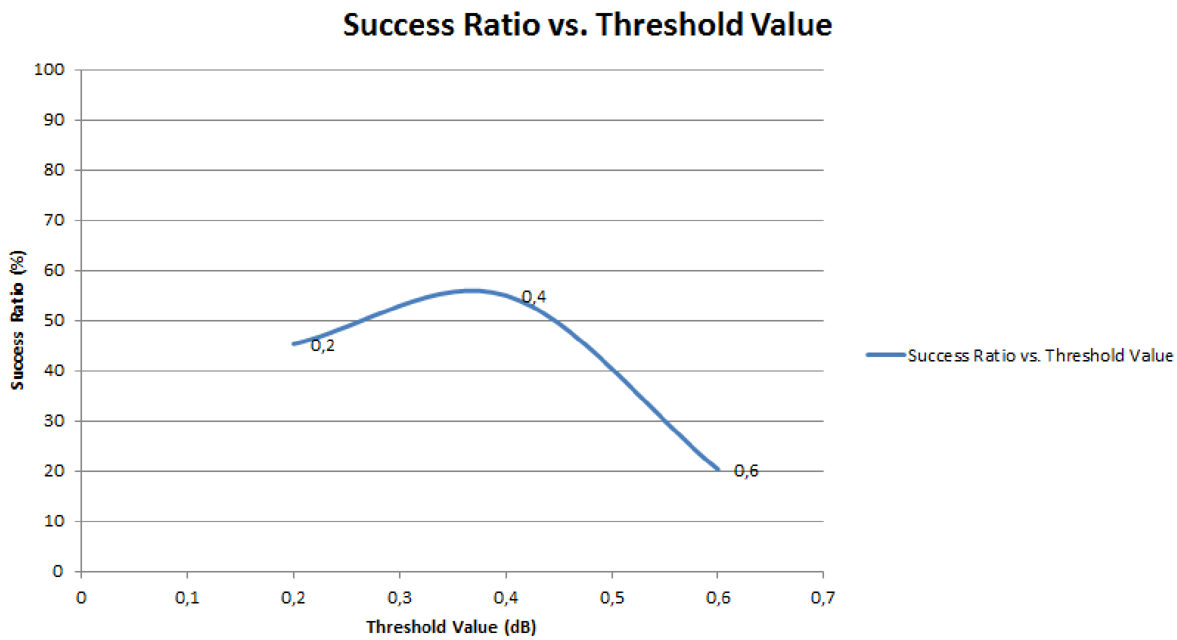


Figure 4-22: Success Ratio vs. Threshold Value (SEA)

Figure 4-22 was plotted to justify threshold selection. There are 3 different thresholds used for having such statistic. Environmental noises and vehicle approaching sounds were analysed for each of the thresholds. In fact having threshold of 0.2 dB is able to detect vehicles earlier, but 0.2 dB is not big enough to avoid unreal alerts. Having alert generations for environmental noises with 0.2 dB threshold has greatly decreased success rate. On the other hand having 0.6 dB threshold is unable to detect vehicles early enough or even unable to detect at all. The overall success rate is calculated to be %56,8 for this method.

4.1.4. Weighted Frequency Spectrum Results (WFS)

The weighted frequency spectrum results are going to be presented in this section. The input signal is plotted by splitting it up into 0.5 second pieces to be able to specify the cases related with time. Therefore there is more than one graph required to explain one case. In order to be brief to the point, some uninteresting or similar plots will be skipped.

In order to decide whether the vehicle is within the detection area or not, there will be a comparison. All the interesting data is between 0-500 Hertz for my project. System automatically finds the maximum amplitude and its frequency within this band. After finding the maximum amplitude and its frequency, the amplitude is compared with the threshold amplitude. Threshold amplitude is set to be 50 in strength. The threshold is settled down after many experiences of background noise analysis and was chosen so that threshold can avoid unreal alerts and generate the alert as early as possible. Background noise tends to remain under this threshold value within the unfiltered frequency band. If the amplitude of the dominant frequency is larger than %95 of the threshold value in amplitude, alert is generated.

The 6 seconds long vehicle approach sound analysis is presented as a result. I let the sound sample name to be Sample 1. 0th second indicates the time vehicle catches up the cyclist. The frequency change and amplitude comparison is separately presented as a table. Using a band-pass filter, the data for analysis is obtained solely from the interesting frequency band and uninteresting frequency bands are damped.

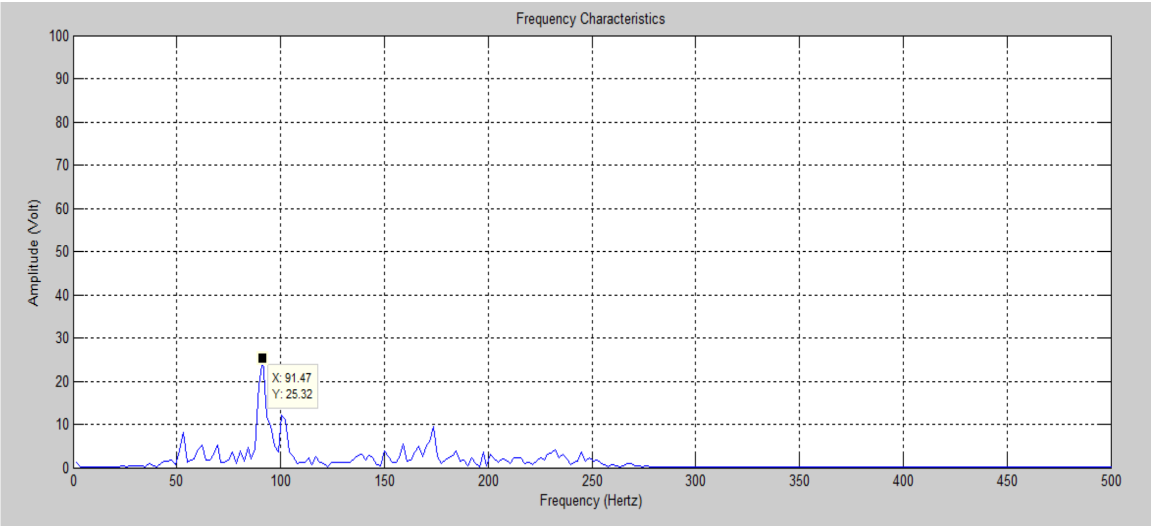


Figure 4-23: Weighted Frequency Spectrum of Sample 1 between -5th and -4.5th Seconds

The figure 4-23 show the case where there is no vehicle detected. It is some external noises seen in the graph. The amplitudes, within the unfiltered frequency band, created by external noises are negligibly weak comparing to threshold value. Though these noises may create large amplitudes in larger frequency bands and could be illusive if it was not filtered out.

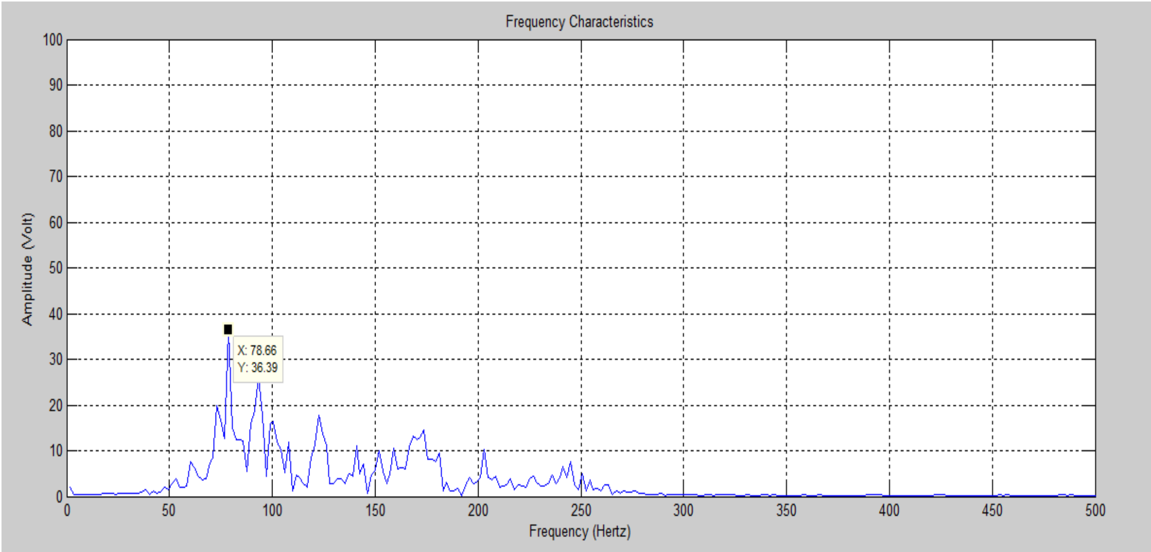


Figure 4-24: Weighted Frequency Spectrum of Sample 1 between -3th and -2.5th Seconds

The figure 4-24 belongs to the case where the vehicle about the get in the detection area, as it can be seen the amplitude of dominant frequency is rather large. If the graph is wanted to be interpreted, the effect of approaching vehicle is sensed but system does not generate any alerts since the amplitude is not large enough and is considered to be a noise effect.

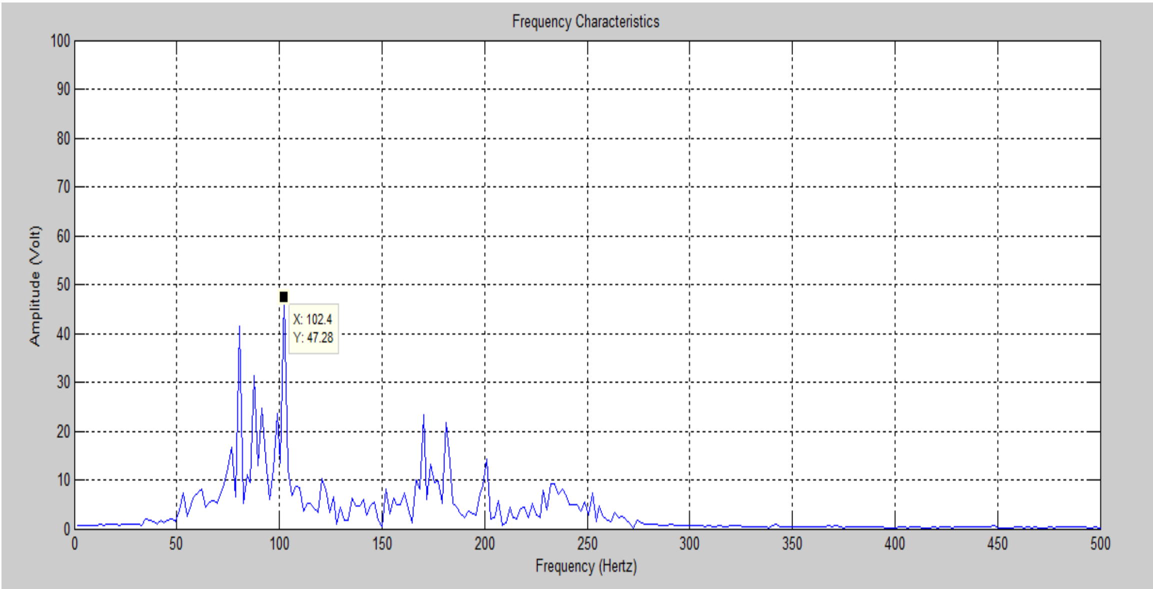


Figure 4-25: Weighted Frequency Spectrum of Sample 1 between -2.5th and -2nd Seconds

The figure 4-25 shows the moment where the vehicle gets in the detection area. The effect of the vehicle was already sensed in previous graph but the possibility of this amplitude to be noise effect is weaker in this graph. The system would recognize this amplitude and generate an alert.

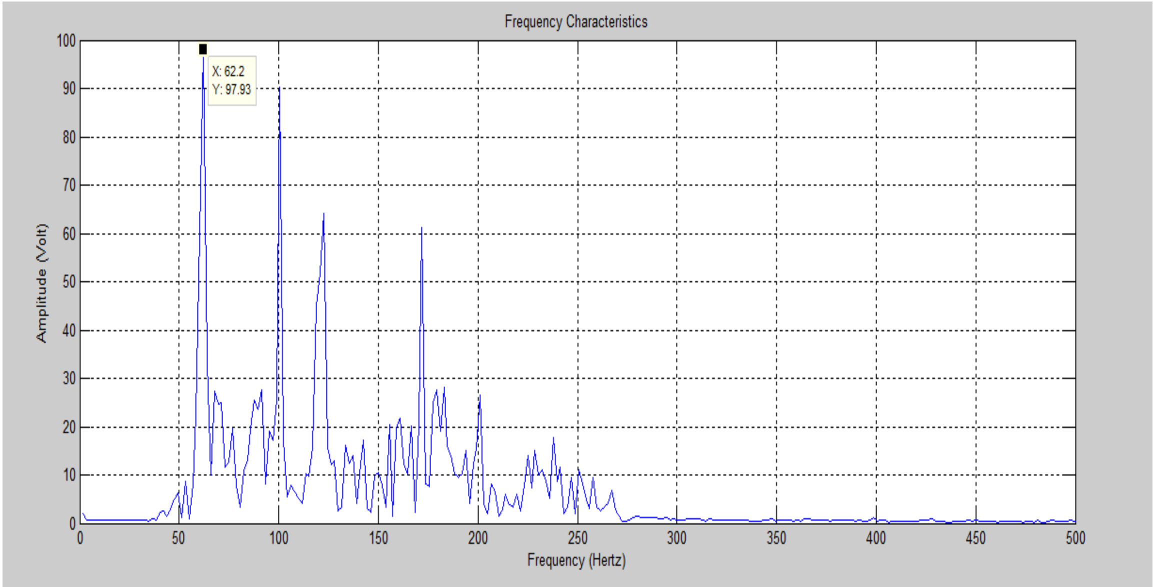


Figure 4-26: Weighted Frequency Spectrum of Sample 1 between -1.5th and -1st Seconds

In the figure 4-26 is where the vehicle is in the detection area and has 1.5 seconds left to catch up the cyclist. The amplitude increment is obvious and far distinct from being a noise effect. There are several peaks emerged in the graph. This is because the vehicle does not create sound in one single frequency bin. Dominant frequency will not differ much after this point but is expected to be shifted.

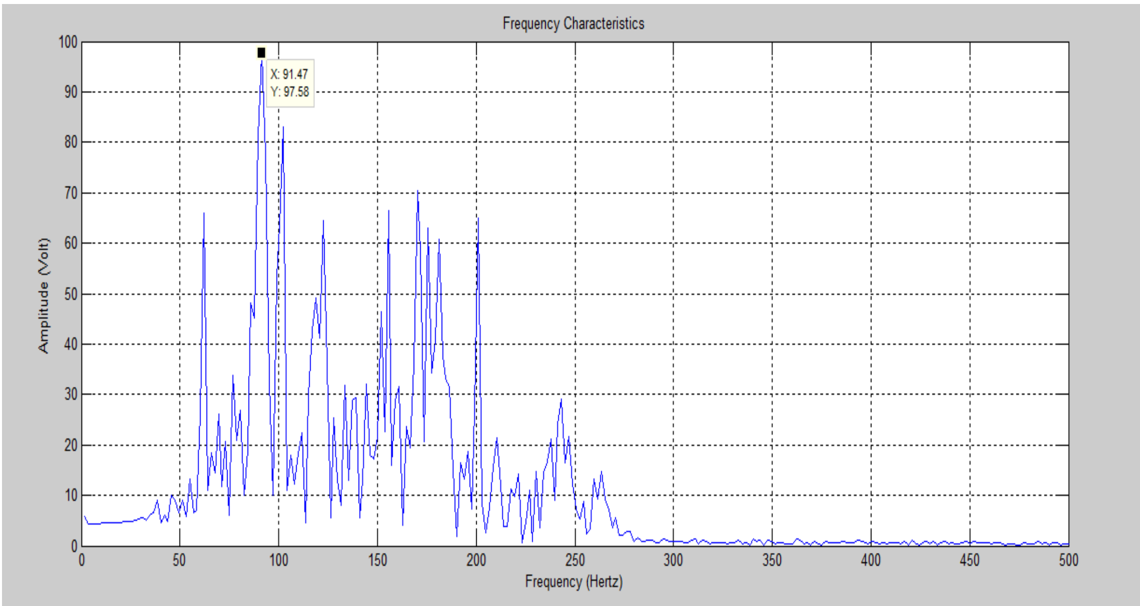


Figure 4-27: Weighted Frequency Spectrum of Sample 1 between -1st and -0.5th Seconds

Figure 4-27 shows the interval just 0.5 seconds after Figure 4-26. The dominant frequency is shifted and all the other parameters are similar as it was in Figure 4-26.

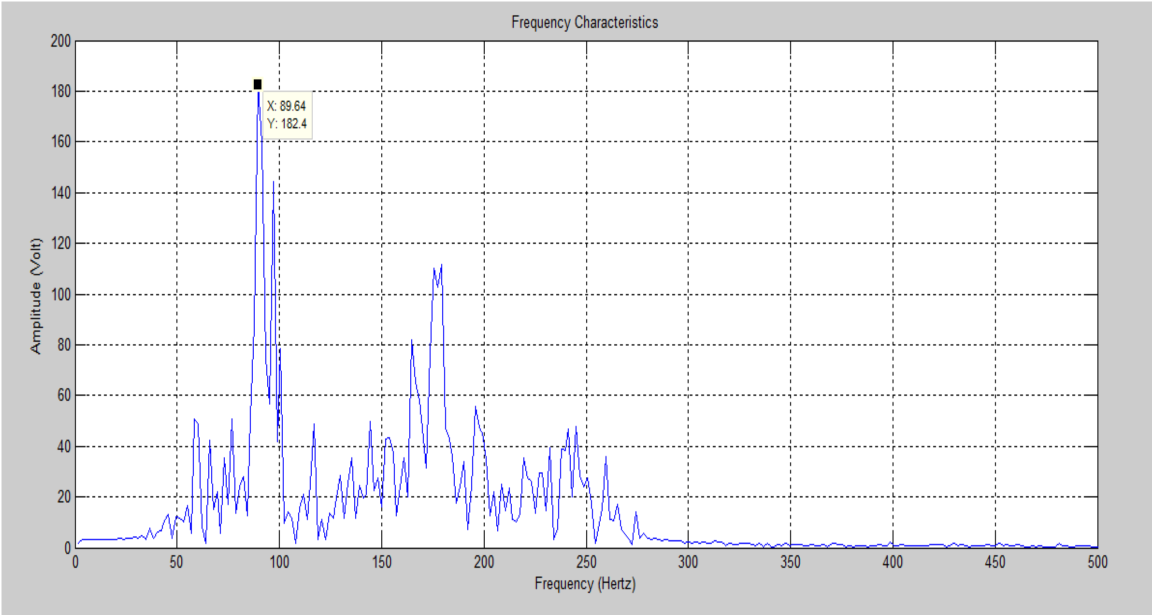


Figure 4-28: Weighted Frequency Spectrum of Sample 1 between -0.5th and 0th Seconds

Figure 4-28 belongs to the moment when the vehicle catches up the cyclist. In this moment amplitude is at the largest point since the vehicle is closest. After this moment, alert may remain alerted for a little while, before settling down.

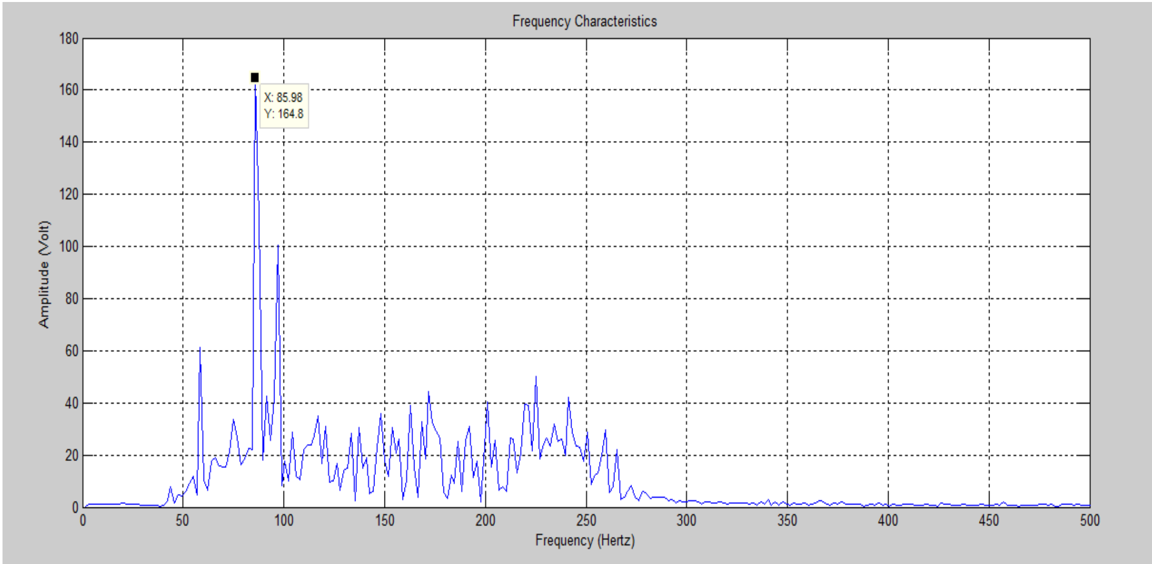


Figure 4-29: Weighted Frequency Spectrum of Sample 1 between 0th and 0.5th Seconds

Figure 4-29 belongs to the moment just after the vehicles passes by the cyclist. System remains alerted for at most 1 second after vehicle passes by. Amplitude is slightly damped. After the indicators of this effect terminate, system will be the same as it had been before vehicle was detected. This can be seen in Table 4-1 numerically.

The case is going to be clearer by putting the numerical data into one single table and evaluating.

Time Interval	Threshold Value	Frequency	Strength of Main Frequency	Percentage (%)	Result
-5.00:-4.50	50	91.47	25	50	No Alert
-4.50:-4.00	50	102.45	19	38	No Alert
-4.00:-3.50	50	102.45	24	48	No Alert
-3.50:-3.00	50	182.94	29	58	No Alert
-3.00:-2.50	50	78.67	36	72	No Alert
-2.50:-2.00	50	102.45	47.3	95	ALERT!
-2.00:-1.50	50	100.62	34	70	No Alert
-1.50:-1.00	50	100.62	97	194	ALERT!
-1.00:-0.50	50	102.45	98	196	ALERT!
-0.50:0.00	50	89.64	182	364	ALERT!
0.00:0.50	50	85.98	164.8	328	ALERT!
0.50:1.00	50	85.36	66.3	132	ALERT!

Table 4-1: Weighted Frequency Spectrum Numerical Chart

Table 4-1 shows the numerical flow of alert generation and the changes with the given parameters.

If the case is wanted to be shown in one single graph, frequency spectrum of the whole signal can be used. The resultant graph of sample 1 and some other environmental noises are as follows;

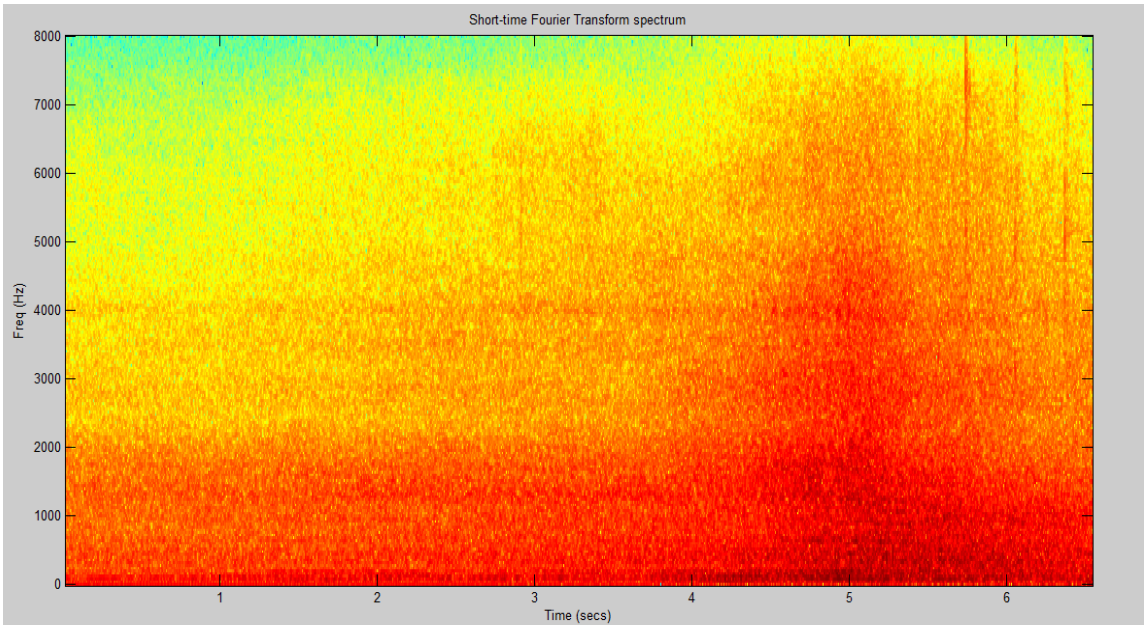


Figure 4-30: Frequency Spectrum of Sample 1 (Vehicle Approach Sound Sample)

Figure 4-30 shows the frequency spectrum versus time of a vehicle approach sound sample. Between the seconds 0-1, radiated energy in higher frequencies and radiated energy intensity in all the frequency values are relatively weak. As the vehicles closes up, the radiated energy gets more intense.

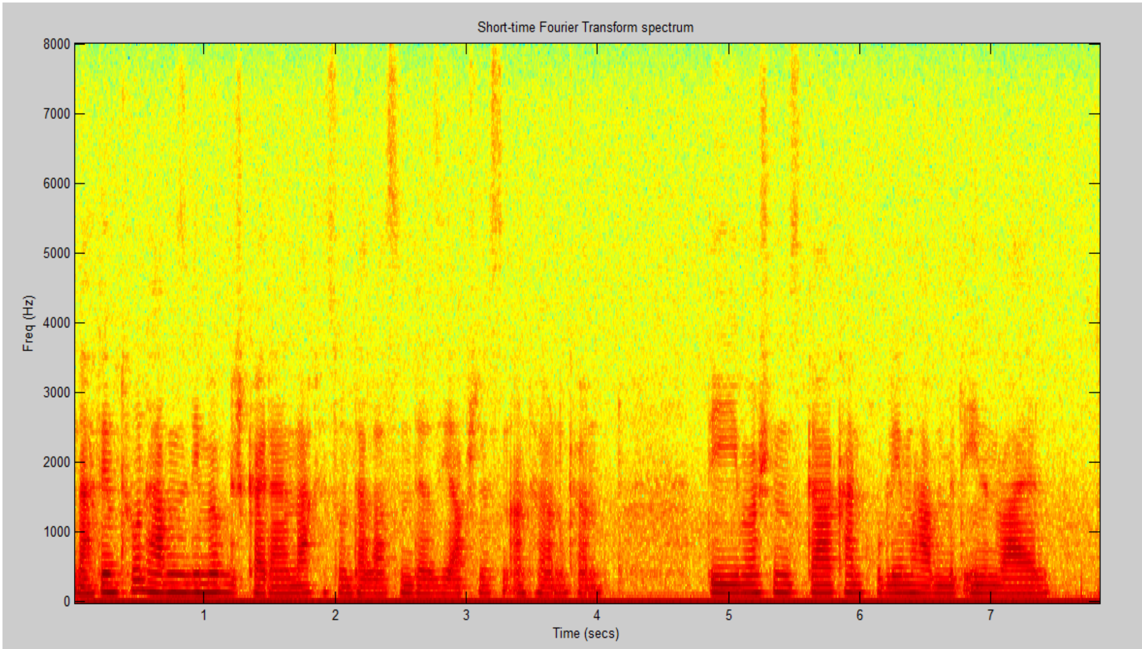


Figure 4-31: Frequency Spectrum of Human Talking Noise

Figure 4-31 shows the frequency spectrum of human talking noise. This sample is collected from a certain distance as it should be between cyclist's mouth and the sensor during the travel. There is no vehicle presence within this sound sample. As it can be seen, there is no continuous radiated energy intensity. In other words, the characteristic features of human talking noise is not similar with vehicles approaching sound and can mostly be avoided from confusion if the proper threshold value is used.

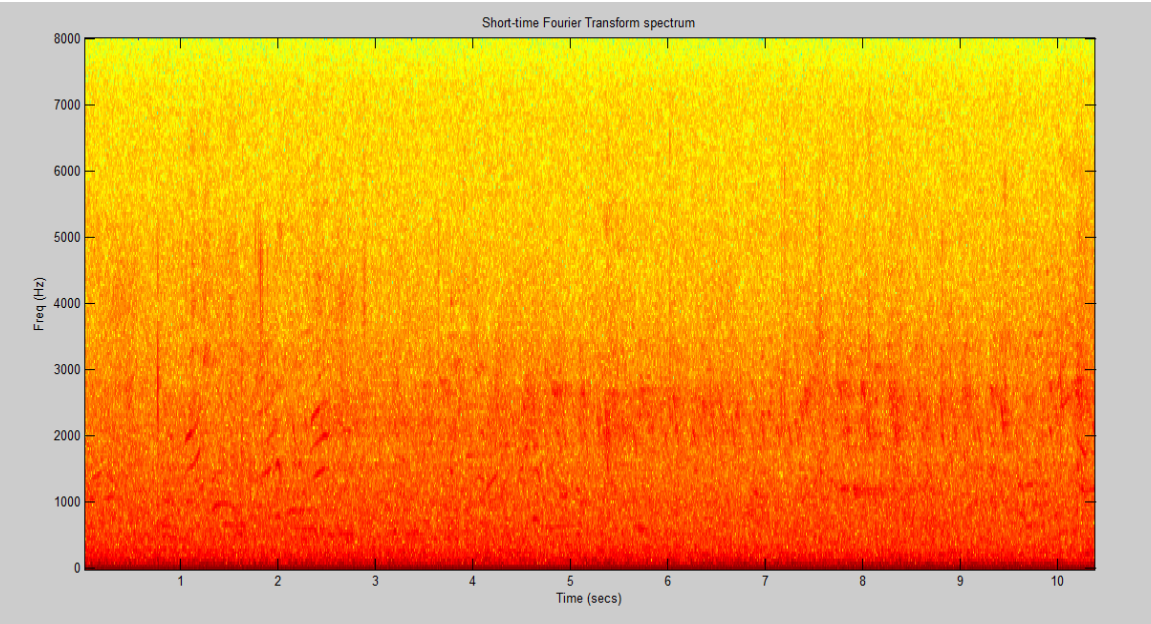


Figure 4-32: Frequency Spectrum of Environmental Noise

Figure 4-32 belongs to the environmental noise which cyclist may face in real life. Environmental noise given in this graph contains pedalling noises as well, though the sensor was faced backwards and pedalling noise is rather weak since the sensor is expected to be mounted backwards or even on the helmet in practical applications. The radiated energy can said to be randomly distributed and no intense points. Comparing to vehicle approach sample, radiated energy is not strong enough in related frequency bands.

It is not possible to say these noises are completely eliminated, though it is minimized as much as possible using proper threshold values and filtering. In order to see the characteristic features of different types of vehicles in size and speed, some statistical graphs are presented. The data used for statistical results contains environmental noises and are considered to be unsuccessful if any unreal alerts generated. The graphs are as follows;

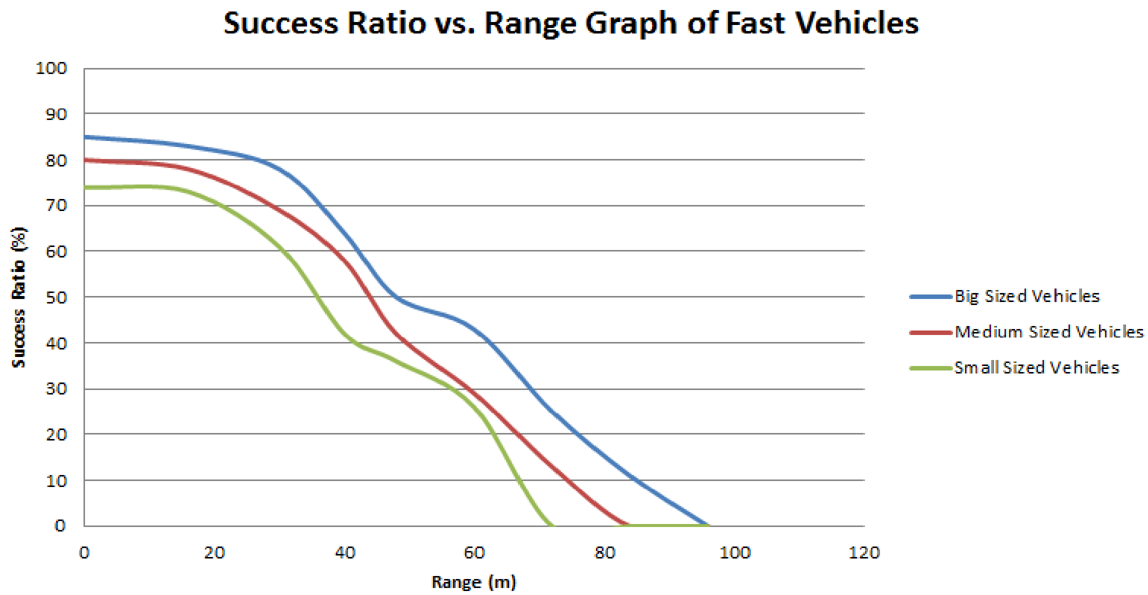


Figure 4-33: Success Ratio vs. Range Graph of Fast Vehicles (WFS)

Figure 4-33 shows the success ratio vs. range graph of fast vehicles. The range is calculated using speed calculation based on Doppler Effect and time. Big sized vehicles are easiest to detect. The average speed of fast vehicle is calculated to be 76,4 km/h and the minimum range is around 30 meters to have the detection early enough.

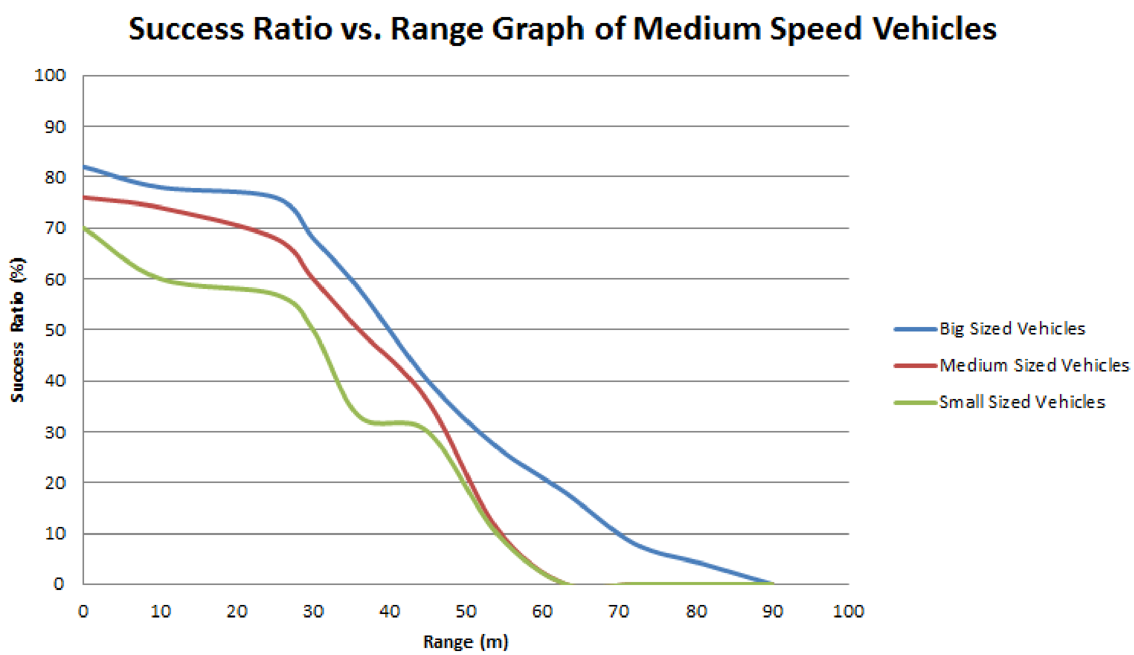


Figure 4-34: Success Ratio vs. Range Graph of Medium Speed Vehicles (WFS)

Figure 4-34 shows the success ratio versus range graph for medium speed vehicles. As it was expected, success ratio is higher for bigger vehicles. The average speed of medium speed vehicles is calculated as 57,6 km/h and the minimum range is around 23 meters to have a detection at the latest 1,5 seconds in advance

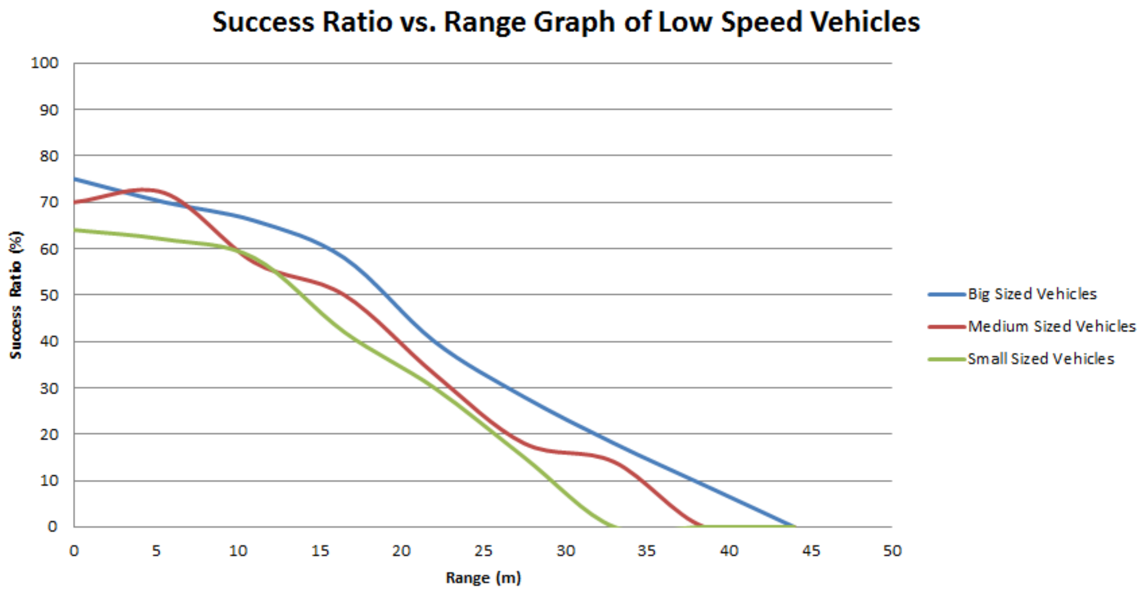


Figure 4-35: Success Ratio vs. Range Graph of Low Speed Vehicles (WFS)

Figure 4-35 shows the success ratio versus range graph for low speed vehicles. As it was mentioned before, low speed small vehicles are the hardest type of vehicle to detect.

The concern about threshold values and size based comparison are going to be presented in following graphs. The data used for threshold values contain environmental noise and are more than 120 samples. The threshold value versus success ratio graph is not time or range based, just shows the overall success ratio. The case is considered to be unsuccessful if the alert is generated later than 1.5 seconds before the vehicle catches up or any unreal alerts were generated.

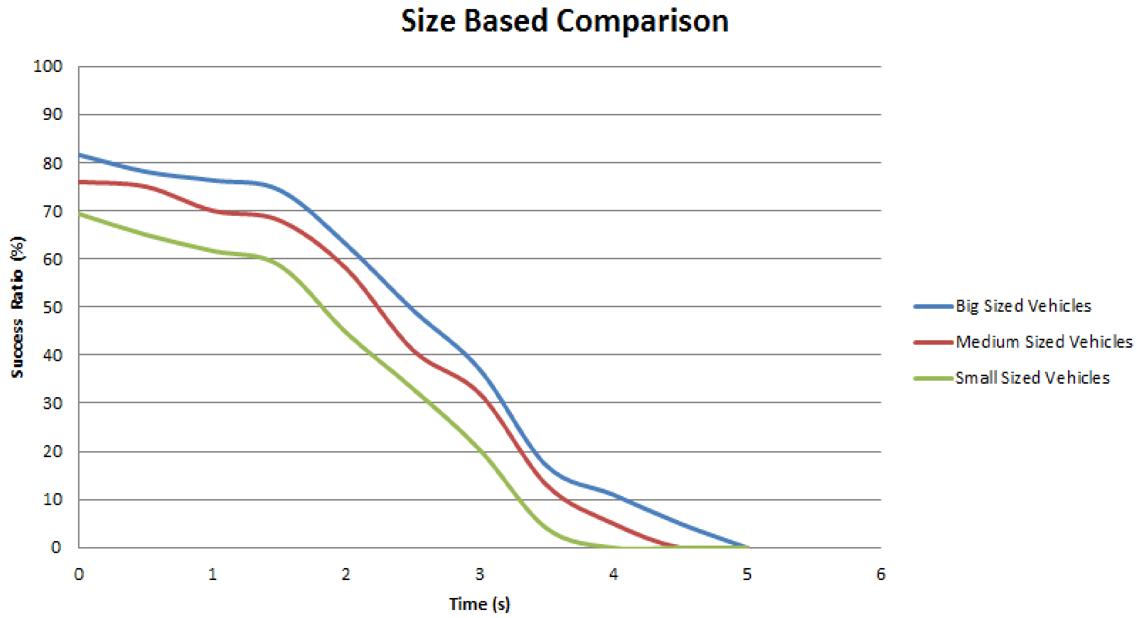


Figure 4-36: Vehicle Size based Success Ratio vs. Range Graph (WFS)

Figure 4-36 is a summary of Figures; 4-35, 4-34 and 4-33. The main difference of this graph is its speed independency. Vehicle sizes are compared regardless of their speeds, weighted mean success ratio was calculated for each type of vehicle and the graph could be obtained.

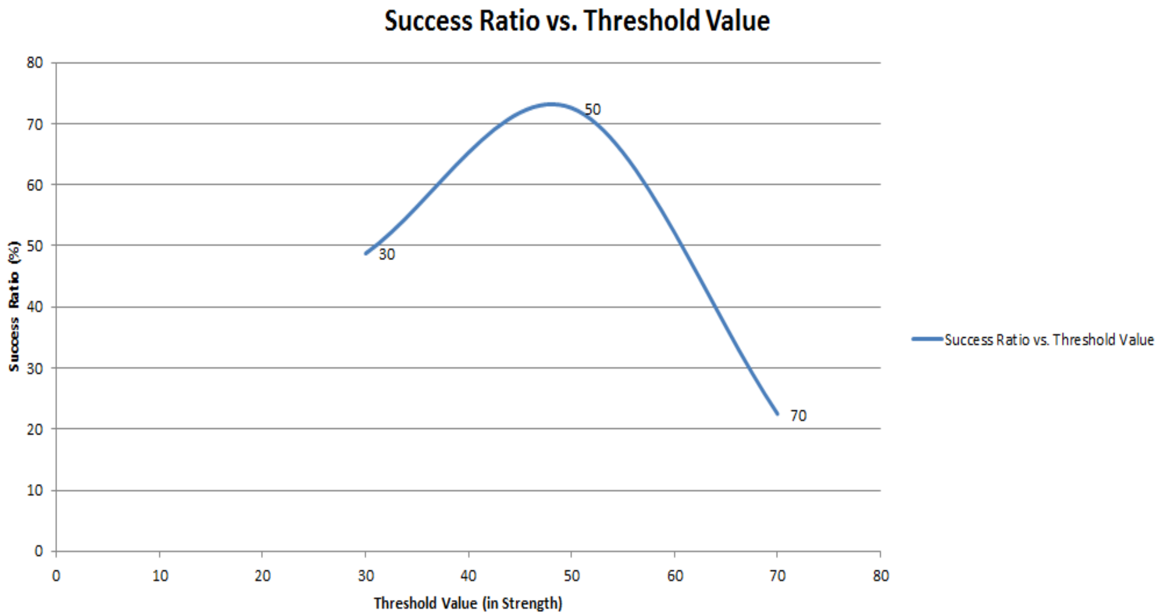


Figure 4-37: Success Ratio vs. Threshold Value (WFS)

Figure 4-37 shows the success ratio versus threshold value graph. There are three different threshold values and 132 different data sample were used for the graph. The success ratio for pre-set threshold value is found to be %71,58 for this detection type.

4.2. Sensor Fusion and Analysis

In this section, the best two results are going to be fused to see if the success rate can be improved. The fusion success rate is calculated based on scenarios. For each scenario/sound sample, detection is executed using this fusion diagram and the success rate is calculated using results.

In order to see two best results clearly, overall success rates for correlations are given in a graph as follows;

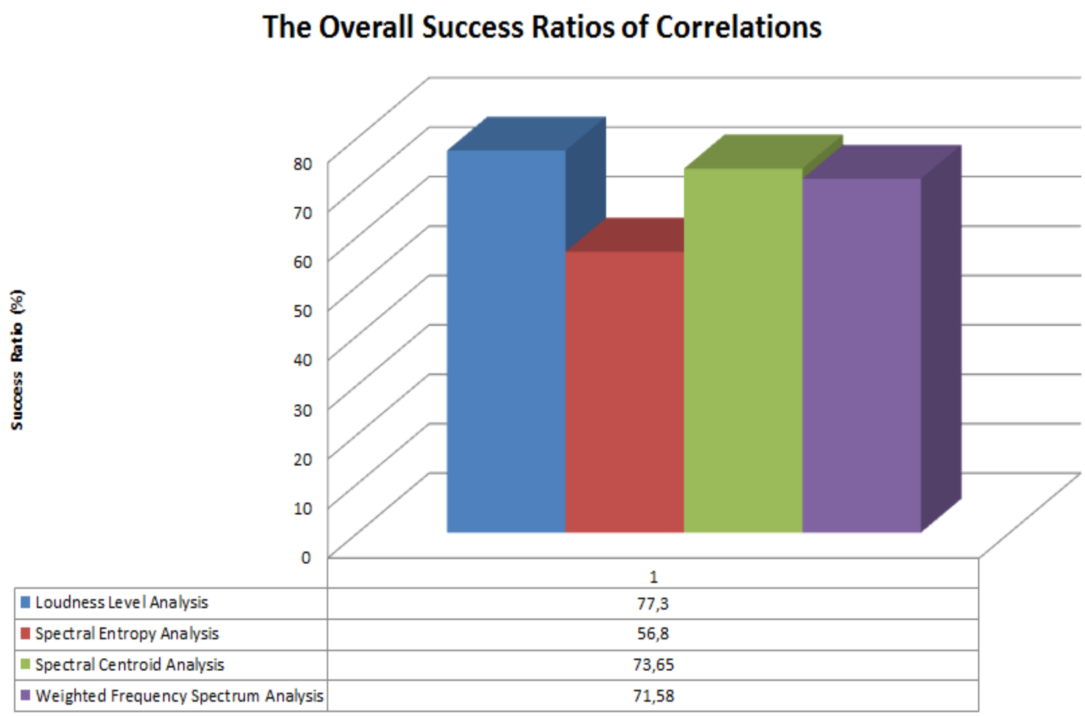


Figure 4-38: Overall Success Ratios of Correlations

As it can be seen in the Figure 4-38, the best two results revealed to be Loudness Level Analysis and Spectral Centroid Analysis. As it is mentioned previously, the cases are going to be analysed based on individual sound samples. The samples are analysed once more using new logical diagrams and the success ratios are re-calculated. There are two different fusion is going to be used for the detection as; parallel connection and serial connection. The purpose of doing two different fusions is to justify the selection of the fusion.

For parallel fusion, detection types are logically parallel connected which means having an alert from one of the correlations will be enough for alert generation for the system. It is more perceptible to see it visually as;

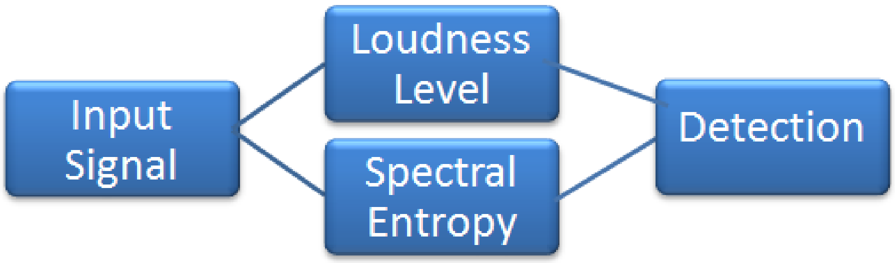


Figure 4-39: Parallel Fusion Diagram

For serial fusion, correlations are logically serial connected which means that it is only possible to generate an alert by having alerts from both of the correlations. The fusion is shown visually as follows;

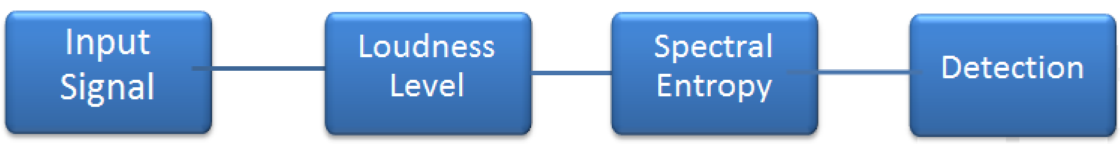
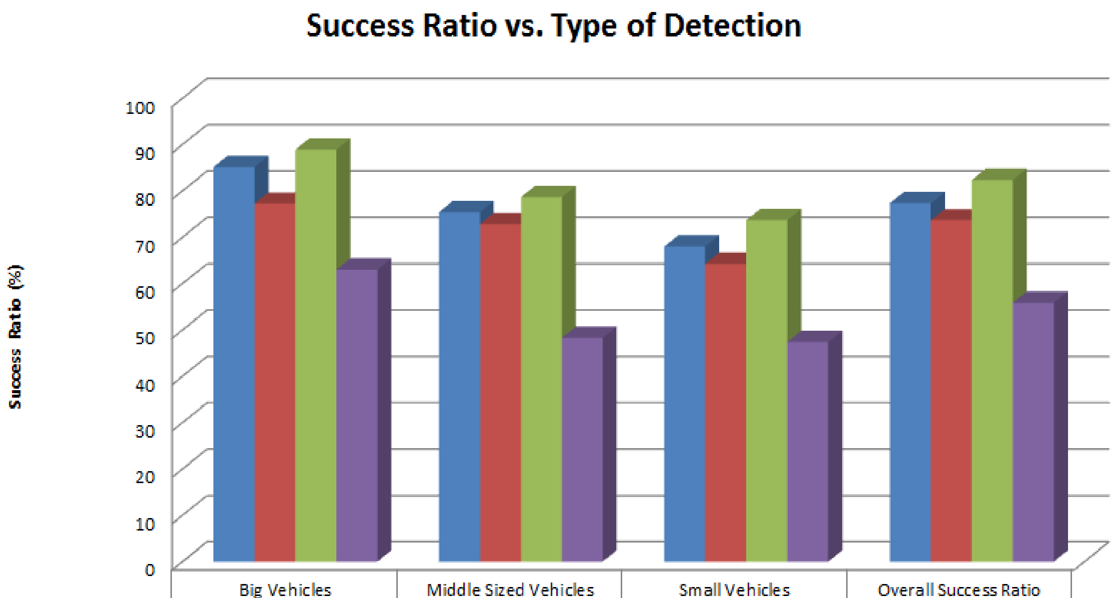


Figure4-40: Serial Fusion Diagram

After re-organizing the samples using the given logical diagrams above, the results are obtained for both serial and parallel fusion. The success ratio for each type of vehicle and the weighted mean of the overall success ratio is re-calculated. As it was mentioned before, successful cases are the detections which are real alerts and generated at the latest 1.5 seconds before vehicle catches up the cyclist. The results are as follows;



	Big Vehicles	Middle Sized Vehicles	Small Vehicles	Overall Success Ratio
Loudness Level	85,12	75,4	68	77,3
Spectral Centroid	77,2	72,8	64,23	73,65
Parallel Fusion	88,88	78,62	73,68	82,32
Serial Fusion	63	48,27	47,36	55,87

Figure 4-41: Success Ratio versus Detection Type Graph

Figure 4-41 summarizes the sensor fusion and resultant success ratios. First of all, the correlations' own success ratios depending on vehicle sizes are shown in the table on the graph. Afterwards, the resultant success ratios of fusion types are also presented.

Resultant success ratios of the parameters given in the graph are based on the results of scenarios and on noises. In order to obtain success ratio of fusions, sound samples are re-analysed. It is shown that parallel fusion of the given correlations gives the best results for vehicle detection.

Chapter 5

Discussions and Conclusions

In this chapter I am going to talk about the conclusions of my work. I am also going to give some advices about how the similar works can be enhanced.

My purpose was to find the suitable sensor for the cyclists that can detect dangerously rear approaching vehicles early enough to make it possible for cyclists to have enough time to take an action as long as possible. I have chosen microphone for this type of detection. Microphone meets the requirements by the means of power consumption and size.

I found some correlations that I can use for my project. I have created the scenarios and collected the data. I have used Matlab for executing the analysis. My first goal was to be able to identify approaching vehicle sound among all the possible noises. After using many correlations I have achieved my goal, though there was a deceptive point in executing sound detection. The microphone should not be emposed by any other mechanical impacts such as wind. If the microphone is not immune against wind, the collected data is more likely to be altered. These alterations may be so strong that they may lead to unreal alerts.

After this stage, I have focused on how to execute detection early enough.The range is wanted to be around 100 meters as I started the project but I have ended up with the approximate range of 30 meters. After making many experiments with the captured sound sample, I have found out that the time is more important than the range. The speed and the sound strength of the approaching vehicle was determinant on the range. Fast approaching vehicles could be detected within a longer range, though slower vehicles could be detected in a rather short range. This is because of frequency changes and the sound patterns that vehicles create on the road and in the environment is more intense for faster and bigger vehicles. Slower vehicles create weaker frequency indicators comparing to faster vehicles. Since most of the correlations I am using are related with the frequency indicators, vehicles creating stronger frequency changes can be detected easier. The thing I am trying to point out is that it is easier to say how early can the vehicle be detected than the distance. This time value for my project is settled to be 1.5 seconds at the latest.

Discussions & Conclusions

- **Discussions;**

According to the results of my project, detecting dangerously rear approaching vehicles is executed with a certain success rate. The success rate of the detection that can be done early enough is %82,32 for my project. I was expecting the success ratio to be better for slow vehicles as well. The data I have used for analysis could be better since it is not always easy to have pure vehicle approach sample. If the more precise data could be collected, the success rate of detection would be higher.

After I made my analysis by grouping them, I have found out that there is a weakness of acoustic detection. If the vehicle is creating rather low noise or really slow, the success rate is even lower. The acoustic detection is not that convenient to detect low noise creating vehicles. In order to make the detection safer, a reinforcing sensor which is not based on audio detection might be added in a future work. Passive photo detectors, for example, might be added as a reinforcing sensor, since the power consumption is limited.

- **Experiences;**

The most important thing that I have learned while working on this project was the importance of disciplinary and planned working. It becomes so much time consuming to collect data and interpret the analysis, if the work is not planned good enough.

It is really important to collect the data systematically. You should know what is it in the data you have collected, as it will maker easier to interpret the analysis. As I said previously, the wind noise is one of the things to be cared about while collecting sound data. It is also really important to choose the environment to collect data in order to know which sounds are there in the sound sample.

It is really important to keep the imaginary components, negativity possibilities and normalizations in mind. Before using signal processing tool in matlab, it is also good to gather some knowledge about all the components you are going to use and build up a background about signal theory.

- **Future Work;**

In addition to my work there are some enhancements that should be done to have a more reliable detection. One of them is directing the microphone; using directed microphone for such detection will lower the environmental noises such as pedalling and wheel noise.

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