VISVESVARAYA TECHNOLOGICAL UNIVERSITY

BELGAUM-590014

A Report on

Detection and Localization of Dynamite Fishing

Submitted in partial fulfillment of the requirement for the award of degree of

BACHELOR OF ENGINEERING

in

TELECOMMUNICATION ENGINEERING

By

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VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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CERTIFICATE

This is to certify that the project entitled ***Detection and Localization of Dynamite Fishing*** is a bona fide work carried out by **Skanda S Bharadwaj, Sumukha B N and Chandan Kumar R**, bearing respective University Seat Numbers **1PI11TE107, 1PI11TE113, 1PI11TE035** in partial fulfillment for the award of **Bachelor of Engineering in Telecommunication Engineering** of the Visvesvaraya Technological University, Belgaum, during the year 2014-2015. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report deposited in the departmental library. The project report has been approved as it satisfies the academic requirements with respect to the project work prescribed for the said degree.

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Abstract

The illegal practice of dynamite fishing upsets the balance of an ecosystem and can endanger human lives as well. Detection and localization of such activity is necessary from several viewpoints. This project explores a methodology for detection and localization that deals with a larger class of impulsive sound signals that includes blasts, gunshots and thunder. Using the periodogram, the power spectrum of the signal is first analyzed to design a pre-processing filter that is best suited for the particular sound signal. Various FIR and IIR filters are investigated to obtain a computationally optimal bandpass filter that effectively satisfies the design specifications. Detection begins with knowing whether or not an impulsive sound has occurred, and then subsequently to classify the sound signal. A two-class problem is considered in this project – blast and non-blast. For proper classification salient features are extracted from the filtered signals. The classes of features considered here include principal components, and those extracted after processing using a wavelet transform and cosine transform. The efficacies of these classes of features are compared for the objective of this project. The extracted features are then used to train an artificial neural network to classify the sound signals. Several methods for localization are also explored. These include the conventional triangularization method and a technique based on the so-called Received Signal Strength Indicator (RSSI). A computationally efficient and implementable algorithm is presented that is not only fast but as well localizes in real-time.

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Chapter 1

INTRODUCTION

Chapter 1

INTRODUCTION

1.1 Digital Signal Processing

Signal Processing is a technology that spans an immense set of disciplines including entertainment, communication, space exploration, medicine, archeology, just to name a few. Sophisticated signal processing algorithms and hardware are prevalent in a wide range of systems, from highly specialized military systems through industrial applications to low cost, high volume consumer electronics. This is even more true today with the emergence of advanced television and multimedia.

The field of signal processing has always benefited from a close coupling between theory, applications and technologies for implementing signal processing systems. The growing number of applications and demand for increasingly sophisticated algorithms goes hand-in-hand with the rapid pace of device technology for implementing signal processing systems. Signal processing is concerned with the representation, transformation, and manipulation of signals and the information they contain. The rapid evolution of the digital computers and microprocessors together with some important theoretical developments such as the Fast Fourier Transform(FFT), developed by cooley-tukey, caused a major shift to digital technologies, giving rise to the field of digital signal processing.

Digital signal processing (DSP) has been a very active area of research and application for more than 40 years. This broad development has occurred at a time of rapid development of high-speed electronic digital computers, microelectronics and integrated circuit fabrication technologies. An ever-increasing assortment of integrated circuits specifically tailored to perform common DSP functions is available to the design engineer as system building blocks or parts-in-trade. DSP methodologies have been applied to consumer electronics, communication, automotive electronics, instrumentation, medical electronics, tomography and acoustic imaging, cartography, seismology, speech recognition, robotics etc.

1.2 Overview

Dynamite fishing or blast fishing is the practice of using explosives to stun or kill schools of fish for easy collection. Often, this illegal practice can be extremely destructive to the surrounding ecosystem. This practice destroys the underlying habitat (such as coral reefs) that supports the life beneath water. The frequently improvised nature of the explosives used also means danger to the fishermen as well, with accidents and injuries.

The aim of this project is to develop algorithms to detect and localize the dynamite blast. From a technical point of view, a blast is considered to be an impulsive sound signal. Hence, the techniques available in digital signal processing are used to tackle the problem. The proposed solution to the problem is segregated into two major stages as shown below.

1. Detection
2. Localization

Detection is the stage, where the dynamite blast is detected and classified. Several techniques are incorporated in order to achieve the goal. The proposed solution is intelligent enough to differentiate between a bomb blast and any other impulsive sounds, like, for example, a thunder, or a bird's chirping.

Localization is a process of reporting the origin of events and to determine physical position or logical location, answer questions on the network coverage, assist group querying of sensors. The technique is used to geographically locate the blast of the dynamite.

In a nutshell, the objective of the project is to develop efficient algorithms to detect, classify and localize a blast or an explosion.

1.3 Scope

The algorithms for the project were developed keeping in mind the constraints posed by hardware, though the implementation was not a part of this project. Implementation on an android platform or any other embedded boards like Raspberry-pi or Intel's Galileo can actually be tried. Real-time implementation is possible since the algorithms do not involve intensive calculations.

Dynamite fishing is being practiced in the Kaveri river in Karnataka. Department of Wildlife Conservation has requested for a technological solution to this problem and hence the project was taken up. Real time implementation is expected in the near future. Either mobiles or embedded boards will be used to acquire the real time sound signals from the river side and run the proposed algorithms.

The scope of this project is not just limited to dynamite blast detection. The proposed solution can also be generalized for detection and localization of impulsive sound source. As a system, it can be implemented to locate illegal mining, quarrying etc.

1.4 Motivation

Digital signal processing (DSP) is currently one of the top trending research fields in modern day technology. DSP has laid its hands on almost every aspect of day-to-day life which includes communication, entertainment, automobiles, multimedia, military systems, to mention a few. Also one can find umpteen systems implemented that has DSP algorithms running on them. One of the greatest real time implementation is the Global Positioning System (GPS) which completely relies on DSP. The efficacy and the beauty of the subject caught our interest to pursue our research in this domain.

Although outlawed, the practice of dynamite fishing remains widespread in Southeast Asia, as well as in the Aegean Sea, and coastal Africa. It has also been spotted along the river sides of Kaveri river in Karnataka. In the Philippines, where the practice has been well-documented, blast fishing was known prior to World War I, as this activity is mentioned by Ernst Jünger in his book Storm of Steel. One 1999 report estimated that some 70,000 fishermen (12% of the Philippines' total fishermen) engaged in the practice. Extensive hard-to-patrol coastlines, the lure of lucrative, easy catches, and in some cases outright apathy or corruption on the part of local officials make enforcement of blast fishing bans an ongoing challenge for authorities. Commercial dynamite or, more commonly, homemade bombs constructed using a glass bottle with layers of powdered potassium nitrate and pebbles or an ammonium nitrate and kerosene mixture are often employed. Such devices, though, may explode prematurely without warning, and have been known to injure or kill the person using them, or innocent bystanders.

Underwater shock waves produced by the explosion stun the fish and cause their swim bladders to rupture. This rupturing causes an abrupt loss of buoyancy; a small number of fish float to the surface, but most sink to the sea floor. The explosions indiscriminately kill large numbers of fish and other marine organisms in the vicinity and can damage or destroy the physical environment, including extensive damage to coral reefs. Figure 1.1 (a) shows the homemade dynamite bomb to kill fish and figure 1.1 (b) shows a school of dead fish floating on water. Figure 1.2 is a photograph of a newspaper article on dynamite fishing in Tanzania.

(a)

(b)

Figure 1.1 : Dynamite Fishing

(a) Homemade dynamite bombs to kill fishes (b) A school of dead fish floating in water

The Express Business Express October 01 - 07, 2009 - Page 10

Dar now leading victim of dynamite fishing

By *The Express* Reporter,
Dar es Salaam

TANZANIA is still hit hardest hit by dynamite fishing that is conducted along its coastline as opposed to the trend in neighbouring countries where the practice is said to be greatly declining hence government intervention is vital.

Dynamite fishing is more practiced in Tanga and Dar es Salaam regions, whereas there is slight decline in the coast lines of Kēnya, Mozambique, Comoro and Mauritius.

Speaking to this paper, a fisherman along Indian Ocean who identified himself as Juma Kakeli said one of the major contributing factors toward an increase of such practices is easy availability of dynamite in Tanzania compared to other countries.

It is believed that most of the dynamite being used for fishing in Tanzania are secured from big projects such as road construction and mining sites.

A life-size dynamite being used in one blast is sold between Tsh. 20,000 and 30,000 it can kill between 150 and 450 kilograms of fish at once.

But only 20 percent of the fish can be consumed whereas 80 percent are not fit for human consumption since they are dismantled by the blasts.

Illegal fishing has cost a lot of human lives in recent years, it was reported that more than 110 people lost their lives in the year 2007 alone.

Mid this month two fishermen at Kigamboni area were killed due to dynamite blasts in the Indian Ocean. They are named as Juma Kupela and Bakari Naeli all were residents of Kigamboni.

He said the government in collaboration with other stakeholders must contain the situation immediately before it take the lives of many people and denies income.

Investigations done by this paper revealed that the blasts are done in several places one place, and illegal fishermen can obtain an income ranging from Tsh.500,000 to 2m per month.

"For that reason, this is a big business hence it has been attracting most of the young people to engage in especially in this period where there is unemployment," said Said Hamis.

But for small illegal fishermen, they can afford to buy dynamite at between Tsh.6,000 and 10,000 and upon applying three blasts, he gets between 15 and 16 kilograms of fish but they kill all marine living organisms and destroys coastline.

Most of the illegal fish are sold in open market near Tanga port and Magogoni in Dar es Salaam. The main buyers are hoteliers, food vendors and ordinary people for home consumption.

Figure 1.2 : Photograph of a newspaper article on dynamite fishing in Tanzania

The practice of dynamite fishing is at it's peak lately. Recently an article was published in "The New York Times".

" "I could feel it in my chest — like a dull, booming sound," she recalled in an interview. After surfacing, her group learned that fishermen had detonated explosives.

The incident, which occurred a year ago, was Ms. Vyvyan-Robinson's first encounter with blast fishing, a highly destructive technique used in impoverished pockets of the world.

The blasts, often from dynamite, leave craters in coral reefs and kill far more fish than can be harvested, and in many places, the tourism industry serves as a powerful voice against blast fishing, which could scare divers and other visitors away. Some nations have successfully clamped down on the practice, which is generally illegal, but it continues in areas where explosives are available and people are desperate.

The effects of blast fishing can be horrifying. Ms. Vyvyan-Robinson, who wrote about her experiences for ScubaDiverLife.com, describes finding waters littered with dead or struggling fish. Only a portion of the fish that are killed is retrieved because many sink to the bottom. Their air bladders, which help fish remain buoyant, and other internal organs can rupture.

Blast fishing is not new. It was introduced to many parts of the world by European armies, said Michel Bariche, an expert on Mediterranean marine issues at the American University of Beirut in Lebanon.

"During the First World War, soldiers used grenades to catch fish for a quick and fresh meal," he said in an email. In Lebanon, for example, blast fishing spread after French soldiers demonstrated the technique.

The nation continues to struggle to contain the practice although it is illegal, Dr. Bariche said. Culprits often seek out areas where fish congregate, and then throw a homemade bomb among them, he said.

The explosions are generally easy to spot — and thus, in theory, easy to police — but Dr. Bariche said that over the past decade or two, some fishermen had taken to dropping explosives deeper and at night, when detection is less likely.

Some Lebanese anglers use lights at night to attract small fish before detonating the charge. As the small fish sink, he explained, they attract bigger fish, which can then be caught with the hook-and-line method. One problem with this practice is that shrimp, crab and lobster larvae are also drawn to the light and killed.

Tanzania has seen a resurgence in blast fishing over the last decade as mining and construction activity in the country have made it easier to obtain dynamite.

"It looks like an old World War II movie where they throw depth charges in the water," said Marcel Kroese, who works on the SmartFish Program, an effort financed by the European Union to improve Africa's fisheries.

Fishermen often resort to dynamite around coral reefs, where nets might snag, Mr. Kroese said. The Tanzanian coast also has relatively few fish, so anglers are desperate to harvest anything they can.

A pilot acoustic study over six weeks last year in Tanzania for the World Wildlife Fund, an environmental group, estimated that 19 blasts per day occurred in one small stretch of water not far from Dar es Salaam, the largest city. More blast-detection microphones will be deployed soon, according to Jason Rubens, a W.W.F. Tanzania representative.

The Tanzanian government and tourism officials would like to combat the problem, Mr. Kroese said, but have lacked the resources. The destruction of small fish and coral reefs receives far less attention than another environmental problem: the poaching of elephants and other wildlife. But this spring the Tanzanian

government plans to begin a $1 million initiative to reduce dynamite fishing,according to The Tanzania Daily News.
Kenya, concerned about terrorist attacks, has cracked down on the availability of explosives, and has essentially eliminated dynamite fishing, Mr. Kroese said.
Experts say that blast fishing remains common in parts of Southeast Asia, particularly Indonesia and the Philippines, while other countries in the region have made progress in stamping it out.
In Cambodia, blast fishing has "pretty much been stopped around the major islands" and now can be found only in outlying areas, said Paul Ferber, who runs an environmental group called Marine Conservation Cambodia.
He describes the aftermath of blast fishing as "fish flapping around in severe shock." Pressure from the growing tourism industry had led to a government crackdown.
Cambodia encouraged fishing communities to manage their own waters, and those communities patrol and spread information about why the practice is harmful and why fishermen should prevent others from doing it.
The idea was: "If you let these guys do it, it's you guys that are going to suffer," Mr. Ferber said. "

Courtesy : The New York Times
http://mobile.nytimes.com/2015/02/05/business/energy-environment/the-horrors-of-fishing-with-dynamite.html?referrer&_r=1

A solution has to be found to the above addressed problem in order to protect the ecosystem. One of the techniques we thought was, to tackle the problem with the help DSP, which happens to be our field of interest. The problems faced by our ecosystem, and the fact that DSP can be used to address the problem motivated us to take up this project.

1.5 Literature Survey

There have been a plenty of approaches proposed in terms of impulsive sound detection such as correlation of audio signal against a template [1], detection using GMM classifier [2], monitoring using wireless sensor network [3], evaluation of preprocessing algorithms for gunshot detection [4]. A detailed research on detection and recognition of impulsive sound signals was carried out by Alain dufaux [5]. Localization based on time delay estimation [2] and Triangulation method to localize [6] etc are proposed to localize an event.

Freire and Apolina [1] have proposed extraction of number of features of the impulsive signal. Valenzise [2] gives a different approach by considering phase of feature selection for event detection. An exhaustive analysis of the feature selection process, mixing the classical filter and wrapper feature selection approaches has been established. In addition to video-camera steering based on localization of the sound source, comparison of time delay estimation errors with theoretical results is done. Heuristic methods for zooming the camera based on the confidence of localization is also discussed. A paper on monitoring of volcanic eruptions [3], event detection is done using wireless network. The network collected infrasonic (low-frequency acoustic) signals at 102 Hz, transmitting data over a 9 km wireless link to a remote base station. During the deployment, for over 54 hours of continuous data was collected which included at least 9 large explosions. Nodes were time-synchronized using *a* separate GPS receiver, and the data was later correlated with that acquired at a nearby wired sensor array. Alfonso [4] has evaluated six algorithms for the detection of firearm gunshots using receiver operating characteristic method as a previous feasibility metric for their implementation on a low-power VLSI circuit.

Localization [2] system employs a T-shaped microphone array composed of 4 sensors, spaced 30 cm apart from each other. The center microphone is taken as the reference sensor and the three Time Difference of Arrivals (TDOAs) of the signal between the other microphones and the reference microphone are estimated. Maximum-Likelihood Generalized Cross Correlation (GCC) method is used for estimating time delays. Sophia and Leelavathy [6] proposed a triangulation method using angle of arrival and time difference of arrival to localize an event.

References [7] and [8] are documentations on Global Positioning System (GPS). GPS is one of the most accurate techniques that is present today which can localizes a given node with very high accuracy. RSSI based rectangulation for position estimation is presented in [7] and [8]. An empirical formulation is done to obtain a relationship between received signal strength and distance. A mathematical view of its working is described by David Royster [9]. Principles, concepts and features of GPS are explained in detail in a document named Field Technique Manual : GPS, GIS and Remote Sensing [10].

1.6 Problem Statement

Detect, classify and localize blast, if and where it occurred. Design reliable and efficient algorithms to meet the objective.

1.7 Proposed Solution

1.7.1 Solution for Detection

The proposed solution is explained with the help of a block diagram which is shown in figure 1.3. The continuous time signal x(t) is picked up by a microphone and sampled at 8KHz. The obtained discrete time signal x[n] is then used to analyse and estimate the power spectrum of

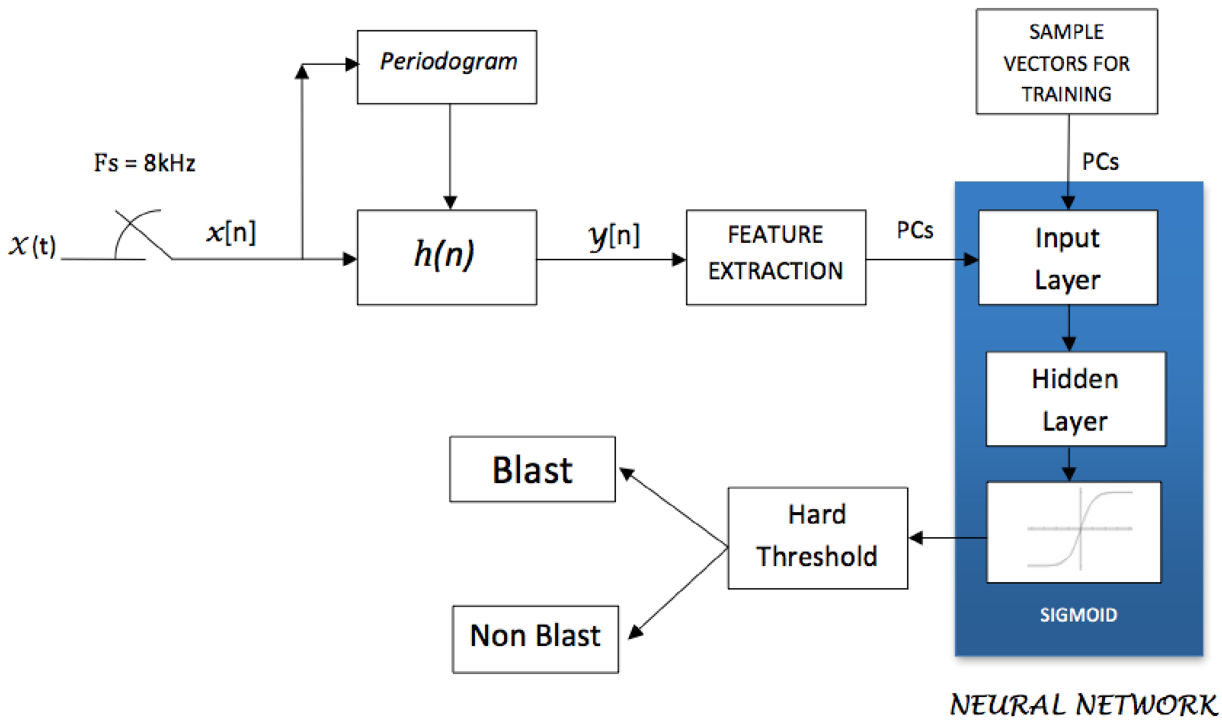


Figure 1.3 : Block Diagram of the proposed algorithm

the signal to design a bandpass filter h[n]. The resulting filtered output y[n] is then fed into a neural network which is trained to classify a signal as blast or non-blast, which is a two class problem. The output of the neural network is subjected to hard thresholding since the output sigmoid function is a smooth curve from 0 to 1. Depending on the output, the signal is classified as a blast or a non-blast.

1.7.2 Solution for Localization

Triangulation technique is incorporated to localize the blast. An arbitrary point is assumed to be the source of the blast signal. The distance of the source from each vertex is calculated using the received strength of the signal (RSSI) obtained at each vertex. A unique solution to the three equations describing the locus of the source along circular paths, with the vertices being their centres and corresponding distances being their radii gives the coordinates of localization.

1.8 Organization of the Report

The rest of the report is organized as follows : Chapter 2 addresses spectrum estimation, different approaches to spectrum estimation, a detailed description on periodogram, its results and conclusions. Filter design is presented in chapter 3. A brief comparison of different types of filters which includes both IIR and FIR is presented. Chapter 4 gives a detailed procedure for feature extraction using principal component analysis. Chapter 5 addresses pattern recognition and different approaches to pattern recognition. A comprehensive description on pattern recognition using neural network is presented along with different experiments performed to increase the efficiency and accuracy of the neural network model. Chapter 6 presents a comparison study of different approaches to extract feature, which can be fed into the neural network. Finally chapter 7 addresses localization of the event using triangulation. It also presents different methods incorporated to develop the relationship between distance and received signal strength which is used to find the coordinates of the point of localization.

Chapter 2

SPECTRUM ESTIMATION

Chapter 2

SPECTRUM ESTIMATION

2.1 Introduction

Spectrum estimation is used to estimate the power spectral density of a wide-sense stationary random process. Power spectrum is the Fourier transform of the autocorrelation sequence. Therefore, estimating the power spectrum is equivalent to estimating autocorrelation. For an autocorrelation ergodic process,

$$\lim_{N\to\infty}\left(\frac{1}{2N+1}\sum_{n=-N}^{N} x(n+k)x^*(n)\right) = r_x(k) \tag{2.1}$$

Thus, if $x(n)$ is known for all n, estimating the power spectrum is straightforward, in theory, since all that must be done is is to determine the autocorrelation sequence $r_x(k)$ using the Eq. (8.1), and then compute its Fourier transform. However, there are two difficulties with this approach that make spectrum estimation both an interesting and a challenging problem. First, the amount of data that one has to work with is never unlimited and, in many cases, it may be very small. It is also possible, however, that a limited data data set is imposed by the requirement that the spectral characteristics of the process remain constant over the duration of the data recorded. The second difficulty is that the data is often corrupted by noise or contaminated with the interfering signal. Thus, spectrum estimation is a problem that involves estimating $P_x(e^{jw})$ from a finite number of noisy measurements $x(n)$. In some applications, estimating power spectrum may be facilitated by having a prior knowledge about how the process is generated. It may be known, for example, that $x(n)$ autoregressive process or that it consists of one or more sinusoids in noise. This type of information may then allow one to parametrically estimate the power spectrum or, perhaps, to extrapolate the data or its autocorrelation in order to improve the performance of a spectrum estimation algorithm.

2.2 Approaches for Spectrum Estimation

The approaches for the spectrum estimation may be generally categorized into one of the two classes. The first includes the classical or nonparametric methods that begin by estimating the autocorrelation sequence $r_x(k)$ from a given set of data. The power spectrum is then estimated by Fourier transforming the estimated autocorrelation sequence. The second class includes the nonclassical or parametric approaches, which are based on using a model for the process in order to estimate the power spectrum. For example, if it is known that $x(n)$ may be used to estimate the parameters of the all pole model, $a_p(k)$, and these estimated model parameters, $\hat{a}_p(k)$ may then, in turn, be used to estimate the power spectrum as follows :

$$\hat{P}_x(e^{jw}) = \frac{1}{\left| \sum_{k=0}^{p} \hat{a}_p(k) e^{-jwk} \right|^2} \tag{2.2}$$

2.2.1 Nonparametric Methods

Nonparametric methods are based on the idea of estimating the autocorrelation sequence of a random process from a set of measured data, and then taking the Fourier transform to obtain an estimate of the power spectrum. Different nonparametric methods are listed below :

1. Periodogram
2. Modified Periodogram
3. Bartlett's Method
4. Welch's Method
5. Blackmann - Tukey Method

2.2.2 Parametric Methods

Parametric approaches involve selection of appropriate model for the process. This selection may be based on a priori knowledge about how the process generated or, perhaps, on experimental results indicating that a particular model "works well". Models that are commonly used include autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and harmonic (complex exponentials in noise).

Once the model has been selected, the next step is to estimate the model parameters from the given data. The final step is to estimate the power spectrum by incorporating the estimated parameters into the parametric form of the spectrum.

2.3 Periodogram

The power spectrum of a time series $x(t)$ describes how the variance of the data $x(t)$ is distributed over the frequency components into which $x(t)$ may be decomposed. The band of frequencies in which the energy of the signal is concentrated can be analyzed using power spectral density.

Periodogram is one of the simplest methods to estimate the power spectrum of a signal. The power spectrum of a wide-sense stationary random process is the Fourier transform of the autocorrelation sequence,

$$P_x(e^{jw}) = \sum_{k=-\infty}^{\infty} r_x(k) e^{-jkw} \tag{2.3}$$

Therefore, spectrum estimation is, in some sense, an autocorrelation estimation problem. For an autocorrelation ergodic process and an unlimited amount of data, the autocorrelation may be found by using time-average

$$r_x(k) = \lim_{N \to \infty} \left(\frac{1}{2N+1} \sum_{n=-N}^{N} x(n+k) x^*(n) \right) \tag{2.4}$$

However, if $x(n)$ is measured over a finite interval, say $n = 0,1,2,.....N-1$, then the autocorrelation sequence must be estimated using, for example, Eq. (2.4) with a finite sum,

$$\hat{r}_x(k) = \frac{1}{N}\sum_{n=0}^{N-1} x(n+k)x^*(n) \tag{2.5}$$

In order to ensure that the values of $x(n)$ that fall outside the interval [0, *N-1*] are excluded from the sum, Eq. (2.5) will be rewritten as follows :

$$\hat{r}_x(k) = \frac{1}{N}\sum_{n=0}^{N-1-k} x(n+k)x^*(n) \quad ; \quad k = 0, 1, 2, ...N-1 \tag{2.6}$$

with the values of $\hat{r}_x(k)$ for $k < 0$ defined using conjugate symmetry, $\hat{r}_x(-k) = \hat{r}_x^*(k)$,and with $\hat{r}_x(k)$ set equal to zero for $|k| \geq N$.

Taking the discrete-time Fourier transform of $\hat{r}_x(k)$ leads to an estimate of the power spectrum known as the *periodogram* ,

$$\hat{P}_{per}(e^{jw}) = \sum_{n=-N+1}^{N-1} \hat{r}_x(k)e^{-jkw} \tag{2.7}$$

Expressing periodogram directly in terms of the process $x(n)$. This may be done as follows. Let $x_N(n)$ be the finite length signal of length N that is equal to $x(n)$ over the interval [0, *N-1*], and is zero otherwise ,

$$x_N(n) = \begin{cases} x(n) & ; 0 \leq n < N \\ 0 & ; \text{otherwise} \end{cases} \tag{2.8}$$

Thus, $x_N(n)$ is the product of $x(n)$ and a rectangular window , $w_R(n)$

$$x_N(n) = w_R(n)x(n) \tag{2.9}$$

In terms of $x_N(n)$, the estimated autocorrelation sequence may be written as follows :

$$\hat{r}_x(k) = \frac{1}{N}\sum_{n=-\infty}^{\infty} x_N(n+k)x_N^*(n) = \frac{1}{N}x_N(k) * x_N^*(-k) \tag{2.10}$$

Taking the Fourier transform and using the convolution theorem, the periodogram becomes

$$\boxed{\hat{P}_{per}(e^{jw}) = \frac{1}{N}X_N(e^{jw})X_N^*(e^{jw}) = \frac{1}{N}|X_N(e^{jw})|^2} \tag{2.11}$$

where $X_N(e^{jw})$ is the discrete Fourier transform of the N - point data sequence $x_N(n)$,

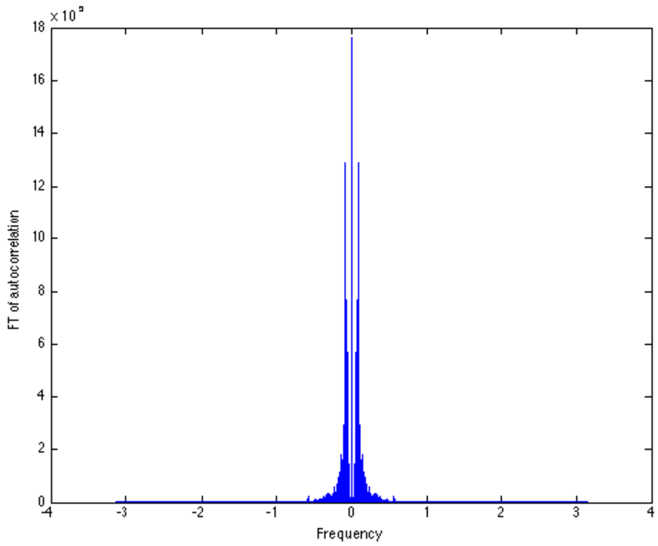
$$X_N(e^{jw}) = \sum_{n=-\infty}^{\infty} x_N(n)e^{-jwn} = \sum_{n=0}^{N-1} x(n)e^{-jwn} \tag{2.12}$$

Thus, by averaging the magnitude squared of Fourier transform of the measured data, power spectrum can be obtained.

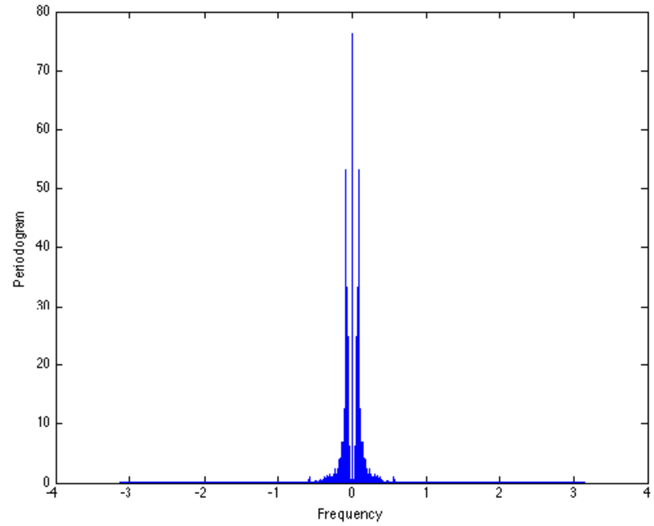
```
measured_data ='/Users/skanda/Desktop/sounds/explosion.wav';
[x,fs]=audioread(measured_data);
N = length(x);
periodogram = (1/N)*power(abs(fft(x)),2);
ws = 2*pi/N;
wnorm = -pi:ws:pi;
wnorm = wnorm(1:length(periodogram));
figure
plot(wnorm,fftshift(periodogram));
```

Figure 2.1 : MATLAB program for computing the periodogram

Figure 2.1 shows the matlab implementation of the periodogram. An explosion was recorded and the power spectrum of the explosion was obtained using the periodogram technique. Figure 2.2 gives a comparison of power spectrum of the same signal obtained by calculating the Fourier transform of the autocorrelation function, which is shown in figure 2.2 (a), and that obtained using periodogram, which is shown in figure 2.2 (b).



(a)



(b)

Figure 2.2 : Power Spectrum

(a) Fourier transform of autocorrelation function ; (b) Periodogram

From the above figure it can be seen that the estimate of the power spectrum obtained by periodogram is almost same as the original power spectrum that is, obtained by taking the Fourier transform of the autocorrelation function.

The estimated spectrum obtained from the periodogram is used to analyze the concentration of the energy of the signal over frequency. This analysis is required to obtain the cut-off frequencies required to design the filter.

2.4 Results and Conclusions

The above procedure was followed to analyze power spectrum of different types of impulsive sound signals. Ten different types of thunders and gun-shot sounds, twenty different types of explosions and blasts were analysed to obtain the frequency range over which the energy of these signals are concentrated. Table 2.1 shows the frequency range for different impulsive sound signals where energy is highly concentrated.

Impulsive Sound Signal	Frequency Range
Thunder	100 Hz - 400 Hz
Gun-shot	60 Hz - 80 Hz
Explosion	100 Hz - 350 Hz
Blast	80 Hz - 250 Hz

Table 2.1 : Frequency range of different impulsive sound signals

From the Table 2.1, it can be seen that, a bandpass filter is required to filter the signal from other noise components. To accommodate all impulsive signals, the lower cut-off frequency was set to 50Hz and the upper cutoff frequency was set to 500 Hz.

The following conclusions were derived from the above given results

1. Maximum frequency is found to be 500 Hz. Therefore, the signal has to be sampled at a minimum frequency of 1kHz to satisfy the Nyquist criteria, which states that $f_s \geq 2 f_{max}$. Where f_{max} is the maximum frequency component of the signal.
2. A sampling frequency of 8kHz is suitable. Even though a sampling frequency 1 kHz is enough to meet the requirement, 8 kHz was chosen since the recording applications provide a range of sampling frequencies starting from 8kHz to 44.1kHz, because all of these applications corresponds to speech recording. Hence, 8 kHz was chosen.

Usually 44.1kHz is used as sampling frequency in most of the sound recording applications. The disadvantage of using f_s = 44.1kHz is that the number of samples will be too huge to further process the signal. Assuming that an impulsive sound lasts for not more than five seconds, the number of samples obtained using f_s = 44.1kHz is, N = 5 x 44100 = 2,20,500. On the contrary, number of samples obtained using f_s = 8kHz is, N = 5 x 8000 = 40000 which is much lesser than the former. The lesser the number of samples corresponds to lesser computational complexity, hence f_s was chosen to be 8kHz.

Chapter 3

FILTER DESIGN

Chapter 3

FILTER DESIGN

3.1 Filters

Digital filters are a very important part of DSP. In fact, their extraordinary performance is one of the key reasons that DSP has become so popular. As mentioned in the introduction, filters have two uses: signal separation and signal restoration. Signal separation is needed when a signal has been contaminated with interference, noise, or other signals. Signal restoration is used when a signal has been distorted in some way. Digital filters can achieve thousands of times better performance than analog filters. This makes a dramatic difference in how filtering problems are approached. With analog filters, the emphasis is on handling limitations of the electronics, such as the accuracy and stability of the resistors and capacitors. In comparison, digital filters are so good that the performance of the filter is frequently ignored. The emphasis shifts to the limitations of the signals, and the theoretical issues regarding their processing.

It is common in DSP to say that a filter's input and output signals are in the time domain. This is because signals are usually created by sampling at regular intervals of time.

The most straightforward way to implement a digital filter is by convolving the input signal with the digital filter's impulse response. All possible linear filters can be made in this manner. When the impulse response is used in this way, filter designers give it a special name: the filter kernel.

There is also another way to make digital filters, called recursion. When a filter is implemented by convolution, each sample in the output is calculated by weighting the samples in the input, and adding them together. Recursive filters are an extension of this, using previously calculated values from the output, besides points from the input. Instead of using a filter kernel, recursive filters are defined by a set of recursion coefficients. The impulse responses of recursive filters are composed of sinusoids that exponentially decay in amplitude. In principle, this makes their impulse responses infinitely long. Because of this characteristic, recursive filters are also called Infinite Impulse Response or IIR filters. In comparison, filters carried out by convolution are called Finite Impulse Response or FIR filters.

3.2 Frequency Domain Parameters

The purpose of these filters is to allow some frequencies to pass unaltered, while completely blocking other frequencies. The passband refers to those frequencies that are passed, while the stopband contains those frequencies that are blocked. The transition band is between. A fast roll-off means that the transition band is very narrow. The division between the passband and transition band is called the cutoff frequency.

Figure 3.1 shows three parameters that measure how well a filter performs in the frequency domain. To separate closely spaced frequencies, the filter must have a fast roll-off, as illustrated in (a) and (b). For the passband frequencies to move through the filter unaltered, there must be no passband ripple, as shown in (c) and (d). Lastly, to adequately block the stopband frequencies, it is necessary to have good stopband attenuation, displayed in (e) and (f).

Why is there nothing about the phase in these parameters? First, the phase isn't important in most frequency domain applications. Second, if the phase is important, it is very easy to make digital filters with a perfect phase response.

The objective is to design a filter that has lesser order (to reduce the computational complexity), is stable, maximum roll off and minimum ripples in the pass band. In order to do so, a survey was conducted by analysing the response of several FIR filters and IIR filters.

3.3 Filter Specifications

The parameters required to design the filter are obtained from spectrum estimation. A bandpass filter has to designed with the following specifications :

1. Sampling Frequency f_s : 8kHz
2. Stopband cutoff Frequency 1 f_{stop1} : 0Hz
3. Passband cutoff Frequency 1 f_{pass1} : 50Hz
4. Stopband cutoff Frequency 2 f_{pass2} : 450Hz
5. Passband cutoff Frequency 2 f_{stop2} : 500Hz
6. Stopband Attenuation 1 A_{stop1} : 30dB
7. Passband Attenuation 1 A_{stop1} : 1dB
8. Stopband Attenuation 2 A_{stop2} : 30dB

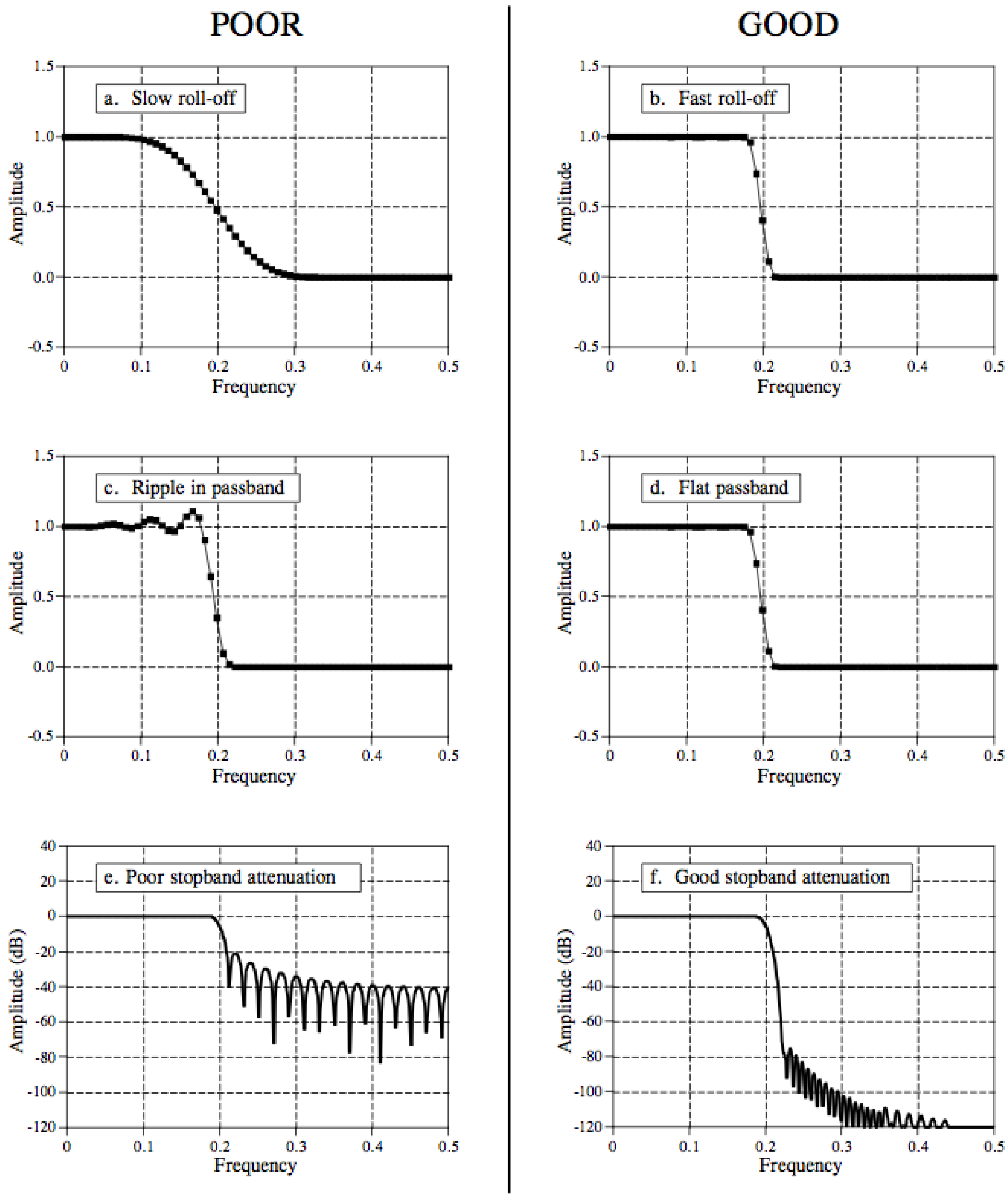


Figure 3.1 : Parameters for evaluating frequency domain performance. The frequency responses shown are for low-pass filters. Three parameters are important: (1) roll-off sharpness, shown in (a) and (b), (2) passband ripple, shown in (c) and (d), and (3) stopband attenuation, shown in (e) and (f).

3.4 FIR Filters

FIR filters are digital filters with finite impulse response. They are also known as non-recursive digital filters as they do not have the feedback (a recursive part of a filter), even though recursive algorithms can be used for FIR filter realization. FIR filters can be designed using different methods, but most of them are based on ideal filter approximation. The objective is not to achieve ideal characteristics, as it is impossible anyway, but to achieve sufficiently good characteristics of a filter. The transfer function of FIR filter approaches the ideal as the filter order increases, thus increasing the complexity and amount of time needed for processing input samples of a signal being filtered. Figure 3.2 illustrates a simple FIR filter.

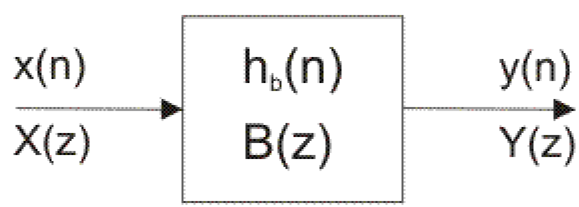


Figure 3.2 : Block diagram of FIR filter

The following windowing filters were designed and compared to select the best filter. Best filter is one that meets all the specifications mentioned above and has a lesser order compared to other filters.

1. Bartlett
2. Blackmann
3. Hamming
4. Hanning
5. Rectangular

Table 3.1 gives a comparison between the above mentioned filters in terms of order of the filter, length of the window and transition width.

Filter	Order (N)	Length of the window(M)	Transition Width(Δw)	Attenuation
Bartlett	566	640	0.0393	30dB
Blackmann	566	960	0.0393	30dB
Hamming	566	640	0.0393	30dB
Hanning	566	640	0.0393	30dB
Rectangular	566	320	0.0393	30dB

Table 3.1 : Comparison table of windowing filters

Order of the filter can be calculated using the formula :

$$N = \frac{-10\log(\delta\delta_s) - 15}{14\,\Delta f / Fs} \tag{3.1}$$

It can be seen that a high order filter is required to meet the required specifications. Since a 30 dB attenuation is required at the stopband, Hamming window is ideal. Frequency response of Hamming window is shown in figure 3.3 designed with order equal to 566, transition width of 0.0393 and 30 dB attenuation at the stopband.

The advantage of using FIR filters is that they are always stable. FIR filters are all zero filters. Since order (N) if is function of Δf order increases significantly when Δf is smaller. The filter that has to be designed has Δf = 500 Hz which is small and hence higher the order. Such high order filters are computationally expensive to run on embedded platforms, though they are absolutely stable.

In order to overcome the disadvantage of FIR filter, IIR filters were designed and was compared with the FIR filters.

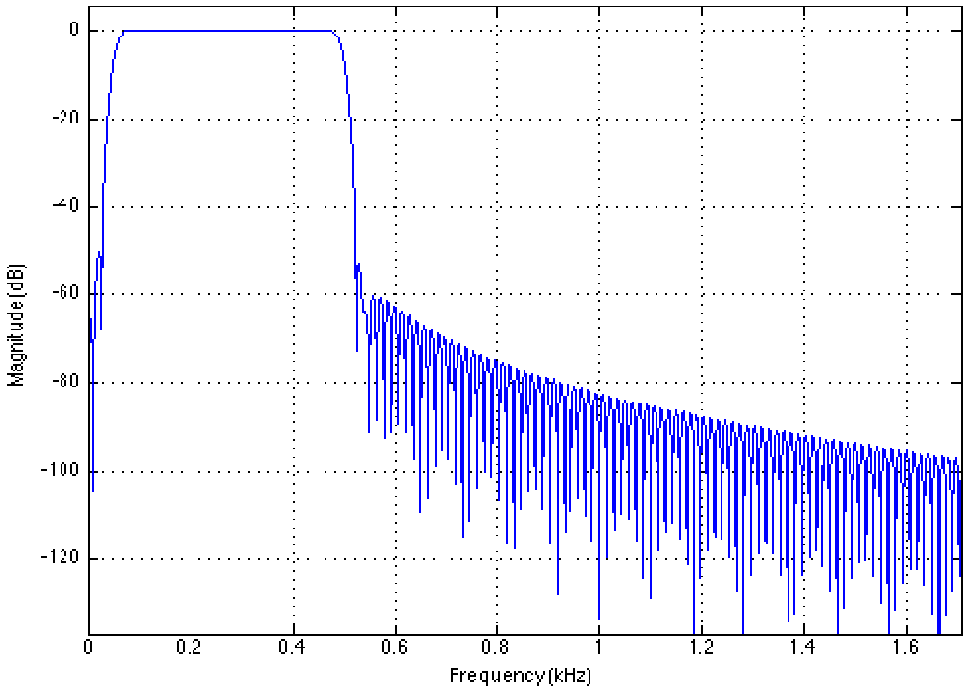


Figure 3.3 : Frequency response of Hamming window

3.5 IIR Filters

IIR filters are digital filters with infinite impulse response. Unlike FIR filters, they have the feedback (a recursive part of a filter) and are known as recursive digital filters therefore. For this reason IIR filters have much better frequency response than FIR filters of the same order. Unlike FIR filters, their phase characteristic is not linear which can cause a problem to the systems which need phase linearity. For this reason, it is not preferable to use IIR filters in digital signal processing when phase is of the essence. Since the linear phase characteristic is not important, the use of IIR filters is an excellent solution. There is one problem known as a potential instability that is typical of IIR filters only. FIR filters do not have such a problem as they do not have the feedback. For this reason, it is always necessary to check after the design process whether the resulting IIR filter is stable or not. IIR filters can be designed using different methods. One of the most commonly used is via the reference analog prototype filter. This method is the best for designing all standard types of filters such as low-pass, high-pass, band-pass and band-stop filters. Figure 3.4 illustrates the block diagram of a simple IIR filter.

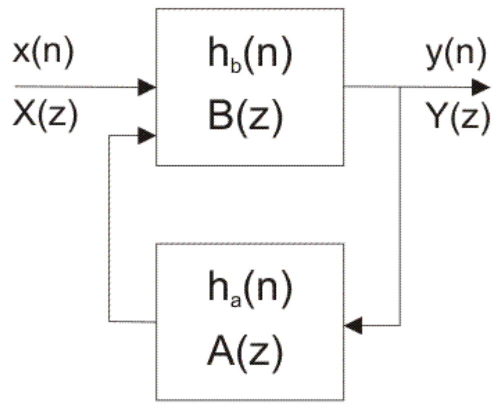


Figure 3.4 : Block diagram of IIR Filter

Following IIR filters were designed for the given specification and were analysed.

1. Butterworth
2. Chebyshev Type - 1
3. Chebyshev Type - 2
4. Elliptical

Table 3.2 gives a comparison between the four filters.

Filters	Order	#Multipliers	#Adders	#Multiplication/IP	#Addition/IP
Butterworth	16	24	24	24	24
Chebyshev I	10	15	15	15	15
Chebyshev II	10	19	19	19	19
Elliptical	8	16	16	16	16

TABLE 3.2 : Comparison between IIR filters

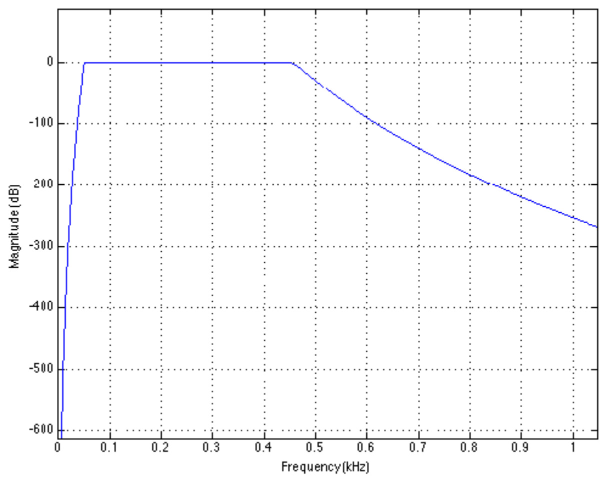
3.6 Results and Conclusions

From tables 3.1 and 3.2, it can be clearly noted that IIR filters are much more computationally efficient than FIR filters. Stability of IIR filters is an issue since they include a feedback loop. For the above filter specifications, all the IIR filters designed were stable. Out of the two categories, IIR was thus selected.

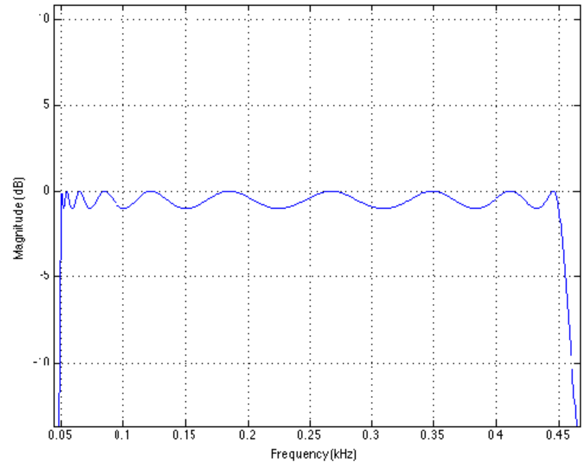
Tables 3.2 gives a comparison between the four IIR filters. It can be seen that elliptical filter has the lowest order. Table 3.2 also shows number of multipliers and adder required to design the filter. Even though Chebyshev I has lowest number of adders and multipliers required to design the filter, it has greater amount of ripples in the passband. Butterworth filter is a maximally flat filter but with a wider transition width. On the contrary, Chebyshev filters have a steeper roll-off but a greater amount of ripples in the passband. Hence the trade off has to be taken into account carefully.

Elliptical filter has the lowest order and has a roll-off which is not as steep as that of Chebyshev filter, but better than that of Butterworth filter. Also, it has passband ripples much lesser than Chebyshev filter, but does not have a response as flat as that of Butterworth filter. Chebyshev II suffers Gibbs phenomenon or ringing effect in the stopband. Though elliptical filters has a similar effect, it is considerably less than that of Chebyshev II filter. Thus elliptical filter was chosen to be implemented in the algorithm.

Figure 3.5 illustrates frequency response of various filters. 3.5 (a) shows the frequency response of Butterworth filter. It can be seen that it has maximally flat response, but the roll-off is quite slow and hence a wider transition width. 3.5 (b) and (c) shows frequency response of Chebyshev I and Chebyshev II filters. Chebyshev I has large amount of ripples in passband and Chebyshev II has ringing effect in the stopband. 3.5 (d) shows the frequency response of the elliptical filter. The passband has an acceptable amount of ripples in the pass band and an acceptable amount of ringing in the stopband. Hence elliptical filter is preferred to other filters, even though table 3.2 suggests that Chebyshev I requires a lesser number of adders and multipliers for the design. Figure 3.6 shows the step response of the elliptical filter and figure 3.7 shows a pole-zero plot of the filter.



(a)



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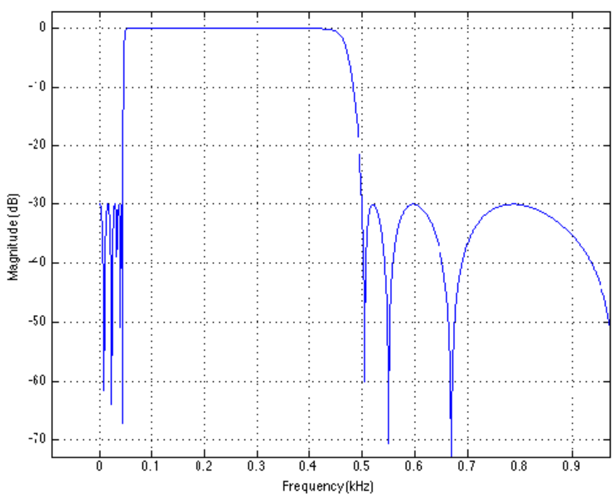

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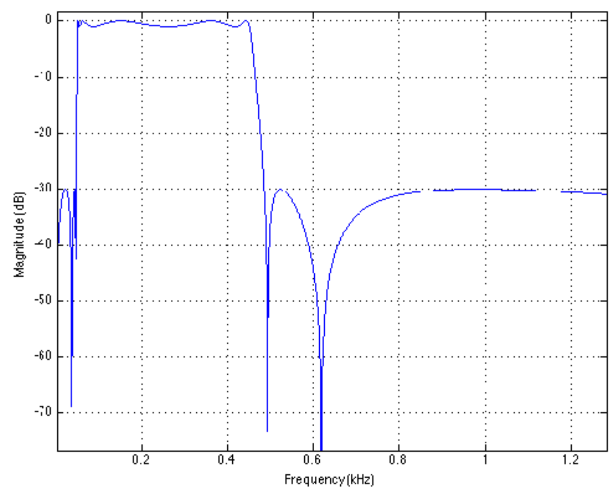


(d)

Figure 3.5 : Frequency response of IIR filters : (a) Butterworth Filter (b) Chebyshev I Filter (c) Chebyshev II Filter (d) Elliptical Filter

The designed elliptical bandpass filter was incorporated as the filter h(n) shown in fig 1.3. A bomb blast was recorded to test the effectiveness of the elliptical filter. The maximum frequency component of the blast was found to be 121.1356Hz. Figure 3.8 illustrates the effectiveness of the elliptical filter. 3.8 (a) is the time domain plot of the recorded signal. 3.8 (b) is the time domain plot of the filtered signal. It can be seen that most of the high frequency components are eliminated.

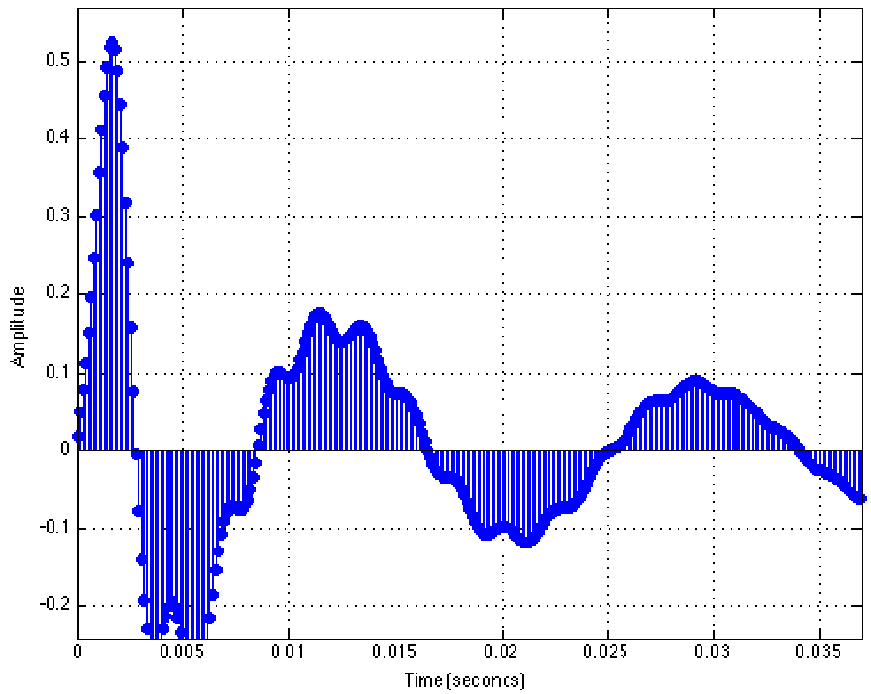


Figure 3.6 : Step response of the elliptical filter

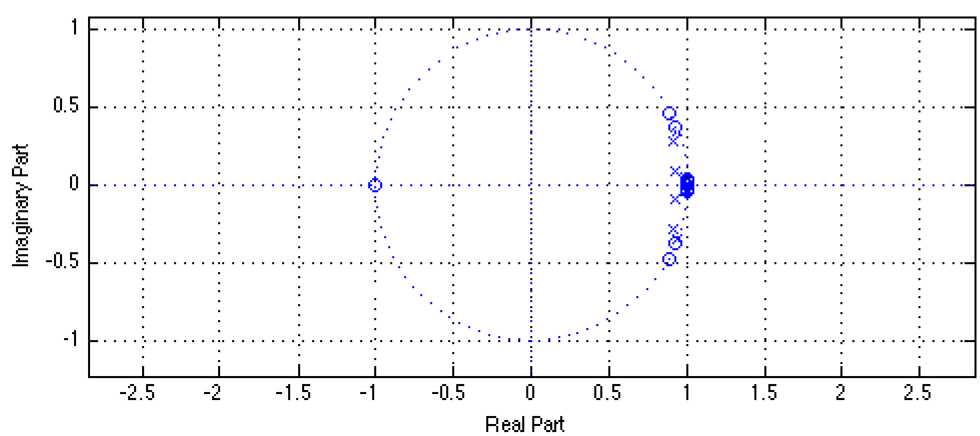
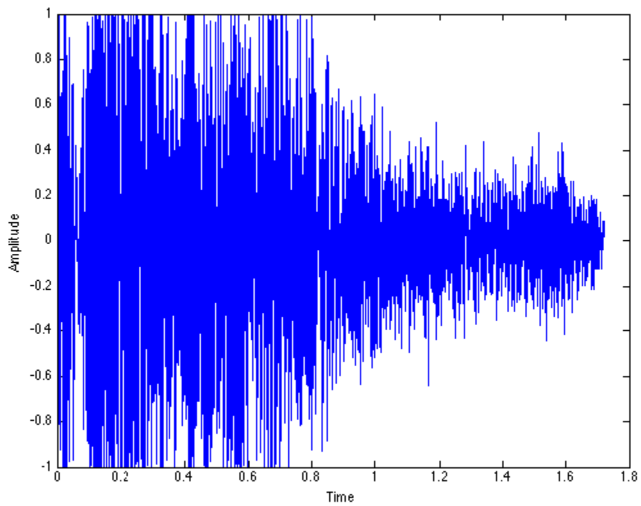


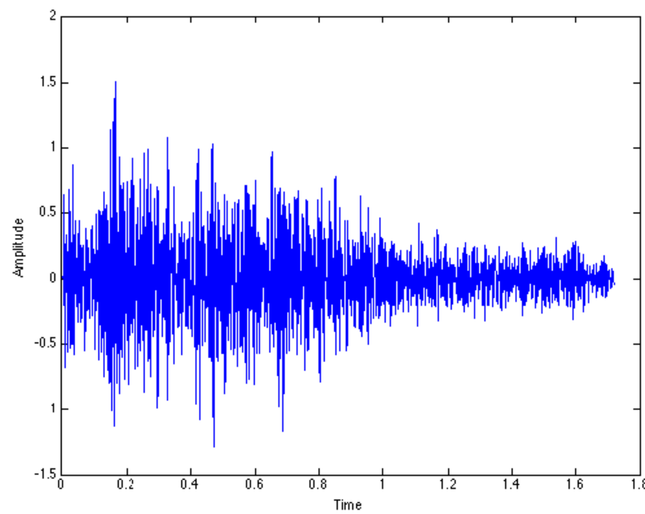
Figure 3.7 : Pole-Zero plot of the elliptical filter

In order to have a better perception Fourier transform of the signals were plotted to analyse. 3.8 (c) illustrates the Fourier transform of the unfiltered signal and 3.8 (d) shows the Fourier transform of the filtered signal. It can be seen that all the frequency above 500 Hz are attenuated and the frequency components where the energy concentrated is retained.

Finally, the output of the filter i.e, the filtered signal was used for feature extraction.



(a)



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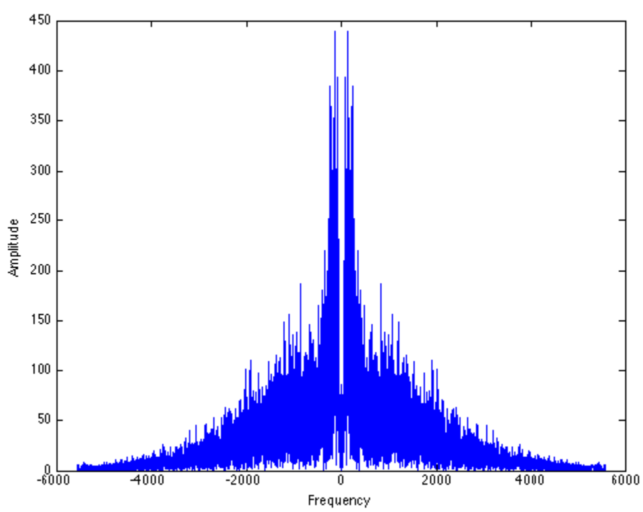
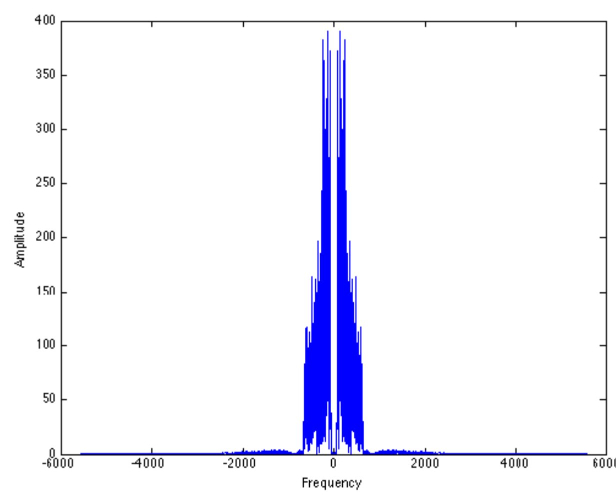


(c)



(d)

Figure 3.8 : (a) Time domain plot of unfiltered signal ; (b) Time domain plot of filtered signal (c) Fourier transform of unfiltered signal ; (d) Fourier transform of filtered signal

Chapter 4

FEATURE EXTRACTION

Chapter 4

FEATURE EXTRACTION

4.1 Introduction

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative, non redundant, facilitating the subsequent learning and generalization steps, in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

When the input data to an algorithm is too large to be processed and if it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named features vector). This process is called feature extraction. The extracted features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

The best results are achieved when an expert constructs a set of application-dependent features. Nevertheless, if no such expert knowledge is available, general dimensionality reduction techniques may help. These include:

1. Principal component analysis
2. Semidefinite embedding

3. Multifactor dimensionality reduction
4. Multilinear subspace learning
5. Nonlinear dimensionality reduction
6. Isomap
7. Kernel PCA
8. Multilinear PCA
9. Latent semantic analysis
10. Partial least squares
11. Independent component analysis
12. Autoencoder

To extract features from the impulsive sound signals principal component analysis (PCA) was employed.

4.2 Principal Component Analysis (PCA)

4.2.1 Introduction to PCA

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. PCA is sensitive to the relative scaling of the original variables.The principal components may then be used as predictor or criterion variables in subsequent analyses. PCA defines a new orthogonal coordinate system that optimally describes variance in a single dataset.

4.2.2 Intuition

Principal component analysis is a variable reduction procedure. It is useful when the obtained data on a number of variables (possibly a large number of variables), and if there is some redundancy in those variables. Redundancy means that some of the variables are correlated with one another, possibly because they are measuring the same construct. Because of this redundancy, it should be possible to reduce the observed variables into a smaller number of principal components (artificial variables) that will account for most of the variance in the observed variables

PCA can be thought of as fitting an n-dimensional ellipsoid to the data, where each axis of the ellipsoid represents a principal component. If some axis of the ellipse is small, then the variance along that axis is also small, and by omitting that axis and its corresponding principal component from the representation of the dataset, only a commensurately small amount of information is lost.

To find the axes of the ellipse, first subtract the mean of each variable from the dataset to center the data around the origin. Then, compute the covariance matrix of the data and calculate the eigenvalues and corresponding eigenvectors of this covariance matrix. Next, orthogonalize the set of eigenvectors, and normalize each of them. Once this is done, each of the mutually orthogonal unit eigenvectors can be interpreted as an axis of the ellipsoid fitted to the data. The proportion of the variance that each eigenvector represents can be calculated by dividing the eigenvalue corresponding to that eigenvector by the sum of all eigenvalues. Principal component analysis computes the most meaningful basis to re-express a noisy, garbled data set. The hope is that this new basis will filter out the noise and reveal hidden dynamics.

4.2.3 Computation of PCA

Step 1: Acquire Data

Step 2: Subtract the mean

Subtract the mean from each of the data sample. The subtracted mean is nothing but the average of the measured data across each dimension. This produces a zero-mean data set.

Step 3: Calculate the covariance matrix

Let X be an *m* x *n* matrix of the measured data set. Each row of X corresponds to all measurements of a particular type x_i. Each column of X corresponds to a set of all the measurements from one particular trial.

$$X = \begin{pmatrix} x_1 \\ x_2 \\ . \\ . \\ x_m \end{pmatrix} \tag{4.1}$$

Thus the covariance of X is defined by ,

$$S_X = \frac{1}{n-1} X X^T \tag{4.2}$$

Step 4: Calculate the eigenvectors and eigenvalues of the covariance matrix

The eigenvectors and eigenvalues can be calculated using the Singular Value Decomposition (SVD) technique. The covariance matrix is written as a product of three matrices as shown below :

$$S = U \Sigma V^T \tag{4.3}$$

Where U is an m x m real or complex unitary matrix, Σ is an m x n rectangular diagonal matrix with non-negative real numbers along the diagonal, and V^T is an n x n real or complex unitary matrix. The diagonal entries of Σ are the singular values of S, always arranged in descending order along the diagonal. m columns of U are called the left-singular vectors and n columns of V are called the right-singular vectors of S, respectively. The Singular Values of Σ are known as the principal components of X**.**

Step 5: Forming the feature vector

The singular values obtained from the diagonal matrix $\sum$, which are arranged in descending order gives the principal components of X. The first singular value is the first principal component, the second singular value is the second principal component and so on. A column vector containing the principal components is called the feature vector. Down the diagonal of the diagonal matrix $\sum$, the values become insignificant and hence can be discarded. The information lost due to this is negligible. To be precise, if the measured data is spread over n dimensions and if only first p principal components are chosen, then the feature vector contains significant information from the first p dimension over which the data was spread out.

4.3 PCA for a One Dimensional Vector

PCA is a dimensionality reduction technique. The application of PCA on one dimensional vector does not make any sense. In order to extract feature from one dimensional data using PCA, the measured data matrix was redefined as an m x n matrix which, in some sense, makes the data multi-dimensional. The redefinition of the matrix involves the following steps :

Consider the 1-D vector X given by equation (4.4)

$$X = \begin{pmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{pmatrix} \tag{4.4}$$

The vector is split in such a way that the matrix formed is of the size 1000 x n , where the columns contain 1000 data samples. The first column of X contains x_1 to x_{1000} and the second column contains x_2 to x_{1001} and so on.

$$X = \begin{pmatrix} x_1 & x_2 & . & . & x_n \\ x_2 & x_3 & . & . & 0 \\ . & . & . & . & . \\ . & . & . & . & . \\ x_{1000} & x_{1001} & . & . & 0 \end{pmatrix} \tag{4.5}$$

4.4 Algorithm Implementation

STEP 1: Data acquisition

The output of the elliptical bandpass filter is the data from which the feature has to be extracted.

STEP 2: Mean Subtraction

The mean of the signal was calculated and was subtracted from each data sample to obtain a zero-mean data set.

Step 3: Calculation of the Covariance matrix

The covariance of the signal is calculated using the equation for the matrix described by (4.2).

Step 4: Calculation of Principal components

The principal components are calculated by using SVD technique given by equation (4.3).

Step 5 : Selection of the Principal Components (PCs)

The singular values from the diagonal matrix $\sum$ in SVD decomposition gives the PCs. Only significant values are considered to form the feature vector.

4.5 Results and Conclusions

It was observed that the impulsive sounds have a maximum of 50 significant principal components after which the values become insignificant.

The autocorrelation matrix XX^T has power of the signal along the diagonal. The first component along the diagonal has power of the entire signal. The second component along the diagonal of the autocorrelation matrix has the power of the signal with samples of the signal taken from x_2 to x_n and so on. All other elements are auto-correlation of the signals taken 1000 samples at a time. The autocorrelation matrix can be represented as shown in equation (4.6)

$$XX^T = \begin{bmatrix} \Sigma_{i=1}^{n} {x_i}^2 & \Sigma_{i=1,j=2}^{i=n,j=1000} {x_{ij}}^2 & . & . & . & . & \Sigma_{i=1,j=n}^{i=n,j=1000} {x_{ij}}^2 \\ \Sigma_{i=2,j=1}^{i=n+1,j=1000} {x_{ij}}^2 & \Sigma_{i=2}^{n} {x_i}^2 & . & . & . & . & . \\ . & . & . & & & & . \\ . & . & & . & & & . \\ . & . & & & . & & . \\ \Sigma_{i=n,j=1}^{i=n+1000,j=1000} {x_{ij}}^2 & . & . & . & . & . & x_n(\Sigma_{i=1000}^{n} x_i) \end{bmatrix} \tag{4.6}$$

The feature vector formed by the above procedure can be fed into the neural network for classification.

Chapter 5

PATTERN RECOGNITION

Chapter 5

PATTERN RECOGNITION

5.1 Introduction

Pattern recognition is a branch of machine learning that focuses on the recognition of patterns and regularities in data, although it is in some cases considered to be nearly synonymous with machine learning. Pattern recognition systems are in many cases trained from labeled "training" data (supervised learning), but when no labeled data are available, other algorithms can be used to discover previously unknown patterns (unsupervised learning).

The terms pattern recognition, machine learning, data mining and knowledge discovery in databases (KDD) are hard to separate, as they largely overlap in their scope. Machine learning is the common term for supervised learning methods and originates from artificial intelligence, whereas KDD and data mining have a larger focus on unsupervised methods and stronger connection to business use. Pattern recognition has its origins in engineering, and the term is popular in the context of computer vision. In pattern recognition, there may be a higher interest to formalize, explain and visualize the pattern; whereas machine learning traditionally focuses on maximizing the recognition rates.

In machine learning, pattern recognition is the assignment of a label to a given input value. In statistics, discriminant analysis was introduced for the same purpose in 1936. An example of pattern recognition is classification, which attempts to assign each input value to one of a given set of classes. However, pattern recognition is a more general problem that encompasses other types of output as well. Other examples are regression, which assigns a real-valued output to each input; sequence labeling, which assigns a class to each member of a sequence of values (for example, part of speech tagging, which assigns a part of speech to each word in an input sentence and parsed which assigns a parse tree to an input sentence , describing the syntax sentence); and parsing, which assigns a parse tree to an input sentence, describing the syntactic structure of the sentence.

Pattern recognition algorithms generally aim to provide a reasonable answer for all possible inputs and to perform "most likely" matching of the inputs, taking into account their statistical variation. This is opposed to pattern matching algorithms, which look for exact matches in the input with pre-existing patterns. A common example of a pattern-matching algorithm is regular expression matching, which looks for patterns of a given sort in textual data and is included in the search capabilities of many text editors and word processors. Algorithms for pattern recognition depend on the type of label output, on whether learning is supervised or unsupervised, and on whether the algorithm is statistical or non-statistical in nature. Statistical algorithms can further be categorized as generative or discriminative.

Classification algorithms (supervised algorithms predicting categorical labels)

i. Parametric:

1. Linear discriminant analysis
2. Quadratic discriminant analysis
3. Maximum entropy classifier (aka logistic regression, multinomial logistic regression)

ii. Nonparametric:

1. Decision trees, decision lists
2. Kernel estimation and K-nearest-neighbor algorithms
3. Naive Bayes classifier
4. Neural networks (multi-layer perceptrons)
5. Perceptrons Support vector machines
6. Gene expression programming

Neural network was employed for the pattern recognition in the proposed algorithm. The feature vectors obtained from different signals are used to train the the neural network to classify the impulsive sound signals.

5.2 Neural Network

5.2.1 Introduction to Neural Networks

In machine learning and cognitive science, artificial neural networks (ANNs) are a family of statistical learning algorithms inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs, and are capable of machine learning as well as pattern recognition thanks to their adaptive nature.

For example, a neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read.

Like other machine learning methods - systems that learn from data - neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition.

5.2.2 Inside a Neural Network

A typical neural network has anything from a few dozen to hundreds, thousands, or even millions of artificial neurons called units arranged in a series of layers, each of which connects to the layers on either side. Some of them, known as input units, are designed to receive various forms of information from the outside world that the network will attempt to learn about, recognize, or otherwise process. Other units sit on the opposite side of the network and signal how it responds to the information it's learned; those are known as output units. In between the input units and output units are one or more layers of hidden units, which, together, form the majority of the artificial brain. Most neural networks are fully connected, which means each hidden unit and each output unit is connected to every unit in the layers either side. The connections between one unit and another are represented by a number called a weight, which can be either positive (if one unit excites another) or negative (if one unit suppresses or inhibits another). The higher the weight, the more influence one unit has on another. (This corresponds to the way actual brain cells trigger one another across tiny gaps called synapses.)

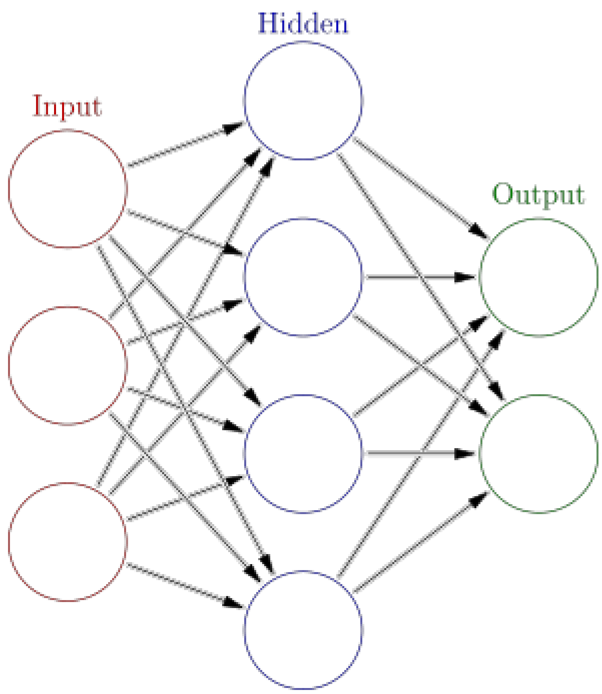


Figure 5.1: 3 Layered Architecture of Neural Network

A class of statistical models may commonly be called "Neural" if they possess the following characteristics:

1. Consist of sets of adaptive weights, i.e. numerical parameters that are tuned by a learning algorithm.
2. Are capable of approximating nonlinear functions of their inputs.

5.2.3 Learning Process

Information flows through a neural network in two ways. When it's learning (being trained) or operating normally (after being trained), patterns of information are fed into the network via the input units, which trigger the layers of hidden units, and these in turn arrive at the output units. This common design is called a feed forward network. Not all units "fire" all the time. Each unit receives inputs from the units to its left, and the inputs are multiplied by the weights of the connections they travel along. Every unit adds up all the inputs it receives in this way and (in the simplest type of network) if the sum is more than a certain threshold value, the unit "fires" and triggers the units it's connected to (those on its right).

For a neural network to learn, there has to be an element of feedback involved. Neural networks learn things typically by a feedback process called backpropagation (sometimes abbreviated as "backprop"). This involves comparing the output a network produces with the output it was meant to produce, and using the difference between them to modify the weights of the connections between the units in the network, working from the output units through the hidden units to the input units—going backward, in other words. In time, back propagation causes the network to learn, reducing the difference between actual and intended output to the point where the two exactly coincide, so the network figures things out exactly as it should.

5.3 Classification Using Neural Network

5.3.1 Pre Requisites

The feature vector of the signal is used to train, validate and test the network.

The PC's are varied in number and fed to the network for training and testing.

5.3.2 The Neural Network Model

The proposed neural network model was designed for a two class problem with a single hidden layer. The hidden layer uses a sigmoid activation function (a smooth function which varies in the interval [0,1]). Output of the network uses a linear activation function. Number of hidden neurons and input neurons were varied to achieve maximum accuracy, minimum mismatch and false positives.

5.3.3 Experiments

Experiments were conducted varying the number of hidden neurons and the number of principal components. The feature vector was fed into the neural network by varying the number of PCs as given below:

1. No. of PCs : 20
2. No. of PCs : 30
3. No. of PCs : 40
4. No. of PCs : 50

In each of the above case, the number of hidden neurons were varied from 10 to 200 neurons.

The training set consisted 32 signals out of which 16 were different types of blast signals and 16 of them were different types non-blast signals. The blast signal set consisted dynamite blast, mortar blast, barrel blasts and different types of explosion. Thunder, gunshots and storm constituted the set of non-blast signals.

The desired outputs of the two class problem were assumed to be

1. $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$ for a Blast Signal (5.1)

2. $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$ for a Non-Blast Signal (5.2)

5.4 Results and Conclusions

Table 5.1 gives a comparison of the results obtained varying the number of principal components that is fed into the neural network. It includes accuracy, mismatch and false positive percentages with respect to the number of PCs.

No of Principal Components	MAX % Accuracy	MAX % Mismatch	MAX % False Positive	Optimal No. of Hidden Neurons
20	70.5	0.0	29.5	15
30	72.5	1.6	26.2	27
40	70.5	0.0	29.5	19
50	87.5	6.2	6.2	95

Table 5.1 : Comparison of results obtained varying the number of PCs

It was concluded from the above table that, the maximum accuracy is obtained when the neural network is fed with 50 principal components.

The network model consisted one input layer, one hidden layer and one output layer. Input layer has 50 input neurons and the hidden layer is made of 95 neurons. The output layer has two output neurons each corresponding to the desired output as given by equations 5.1 and 5.2. Neural network toolbox in MATLAB was used to obtain the results of the experiment. Figure 5.1 shows the neural network model.

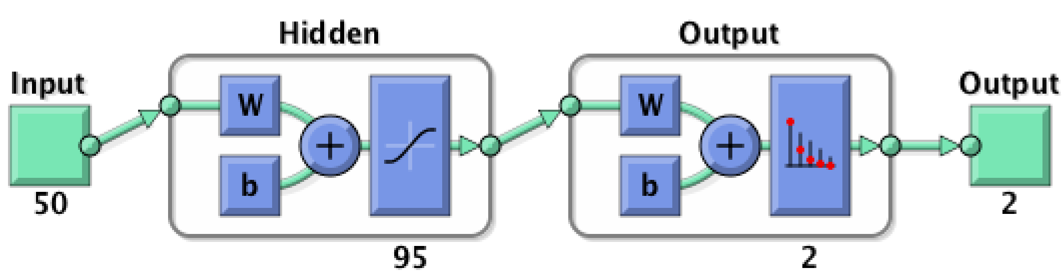


Figure 5.2 : Model of the Neural Network

The confusion matrix is shown in figure 5.3. It can be seen that the overall accuracy attained is 87.5%, 6.2% mismatch and false positive each. Out of the 32 signals, 12 blast signals and 14 non blast signals are used to train. Out of the remaining 6 signals, 3 signals are used to test the network and the other 3 signals to validate the network. There is flexibility to choose the number of signals that can be used to train the neural network. Number of signals for training was set to 80% of the total number of signals, 10% of the whole set to test and validate the network.

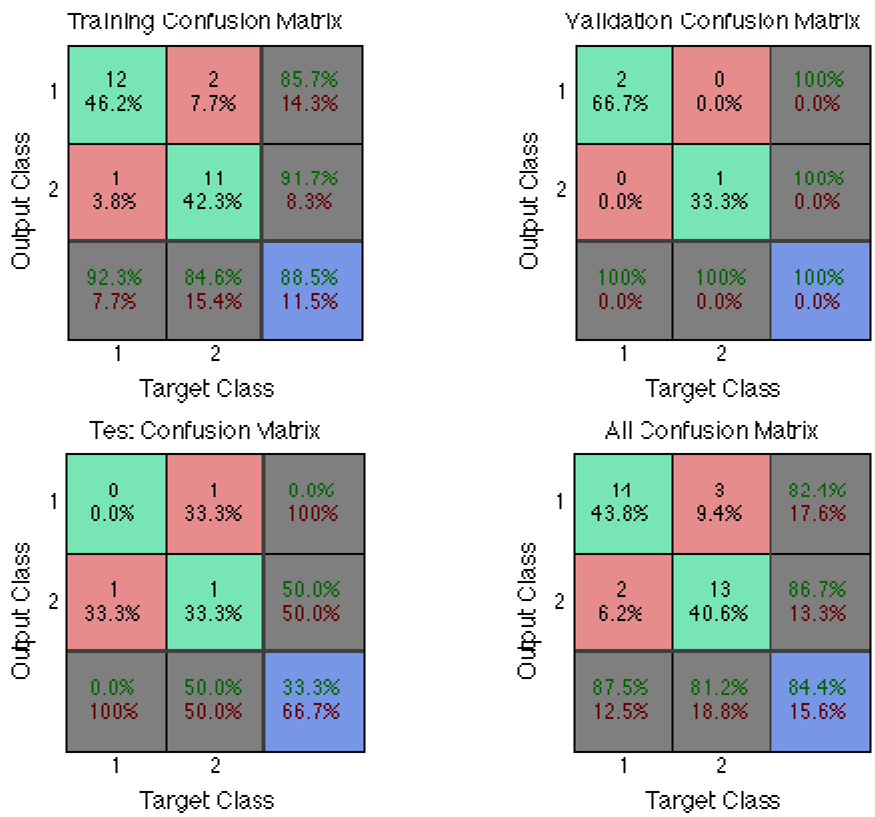


Figure 5.3 : Confusion Matrix of the Neural Network

The desired output is either $\begin{pmatrix}1\\0\end{pmatrix}$,for a blast signal, or $\begin{pmatrix}0\\1\end{pmatrix}$, for a non-blast signal. But the output of the neural network is mostly decimal between 0 and 1. In order to force it to the desired output, hard thresholding is done by forcing the value to 1 if it is greater than or equal to 0.6and to 0 if it is less than 0.4.

Though the neural network has a very good accuracy, the accuracy attained here was limited to 87.5%. Following were the observations made which accounts for lesser accuracy. Owing to those observations, the thresholding was relaxed. The upper threshold was set to 0.6 and the lower threshold was set to 0.4.

1. **Lack of exhaustive training set :**

   In order to have a very good accuracy, an exhaustive training set is essential. The set should contain all possible variations of the data. In the above mentioned case, the training set should contain all kinds of bomb blasts. The accuracy mentioned was obtained using 16 blast signals. Therefore it can be concluded that, with more signals, higher accuracy can be attained.

2. **Lack of standardized signal set :**

   The signals used to train the neural network do not have common length, or in other words different number of samples. The signals are downloaded online from different sources. Hence they have varying sampling frequency. Signals that were too long were truncated to make it computationally feasible. It is not possible to process a signal which lasts for more than a minute. Truncating the signal results in loss of information. Hence lesser accuracy. But the proposed methodology assumes that an impulsive sound does not last for more than five seconds. With 8 kHz sampling frequency 40000 samples are produced which is a viable number for any kind of processing.

3. **Constraints posed by the processor :**

   The processors in the laptops pose computational constraints. The MATLAB simulations were carried out on a OS X version 10.9.5 Macintosh with inbuilt 2.5 GHz intel core i5 and a 4 GB RAM. The processor could only handle up to 1,00,000 samples. Anything beyond that was not handled by the processor. Hence the signal was truncated, which results in a lesser accuracy.

CHAPTER 6

COMPARISON STUDY

CHAPTER 6

COMPARISON STUDY

6.1 INTRODUCTION

The front end of a recognition system is usually composed of an analysis stage to extract specific features from the signal to be classified. Those features must be provided to the classifier in order to discriminate between the different classes involved.

Chapter 4 gave an insight into the feature extraction using principal component analysis. Many other feature extraction methods were performed and their accuracies were compared. The features extraction methods that were performed were Linear Predictive Coding(LPC), 2-D Discrete Wavelet Transform(DWT), Discrete Cosine Transform(DCT), PCA on the Fourier transform of the signal and covariance of the power. The features extracted from these methods are fed into the neural network and their corresponding accuracy computed.

Linear predictive coding (LPC) is a tool used mostly in audio signal processing and speech processing for representing the spectral envelope of a digital signal of speech in compressed form, using the information of a linear predictive model. It is one of the most powerful speech analysis techniques, and one of the most useful methods for encoding good quality speech at a low bit rate and provides extremely accurate estimates of speech parameters.

In Fourier analysis, the Discrete Fourier Transform (DFT) decompose a signal into sinusoidal basis functions of different frequencies. No information is lost in this transformation; in other words, we can completely recover the original signal from its DFT (FFT) representation. In wavelet analysis, the Discrete Wavelet Transform (DWT) decomposes a signal into a set of mutually orthogonal wavelet basis functions. These functions differ from sinusoidal basis functions in that they are spatially localized – that is, nonzero over only part of the total signal length. Furthermore, wavelet functions are dilated, translated and scaled versions of a common function φ, known as the mother wavelet. As is the case in Fourier analysis, the DWT is invertible, so that the original signal can be completely recovered from its DWT representation.

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical for compression, since it turns out (as described below) that fewer cosine functions are needed to approximate a typical signal, whereas for differential equations the cosines express a particular choice of boundary conditions.

6.2 EXPERIMENTS

6.2.1 Linear Predictive Coding

The number of Linear Predictive coefficients were chosen to be 100. These 100 coefficients were fed to the neural network as feature.

6.2.2 Discrete Wavelet Transform

The signal was transformed using the Haar transform. The low pass filter's coefficients were used as the features to the neural network. The no of coefficients used were 50.

6.2.3 Discrete Cosine Transform

The Discrete Cosine Transform is performed on the matrix given by the equation. The first 50 significant components are fed as features to neural network.

6.2.4 PCA of Fourier Transformed Sequence

The Principal Component analysis is tried differently to achieve better accuracy. The Principal components are found out on the Fourier transform of the filtered signal as specified in chapter 4. The first 50 significant components are fed to neural network as features of the signal.

6.2.5 Covariance of Power

The samples of the signal are arranged as given in the matrix . Now the covariance of the matrix is found out using the equation. The diagonal elements of the matrix constitute the power of the signal. Now, the Principal component analysis is performed on the signals as shown in chapter 4. The first 50 significant Principal components of the signal are fed to the neural network ad features of the signal.

6.3 Results

Table 6.1 shown below gives a comparison of accuracies of the different methods used to extract feature.

Method	MAX % Accuracy	Max % Mis-Match	Max % False Positives	Optimal no. of hidden neurons
LPC	84.2	0	15.8	15
DWT	76.9	0	23.1	10
DCT	74.1	0	25.9	40
Covarience of power	77.8	0	22.2	21
PCA on Fourier Transformed Sequence	77.8	0	22.2	35

Table 6.1 : Comparison of accuracies for different methods

6.4 Conclusions

It can seen from the above table that all methods have no mismatches, and yet the accuracy is less. LPC method is the only methods that can be used instead of the actual PCA as it has higher accuracy, minimum mismatch, minimum false positive and not computationally very complex.

The above table substantiates the use of PCA on filtered time signal as the best method for classification.

Chapter 7

LOCALIZATION

Chapter 7

Localization

7.1 Introduction

Localization is a process of reporting the origin of events and determine physical position or logical location. The main objective of localization is to determine the location of an unknown node or an event as accurately as possible from the information obtained from a set of nodes, whose location are predefined.

According to the dependency of range measurements, the existing localization schemes can be classified into two major categories: the range-based approaches and the range-free approaches. The range-based schemes are based on range measurement techniques for location estimation. The range-free schemes ignore the usage of range measurement techniques. Thus, in order to estimate the location of the unknown node, these schemes are based on the use of the topology information and connectivity.

Almost all existing localization schemes consist of two phases:

1) Distance/angle estimation

2) Position computation.

In distance/angle estimation, the most common range measurement techniques are TDOA (Time Difference Of Arrival) , TOA (time of arrival) ,RSSI (Received Signal Strength Indicator), AOA (angle of arrival) and Hop-count.

7.2 RSSI based Localization

Received signal strength indicator (RSSI) is a parameter which is used to determine the distance between the sensor nodes. Technique which estimates the distance between the neighboring nodes is based on a standard feature found in most wireless devices popularly known as the received signal strength indicator (RSSI). Based on the known transmitted power, the effective propagation loss can be calculated.

The Received Signal Strength Indicator (RSSI) is based on fact that the signal strength is inversely proportional to the squared distance between the transmitting node and the receiving node. A known radio propagation model is used to convert the received signal strength into distance. In RSSI techniques, either empirical or theoretical models are used to translate signal strength into distance .

Among the range-based measurement techniques, the RSSI technique is the most common techniques, cheapest and simplest, since its low cost because it does not require additional hardware.

RSSI technique to find the distance was incorporated in the project because, the proposed methodology involves implicit computation of strength of the signal. The first element of the covariance matrix as given by equation 4.6 gives the strength of the signal. Hence no more additional hardware or software resources are required to obtain RSSI.

7.3 Proposed Approach

The audio recording sensors called the nodes are arranged in such a way that, the point of blast is always inside a triangle with vertices formed by the sensors. Considering a special case, the sensors were assumed to be placed along two parallel lines where each node is at a constant distance from the other. A triangle is formed by taking one node from one of the lines and two consecutive nodes from other. Each node is placed at known coordinates. Thus the position of the nodes is known a priori. Following are the steps involved in localization of a blast :

1. Each node records the impulsive sound and covariance of the signal is calculated using equation 4.2. The first element of the matrix S_X gives the power of the signal.
2. Three nodes that indicates highest signal strength are used to form the vertices triangle as shown in figure 7.1.
3. Let the location of the sensor nodes be (x_1,y_1) , (x_2,y_2) and (x_3,y_3) which represents the three vertices of the formed triangle. An arbitrary point p is assumed to be the point of blast. It is assigned with the coordinates (x,y). The point (x,y) is the point to be localized. Taking each vertex as the centre of a circle, three circles are drawn with radii d_1, d_2 and d_3 respectively as shown in figure 7.2.

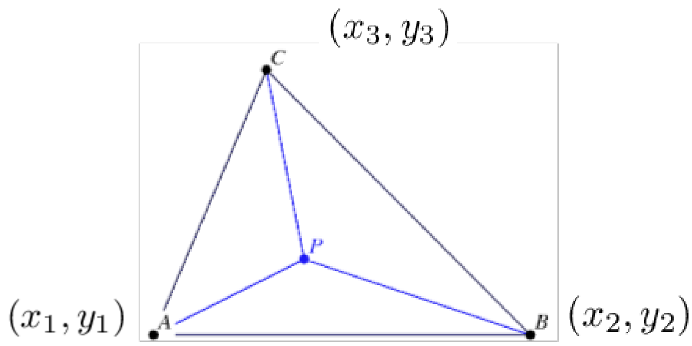


Figure 7.1 : Triangulation

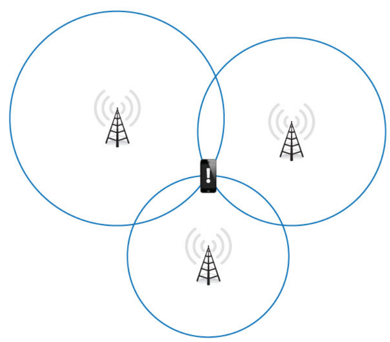


Figure 7.2 : Point of Localization

4. The radii d_1, d_2 and d_3 are related to the corresponding received signal strengths at each node respectively by inverse square law. The relationship between distance and strength of the signal can be developed using different methods. Each of these methods are explained in the following section.
5. The point of intersection of the three circles gives the point of localization. The equation of these three circles are given by

$$(x - x_1)^2 + (y - y_1)^2 = {d_1}^2 \tag{7.1}$$

$$(x - x_2)^2 + (y - y_2)^2 = {d_2}^2 \tag{7.2}$$

$$(x - x_3)^2 + (y - y_3)^2 = {d_3}^2 \tag{7.3}$$

7.4 Relationship Between Distance and Power

To develop a relationship between d and P, a set of measurements of power against distance is essential. Experiments were conducted to obtain these measurements. A single audio signal was recorded at distances starting from 0.5m to 14m in steps of 0.5m. A total of 28 reading were recorded. The sensor used for recording was a OnePlus One cyanogen mobile phone that has tri-microphone with noise cancellation. The above experiment was repeated in different environments and the average signal strength value was calculated for all 28 readings. The values were made monotonic by discarding absurd values that might have occurred due to several kinds of perturbation in the environment. This standardised set is shown in the figure 7.3. With the help of this graph, a mathematical formulation can be developed where distance *d* can be represented in terms of the received signal strength, or in other words power *P*.

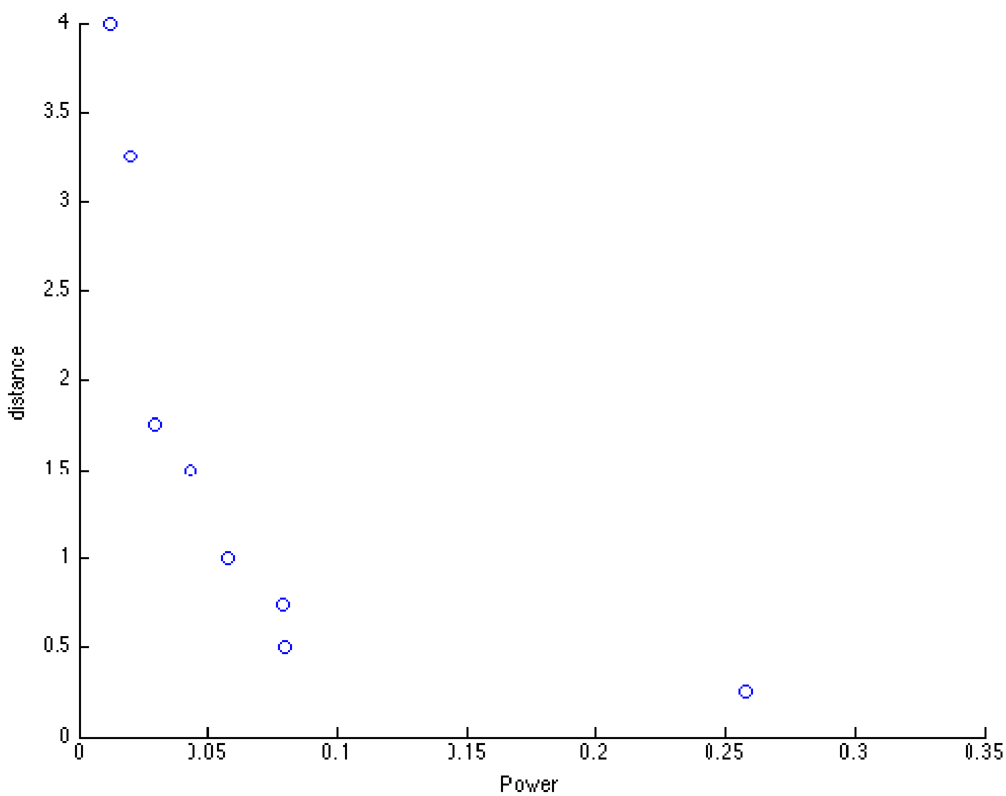


Figure 7.3 : Distance vs power plot

Following were the methods used to relate distance *d* and power *p*.

1. **Bisection algorithm**
2. **Curve Fitting using Nonlinear Regression**
3. **Function approximation using Neural Network**

7.4.1 Bisection algorithm

Power or strength of the signal varies inversely with the distance squared. It can be written as shown by the equation 7.6.

$$P \; \alpha \; \frac{1}{d^2} \tag{7.6}$$

To equate L.H.S and R.H.S a proportionality constant has to be introduced as represented by equation 7.7.

$$P = \frac{k}{d^2} \tag{7.7}$$

It is straightforward that distance is can be written in terms of *k* and *P* as shown in equation 7.8.

$$d = \sqrt{\frac{k}{p}} \tag{7.8}$$

Constant *k* in the equation 7.8 is found out using bisection algorithm. The steps are as follows :

1. Three mobiles were placed at the vertices of a triangle.
2. A sound source was placed inside the triangle at known coordinates and a sound signal was recorded at the vertices of the triangle.
3. The same procedure was repeated for different positions of the source inside the triangle.
4. Since the power obtained at the nodes are known, *k* is varied to increase the radii of the circles drawn centered at the vertices of the triangle.
5. The intersection of the circles gives the value of *k*.

The value of *k* was found to be 0.75. However, the above method does not definitively justify equation 7.8. Intersection of the circles is not assured due to error in processing of the signal. The three circles might not have a unique solution as against to the ideal case. Hence, the accuracy becomes less. To improve accuracy, other methods were tried.

The coordinates can be calculated by solving the three circles equations. *d* can be replaced in terms of *P* using the equation 7.8. The localization coordinates obtained are given by the equations 7.9 and 7.10.

$$x = \frac{1}{2}\left(\frac{y_3 - y_1}{(y_3 - y_1)(x_2 - x_1) - (y_1 - y_2)(x_1 - x_3)}\right) \tag{7.9}$$

$$\left(k\left(\frac{1}{P_1} - \frac{1}{P_2}\right) - ({x_1}^2 - {x_2}^2) - ({y_1}^2 - {y_2}^2) + \left(\frac{y_1 - y_2}{y_3 - y_1}\right)\left(k\left(\frac{1}{P_1} - \frac{1}{P_3}\right) - ({x_1}^2 - {x_3}^2) - ({y_1}^2 - {y_3}^2)\right)\right)$$

$$y = \frac{1}{2}\left(\frac{1}{y_3 - y_1}\right)\left(k\left(\frac{1}{P_1} - \frac{1}{P_3}\right) - ({x_1}^2 - {x_2}^2) - ({y_1}^2 - {y_3}^2) + 2x(x_1 - x_3)\right) \tag{7.10}$$

7.4.2 Curve Fitting using Nonlinear Regression

This method involves nonlinear regression analysis to bring distance *d* in terms of power *p.* A relation between the power and distance is approximated using a nonlinear function, that fits best on the data set shown in figure 7.3. An exponential curve was fit to the data set which is shown in figure 7.4. This generates a relation between distance *d* and power *p* given by the equation 7.11.

$$d = 12.47\ e^{-52.46P} + 1.66\ e^{-4.581P} \tag{7.11}$$

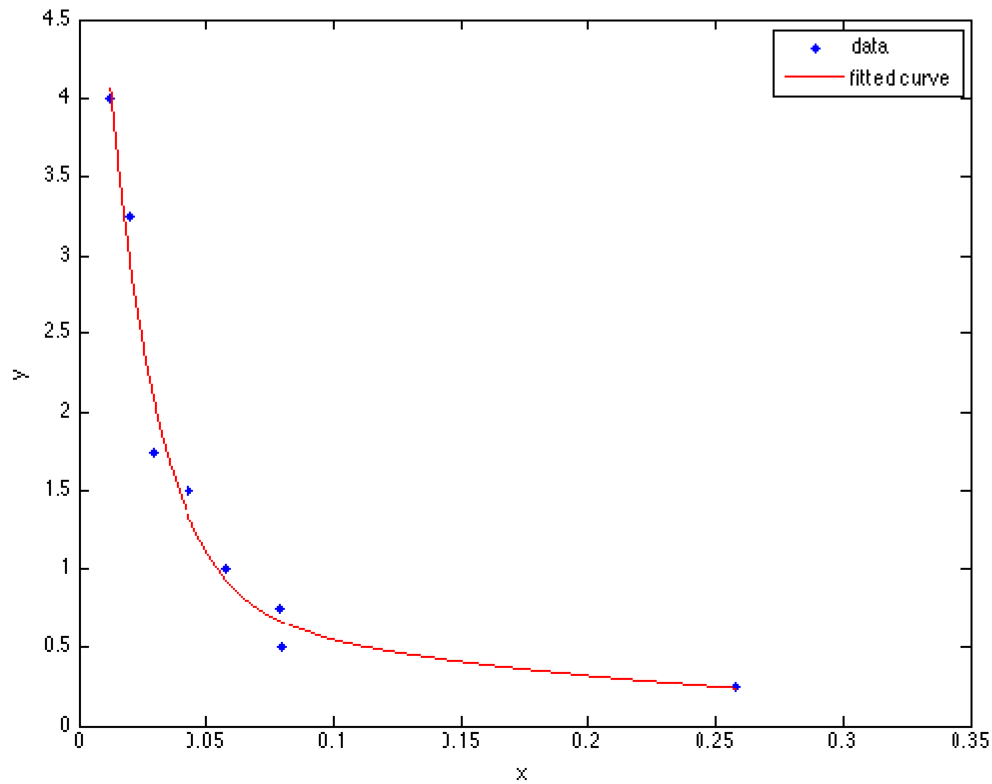
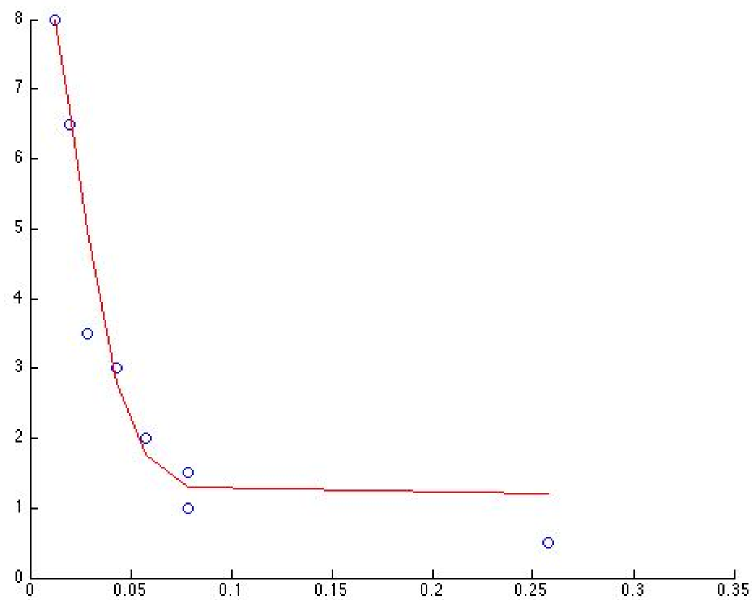


Figure 7.4 : Exponential curve fit on the data set

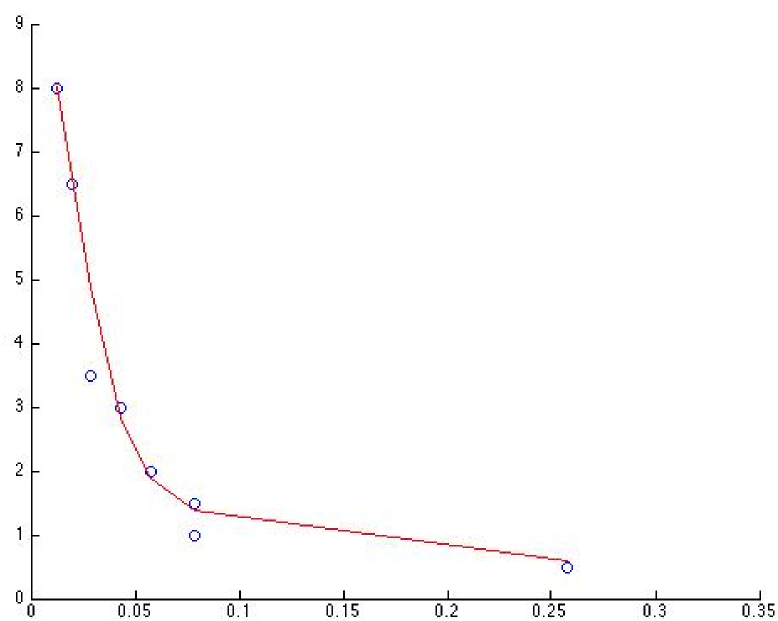
7.4.3 Function approximation using Neural Network

Function approximation using neural network is very much similar to the regression analysis mention in the previous section. The advantage of the neural network is that, when a particular function is not available to fit a given data set, neural network learns the pattern of the data and fits the curve. The corresponding weights obtained has to be multiplied to obtain the relation. Finally, it all boils down to matrix multiplication which is much simpler computational wise. The neural network fits a curve which has the least mean square error. The neural network comprised one input layer, one hidden layer and one output layer. The input and output layer consisted of one neuron. The hidden neurons were varied from one to three. The hidden layer activation function is a sigmoid and that of output layer was a linear function. The number of epochs was set to a value of 5000. The following are the plots with best fit curve on the data set :



0
1
2
3
4
5
6
7
8
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35

(a)



0
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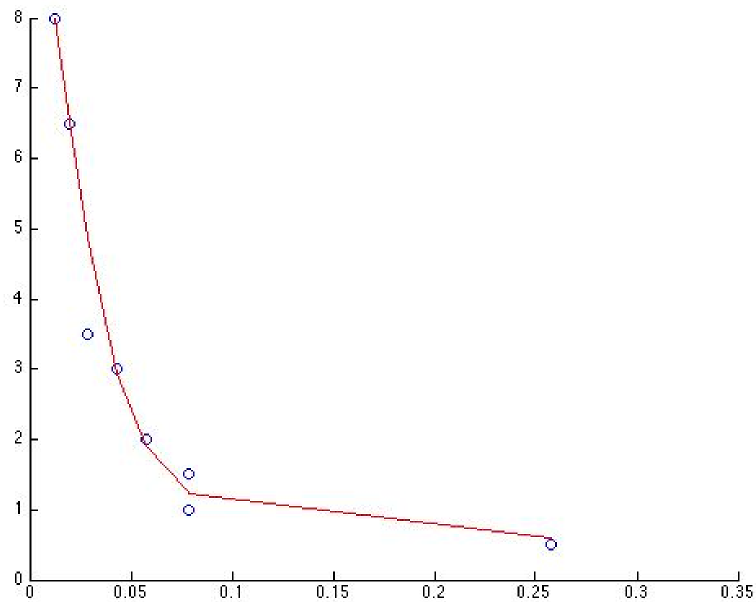
0.05
0.1
0.15
0.2
0.25
0.3
0.35

(b)



(c)

Figure 7.5 : Function approximation using Neural network : (a) using 1 hidden neurons (b) using 2 hidden neurons (c) using 3 hidden neurons

7.4 EXPERIMENT

To evaluate the performance of the three proposed methods, an experiment was conducted to find out the accuracy of the estimated position of the recorded sound source. Three sensor nodes were placed at the coordinates (0,0), (8.2,1.95), (5,11.3). Source was placed at different coordinates and and the sound signal was recorded in each of the nodes. The power received at each node was calculated and fed into the equations of the proposed methods to localize the point of blast.

7.6 RESULTS

The accuracy of the three methods are given below,

1. Bisection algorithm

   The accuracy obtained was 83%.

2. Non linear regression analysis

   The accuracy obtained was 94%.

3. Function approximation using neural network

   The accuracy with different number of hidden neurons was found to be,

   a. with 1 hidden neuron - 93%
   b. with 2 hidden neurons - 92%
   c. with 3 hidden neurons - 91%

7.7 CONCLUSIONS

The above results showed that the best method to estimate the relationship between *d* and *P* was the non linear regression analysis.

The bisection algorithm has a lesser accuracy since the intersection of the three circles might not turn out to be single point. Or in other words, the three equations might not have a unique solution always.

The neural network has a lesser accuracy than expected. This is because of the fact that the number of data points that were available for the function approximation was considerably less.

The estimation of the relationship between *d* and *p* was found to be highly dependent on the sensor used and the background noise level. So an ideal relationship where the equation is independent of environment noise level and sensor is unachievable. Thus, regression analysis or function approximation has to be done on the data that is obtained from particular type of sensor, deployed in that particular environment under consideration.

The accuracy can be increased by having a better quality sensor and a universal data set obtained by taking all the constraints into account.

CONCLUSIONS

CONCLUSIONS

This project was aimed at developing an effective and computationally efficient algorithm for dynamite blast detection. A sequence of procedures was formulated to detect the blast. It consisted of filtering, feature extraction, classification using neural network and localization of a blast.

To determine the range of frequency of the impulsive signals spectrum estimation was carried out. It was seen that the energy of the signal lies between 50 Hz and 500 Hz.

The filtering of the signal was tried with many different filters. The filter, which had high stop band attenuation and a smaller roll off, was chosen. The filter, which satisfied these specifications, was elliptical filter.

The features of the signal were extracted using the principal component analysis (PCA). It was a simple procedure that can be implemented on any embedded platform.

The niche concept of neural networks was used to discriminate between a blast and a non-blast signal. The features i.e. the PCs were used as training set. The PCs of the unknown signal when fed to the neural network consisting of 95 hidden neurons was classified with accuracy 87.5%.

Upon detection of blast, it has to be localized. RSSI based localization was used to determine the position of the blast. The RSSI information was used to get distance of the blast from each sensor and the location was computed using triangulation. The blast with the above algorithm was localized with an accuracy of 94%.

The accuracy was reasonable enough to detect the problem of dynamite fishing. The above formulated solution helps the authorities keep the dynamite fishing in check and save the environment. With extra real time signal set for training of the neural network, the accuracy can be increased and implemented in the practice.

Thus it can be seen that environmentally detrimental activity that has been plaguing the environmentalists and officials can be solved using digital signal processing and machine learning techniques.

Future Scope

Generally the accuracy of a neural network classifier is greater than 90%. This project has accuracy lesser than 90%. This can be improved by obtaining real time signals of the blast for training the neural network. A better processor can be used to train the neural network to handle a large number of signals.

Next step of the project is the real time deployment of the algorithms along the riverside for detection and reporting of the blast. The algorithm is to be integrated into an embedded module and used as the sensor modules for deployment.

The above algorithms can be modified to use for gun shot detection in forests for detecting illegal poaching. Also it can be used as a method to detect illegal quarrying. The methods can also be used for detection of any objects or living things that has characteristic sound.

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