DIGITAL ENHANCEMENT OF THE QUALITY OF A NOISY RADIO NIGERIA NEWS BROADCAST

BY

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B.TECH

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CERTIFICATION

This work has not been presented elsewhere for the award of a degree or any other purpose.

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(Candidate)	Signature	Date

I certify that this work has been carried out by Mr. Alimi, Isiaka Ajewale in the Department of Electrical and Electronics Engineering of the Federal University of Technology, Akure.

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(Supervisor)	Signature	Date

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DEDICATION

This project work is dedicated to Almighty Allah, The Most Merciful and The Most Compassionate as well as to my late parents (May their souls rest in perfect peace).

This project work is also dedicated to my honey, 'Biola Alimi, for her unflinching support and love.

ABSTRACT

This work presents the results of applying digital techniques to study and improve the quality of Federal Radio Corporation of Nigeria (FRCN) news broadcast signals. Until May 2008, the major FRCN live news broadcast was of very unsatisfactory quality and characterized by noisiness, poor intelligibility and distortion. While many solutions have been tried in the past, improvements were usually short-lived because of inadequate information about the technologies and the inevitable high rate of obsolescence of cutting edge technologies that tended to be adopted by anxious executives.

This work is an attempt at employing proven "state of the art" technologies within an indigenous implementation initiative. During the course of the study, a noisy broadcast signal was digitized and captured onto a computer and processed using MATLAB® Software (environment). Important characteristics including the spectral features of both signal and channel noise were determined. Following a survey, a spectral subtraction method which uses the properties of the noise to enhance quality was implemented.

Subsequently, the statistical properties of the background and channel noise of the environment were determined. The results indicated that it was very close to synthetic and available white noise. Experiments to extract signals from signal and additive noise mixes verified that the spectral subtraction method could improve the signal to noise ratio by 15dB.The method was applied to the real-life broadcast and a significant improvement in quality was observed.

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CHAPTER ONE

INTRODUCTION

1.1 Background

All over the world, news broadcasts constitute an important avenue for information dissemination. Except in the case of single station facilities, most radio and television stations are organized as networks that share programs which have to be communicated through various means especially satellite and terrestrial radio. One notable example is the network news broadcast of the Federal Radio Corporation of Nigeria (FRCN) which takes place early in the morning across the country providing a very essential bell-weather indicator of the day for majority of Nigerians. For many decades, listeners have expressed great displeasure with the quality of the audio signal, especially, aspects involving noise, intelligibility and distortion.

The FRCN is a network of sub-radio stations that operate semi-autonomously most of the time. The network, however, is serviced by the same news broadcast at specific times in the day. Investigations confirm that the degradation of the audio signal occurs during the transfer of the signals between stations. During that process, channel noise and amplifiers contribute unwanted components to the received signal. The result is a nearly unintelligible and extremely noisy signal being re-broadcast by most of the network stations.

This unsatisfactory state of affairs has been addressed by many solutions in the past two decades. Unfortunately, most improvements last for a short while and soon the original problem re-emerge. A preliminary study of the cause of the limited duration of improvements revealed that technology changes coupled with incompatibilities with the existing facilities often render the add-ons ineffective. It is in the light of this that this project has been configured to employ indigenous efforts to address the problem of noise management in the FRCN network news broadcasts.

Under this initiative, a number of options will be studied. The one considered in this study will focus on using noise reduction techniques to enhance the quality of some of the broadcasts.

1.2 Problem Statement

The problem addressed in this project is to evolve a method using extant technology (that could be installed at the remote receiving radio stations) to improve the quality of channel noise-corrupted broadcast signals emanating from the national studios based in Abuja.

1.3 Project Objectives

The objectives of this project are to:

i. evaluate the quality of a Federal Radio Corporation of Nigeria noisy news broadcast; and

ii. develop a signal processing technique to improve the quality of the news broadcast.

1.4 Research Methodology

A noisy news broadcast of the FRCN was monitored and recorded. The quality of the broadcast signal was evaluated and it was observed to be corrupted by additive channel noise. The noisy broadcast was digitized and captured onto a computer and the data were then imported into the MATLAB® software (environment). The captured signal was studied to establish important characteristics, including the mean, standard deviation, autocorrelation and spectral properties of both the signal and the channel noise. The spectral subtraction technique which requires the computation of the Fast Fourier Transform (FFT) and the Inverse Fast Fourier Transform (IFFT) was implemented on a contemporary personal computer using MATLAB®.

Studies of the channel noise (determined during pauses in speech) were completed followed by a comparison with both synthesized and other available white noise samples. Using the statistical properties of the background and channel noise, experiments to improve signal to noise ratio by the spectral subtraction method were carried out.

1.5 Contributions

This research work provided the following contributions to knowledge:

- During the course of this work, the noise on the FRCN channel has been characterized and shown to be essentially stationary.
- The Spectral Subtraction technique was studied and verified to provide an enhancement of up to 15dB.
- An arrangement that is versatile and requires minimal additional hardware besides a laptop or desk PC and software was innovated.

1.6 Thesis Outline

Chapter two starts with a review of communication systems. Also, it treats sources of link degradation before going into the characteristics of speech and fundamental concepts of acoustics. It then focuses on digital signal processing and techniques for the recovery of speech signal from noise signal. It also contains literature review of previous work done on Spectral Subtraction approach. It ends with explanation of the Fast Fourier transform and Window function.

Chapter three presents detailed investigations carried out on spectral subtraction technique to recovery clean signal from noisy broadcast. It also focuses on signal acquisition and hardware setup for the work. It also presents experiments that characterized the noise on the FRCN channel. It ends with experimental studies of the spectral subtraction technique for signal enhancement.

Chapter four contains realization stages of Spectrål Subtraction based-speech enhancement. Chapter five presents contributions, conclusions and recommendation.

CHAPTER TWO

LITERATURE REVIEW

2.1 Causes of Degradation in the Radio Nigeria News Broadcast

The context of the problem addressed in this work may be represented as shown in figure 2.1. Typically on radio networks, speech captured in a studio from a newscaster is processed and broadcast to affiliate stations using channels that may include one or more of the following - terrestrial phone links, coaxial cable, microwave and/ or satellite paths.

Most of the signals are derived from a studio where noise sources are minimal. The problems arise as shown in figure 2.2 when electrical noise is added in the channel and distortion occurs through anomalies in the equipment at both ends (Hsu, 2003).

Electrical noise is a random phenomenon which has been extensively studied and is briefly discussed in the subsequent section. The other type of anomaly occurs due to actions inside the equipment that modify the amplitude of the signal non-linearly. Other forms of distortion may also occur such as the case of phase distortion (Lynn, et al, 1998). However, since this is not random, it can often be compensated by the designers and operators of the radio station.

The principal offensive problem is due to noise which, in the electrical context, may be assumed to arise from several sources. Due to the multiplicity of noise sources in a communication link, it is difficult to define the properties (frequency range, level and instantaneous phase) of noise and also difficult to reduce its effect on the performance of a communication link except where digital techniques are used.

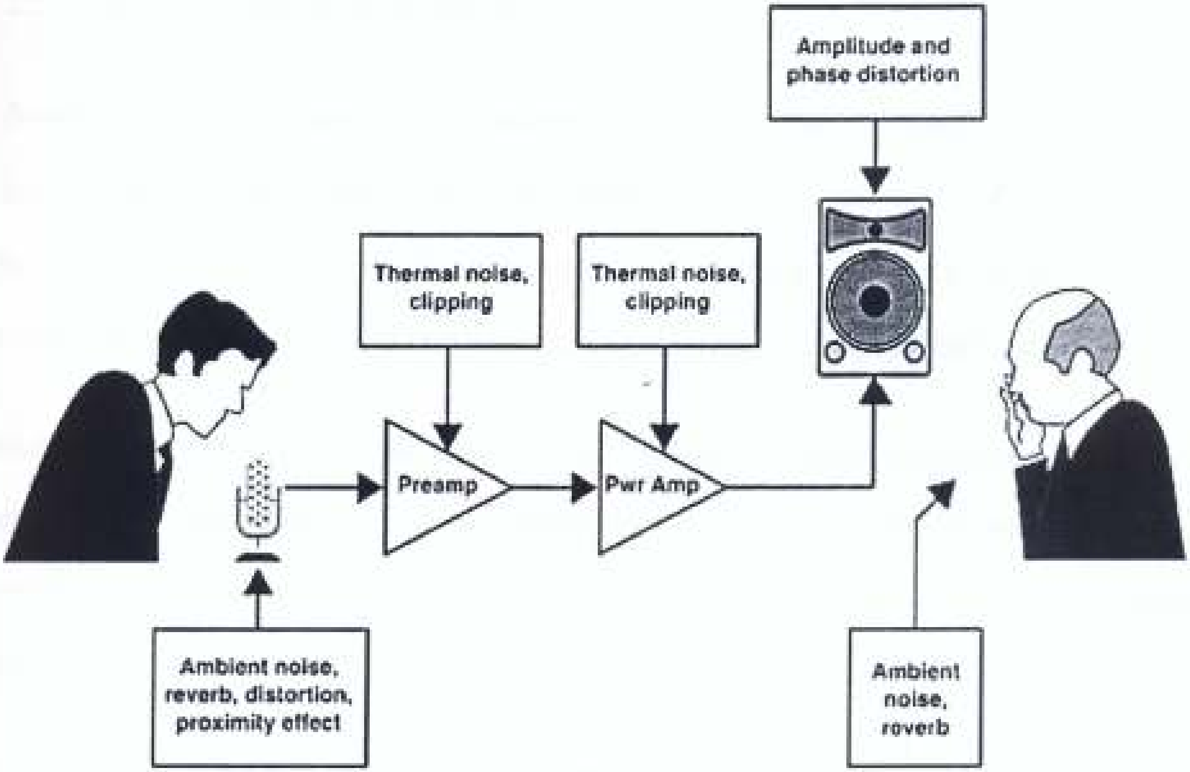


Fig. 2.1: Speech Communication Systems

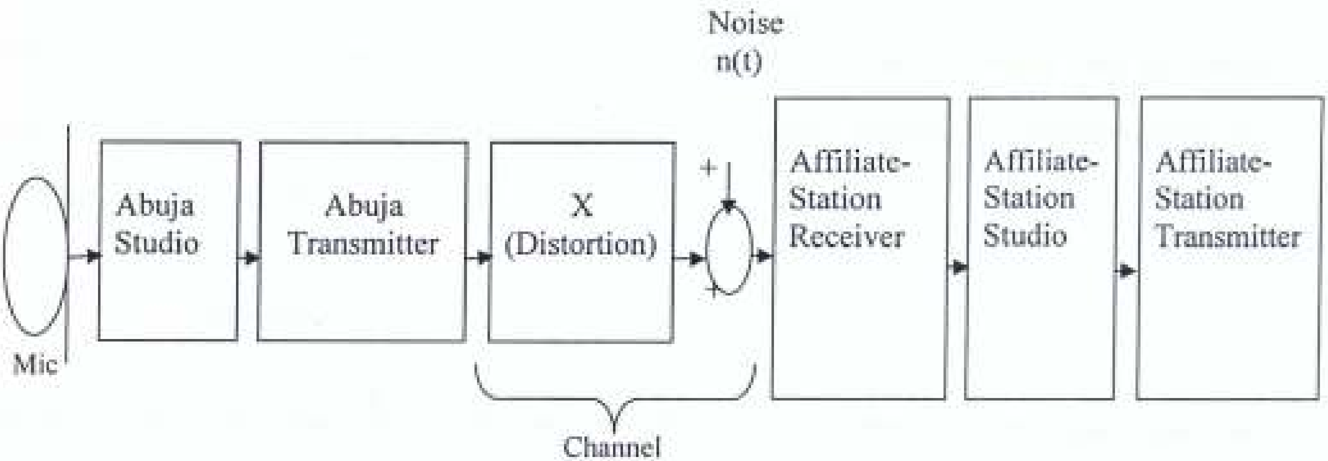


Fig. 2.2: FRCN Communication System Model

2.2 Sources of Signal Degradation

People use speech to communicate messages. When the speaker and listener are near each other in a quiet environment, communication is generally easy and accurate. However, at a distance or in a noisy environment, the listener's ability to understand suffers. In broadcasting, special environments with very good acoustics properties are used to create the information.

Speech can also be sent electrically; the conversion media (microphone, loudspeaker, earphones), as well as the transmission media (telephone, radio), typically introduce distortions, yielding a noisy audio signal. Such degradation can lower the intelligibility and/or quality of speech (Schwartz, 1990).

All communications links are ultimately limited by channel noise in the system, and so, it is essential to determine the statistical properties of noise as they affect data communications performance. Also, many channels are subject to interference, usually man-made, which can be equally detrimental to communication integrity. Thirdly, no communication is truly distortion free, whether this is caused by imperfections in the processing hardware or defects within the channel (Williams, 1987).

2.2.1 Distortion

As stated above the other source of signal deformation arises from a phenomenon known as distortion. Distortion is the alteration of the original shape (or other characteristic) of an object, image, sound, waveform or other form of information or representation. The addition of noise or other extraneous signals (hum, interference) is not considered to be distortion, though the effects of distortion are sometimes considered noise (Bateman, 1999).

The common types of link distortion are:

- Frequency-dependent phase shifts, giving rise to differential group delay;
- Gain variations with frequency caused by the channel filtering effect;
- Gain variations with time as experienced in a radio/infrared channel; and
- Frequency offsets between transmitter and receiver due to Doppler shift or local oscillator error.

Distortion can be introduced within the transmitter, the receiver and the channel. In some cases, it can be corrected using channel equalizers, gain and frequency control systems. Unlike noise and interference, distortion disappears when the signal is turned off.

2.2.1.1 Gain Distortion

Most communications hardware-filters, mixers, amplifiers, and so on, and most channel types-cable, fiber, radio, infra-red, introduce a frequency dependent amplitude distortion into a signal. Wired channels exhibit a general roll-off of amplitude with frequency due to the capacitive nature of long lengths of cable causing a low pass filtering effect.

Also, poor termination of cables at the end-user equipment can itself introduce distortion. Wireless links do not suffer the capacitance problems of cables, but instead, suffer from variable path loss due to the unpredictable nature of the communications path.

2.2.1.2 Phase Distortion

The second form of distortion arises when the phase response β (f) of the system is not linear with frequency. Then, if the input signal is divided into a set of components, each one of which occupies a narrow band of frequencies, each of them is subjected to a different delay in passing through the system, with the result that the output signal has a different waveform from the input. This form of distortion is called phase or delay distortion (Bateman, 1999).

The effect of a non-linear phase response in a filter is to cause the various frequency components that make up the data signal to undergo slightly different amounts of phase shift. If the phase response is not flat, or does not increase linearly with frequency (termed as linear phase response), distortion will be introduced into the waveform of the data pulse or symbol. If the component has a linear phase response, then it translates into a fixed time delay of the signal passing through it, otherwise the signal will be distorted.

The filtering effect of most wired channels will introduce some phase and hence group delay distortion into the signal. Equalizers are used for measuring and compensating for much of this type of distortion.

In the wireless channel, phase distortion is not a problem for signals traveling along any individual path between source and receiver. However, in applications where the signal travels by multiple paths, where each path may have a different length and hence a different time delay, the phases of the components making up the composite received signal will all be different. This can create significant problems for data.

2.2.1.3 Conditions for Distortionless Transmission

Distortion-less transmission is said to have occurred when the output signal of a system is an exact replica of the input signal, except for a possible change of amplitude and a constant time delay. This may be expressed as follows:

$$y(t) = kx(t - t_0) \qquad (2.2.1)$$

Where:

$x(t)$ is a signal transmitted through the system;

$y(t)$ is the output signal;

k is a constant introduced to account for the change in amplitude; and

t_0 is a constant that accounts for the delay in transmission.

Let $X(f)$ and $Y(f)$ denote the Fourier transforms of $x(t)$ and $y(t)$, respectively. Then, applying the Fourier transformation to equation (2.2.1) and using time-shifting property of the Fourier transformation, we get

$$Y(f) = kX(f)exp(-j2\pi f t_0) \qquad (2.2.2)$$

The transfer function of a distortion-less system is therefore

$$H(f) = \frac{Y(f)}{X(f)} = kexp(-j2\pi f t_0) \qquad (2.2.3)$$

The corresponding impulse response of the system is given as:

$$h(t) = k\delta(t - t_0) \qquad (2.2.4)$$

Where $\delta(t - t_0)$ is a Dirac delta function shifted by t_0 seconds.

Equation (2.2.3) indicates that in order to achieve distortionless transmission through a system, the transfer function of the system must satisfy two conditions (Denbigh, 1998):

1. the amplitude (magnitude) response $|H(f)|$ is constant for all frequencies as given by

$$|H(f)| = k \qquad (2.2.5)$$

2. the phase (shift) $\beta(f)$ is linear with frequency, passing through zero as shown by

$$\beta(f) = -2\pi f t_0 \qquad (2.2.6)$$

It is not enough that the system attenuates (or amplifies) all frequency components equally. All these frequency components must also arrive with identical time delay in order to add up correctly (Gabel and Roberts, 1999).

2.2.2 Interference

This occurs because of contamination of the channel by extraneous signals, for example, from power lines, machinery, ignition systems, other channel users (adjacent channel and co-channel interference) and so on. If characteristics are known, then interference can often be suppressed by filtering or subtraction.

2.2.3 Noise

Electrical noise is the type of noise that is encountered in this project. Noise in this context is the random and unpredictable electrical signal that is due to natural phenomena including atmospheric noise, thermal noise, shot noise etc. In audio recording and broadcast systems, audio noise refers to the residual low level sounds (usually hiss and hum) that is heard in quiet periods of programme (Roden, 1998).

The types of noises that are relevant to this project include:

2.2.3.1 Thermal Noise

This is dominant in communication systems and originates from the free movement of electrons within a conductor. The energy and degree of movement of electrons increases proportionally with the temperature of the conductor measured in degrees Kelvin.

Thermal noise can be reduced by cooling the noise source and this principle is being applied in some radio receivers using cryogenic coolers to improve the receiver sensitivity.

2.2.3.2 Shot Noise

This is generated within semiconductor junctions when electrons cross a potential barrier. Its power is proportional to the bias current in the semiconductor.

2.2.3.3 Flicker Noise

This form of noise is also generated in semiconductors and is proportional to the dc bias current but differs in that the noise power decreases with frequency. Because the power variation is almost directly proportional to *1/f*, it is sometimes called *1/f* noise.

2.2.3.4 Atmospheric Noise

This is the term given to noise arising from electromagnetic radiation from solar and galactic sources, and also from terrestrial lightning discharges. The level of noise varies considerably with frequency, with the higher levels of noise occurring in the microwave region of the spectrum.

2.2.3.5 Characteristics of Noise

Noise is usually classified as white or coloured depending on the behavior of the spectral density of the noise power in the frequency range of interest (Wilson, 1989).

2.2.3.6 White Noise

White noise has a flat power spectral density over all frequencies of interest, with a value usually denoted as N_o Watts/Hz (Shanmugan, 1979).

2.2.3.7 Coloured Noise

There are different types of coloured noise depending on the nature of the power spectral density. Some notable types are: Pink (or 1/*f*) noise; Red (or Brown) noise; Blue (or azure) noise; Violet (or purple) noise and Grey noise.

Colored noise has a non-uniform spectral distribution; however, over a finite bandwidth corresponding to a single communications channel, the power spectral density might appear flat, hence the term band limited white Gaussian noise is used to simplify analysis.

2.3 Speech

The broadcast encountered in this work is principally speech and speech is referred to as the processes associated with the production and perception of sounds used in spoken language (Stassen and Kuny, 2003).

2.3.1 Speech Characteristics

Speech characteristics can be described by a few major features: speech flow, loudness, intonation and intensity of overtones (Stassen and Kuny, 2003).

2.3.2 Speech Flow: This describes the speed at which utterances are produced as well as the number and duration of temporary breaks in speaking.

2.3.3 Loudness: Loudness reflects the amount of energy associated with the articulation of utterances.

2.3.4 Intonation: Intonation is the manner of producing utterances with respect to rise and fall in pitch, and leads to tonal shifts in either direction of the speaker's mean vocal pitch.

2.3.5 Overtones: These are the higher tones which faintly accompany a fundamental tone, thus being responsible for the tonal diversity of sounds.

Since the process studied in this work involves issues of acoustics and signal modification, the principles will be briefly summarized as follows.

2.4 Acoustics

Acoustics is the interdisciplinary science that deals with the study of sound, ultrasound and infrasound (all mechanical waves in gases, liquids, and solids).

2.4.1 Fundamental Concepts of Acoustics

The study of acoustics revolves around the generation, propagation and reception of mechanical waves and vibrations.

The steps shown in figure 2.3 can be found in any acoustical event or process. There are many kinds of causes, both natural and volitional. There are many kinds of transduction processes that convert energy from some other forms into acoustical energy, producing the acoustic wave. (Stephens and Bate 1966).

The wave carries energy throughout the propagating medium and it is eventually transduced again into other forms, in ways that again may be natural and/or volitionally contrived. The final effect may be purely physical or it may reach far into the biological or volitional domains.

The central stage in the acoustical process is wave propagation. This falls within the domain of physical acoustics. In fluids, sound propagates primarily as a pressure wave. In solids, mechanical waves can take many forms including longitudinal waves, transverse waves and surface waves.

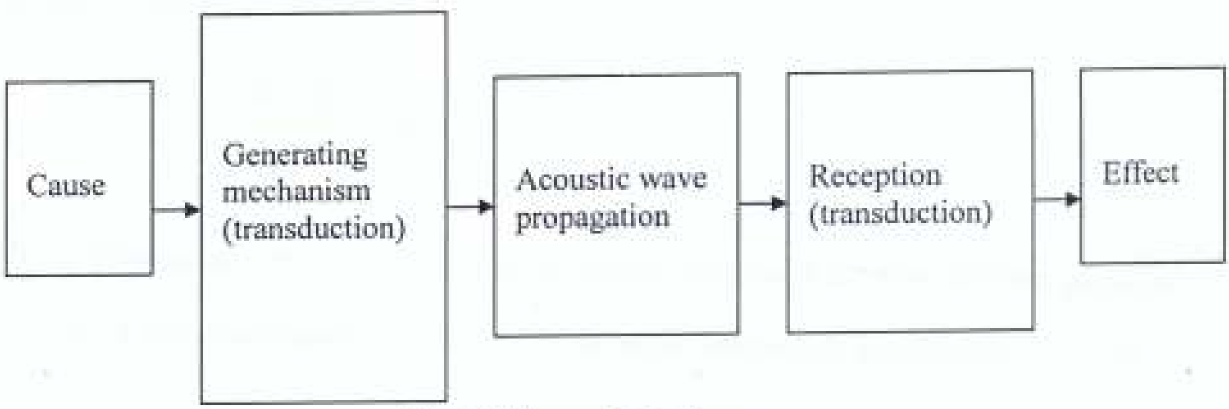


Fig. 2.3: Acoustic Systems

2.4.2 Wave Propagation: Pressure Levels

In fluids such as air and water, sound waves propagate as disturbances in the ambient pressure level. While this disturbance is usually small, it is still noticeable to the human ear. The smallest sound that a person can hear, known as the threshold of hearing, is nine orders of magnitude smaller than the ambient pressure. The loudness of these disturbances is called the sound pressure level, and is measured on a logarithmic scale in decibels. Mathematically, sound pressure level is defined by equation 2.4.1

$$SPL = 20\log_{10}\frac{P}{P_{ref}} \tag{2.4.1}$$

Where P_{ref} is the threshold of hearing and P is the change in pressure from the ambient pressure. Table 2.1 gives a few examples of sounds and their strengths in decibels and Pascals.

Table 2.1: Sound Intensity

Example of Common Sound	Pressure Amplitude	Decibel Level
Threshold of Hearing	$20*10^{-6}$ Pa	0 dB
Normal talking at 1m	.002 to .02 Pa	40 to 60 dB
Power lawnmower at 1m	2 Pa	100 dB

2.4.3 Wave Propagation: Frequency

The entire spectrum can be divided into three sections: audio, ultrasonic, and infrasonic. The audio range falls between 20 Hz and 20,000 Hz. This range is important because its frequencies can be detected by the human ear. This range has a number of applications, including speech communication and music. The ultrasonic range refers to the very high frequencies: 20,000 Hz and higher. This range has a shorter wavelength which allows better resolution in imaging technologies. Medical applications such as ultrasonography and elastography rely on the ultrasonic frequency range. On the other end of the spectrum, the lowest frequencies are known as the infrasonic range. These frequencies can be used to study geological phenomenon such as earthquakes (Bies and Hansen, 2003).

2.5 Digital Signal Processing

Due to the anomalies discussed earlier, the digital signal is usually processed using some form of digital filter.

A digital filter is a numerical procedure, or algorithm, that transforms a given sequence of numbers into a second sequence that has some more desirable properties, such as less noise or distortion (Haykin, 1978). A digital filter employs a digital processor to perform numerical calculations on sampled values of the signal. The processor may be a general-purpose computer such as a PC, or a specialized DSP (Digital Signal Processor) chip. The overall process is as shown in figure 2.4.

The problem addressed in this work involves determing what type of signal processing can be used to recover an improved signal from the noisy ones.

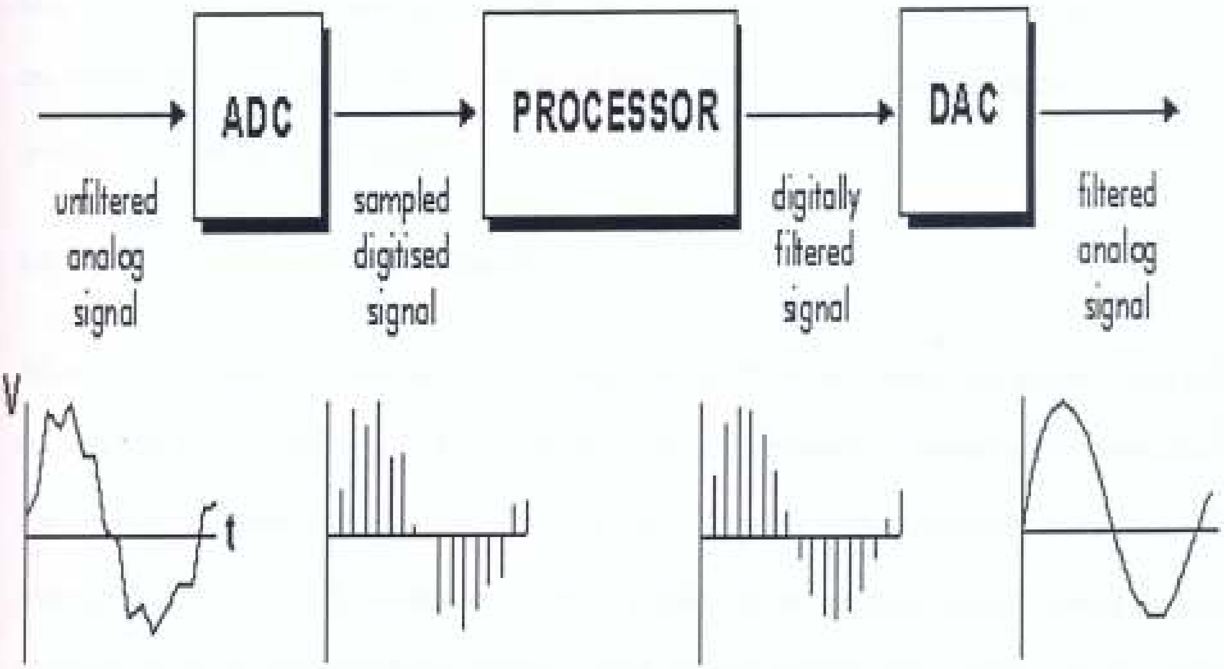


Fig. 2.4: An Illustration of Digital Signal Processing Technique

2.6 Techniques for the Recovery of Signals from Noise

The problem of recovering signals from noise has existed since the infancy of radio and telephone communications in the early part of the twentieth century. The question addressed then was how to reduce the random phenomena described in the previous section. The pioneer works were done by Wiener, Kolmogorov, Hopf and others using analog methods. Digital methods have since superceded them starting with the works of Kalman (1957) and the Fast Fourier transforms (FFT) of Cooley and Tukey in the late 1960's. Most of the subsequent work has been developments on the above ones.

2.6.1 Channel Noise Estimation

All speech enhancement methods aimed at suppressing the channel noise are based in one way or the other on the estimation of the background noise. It is, therefore, important to determine the characteristics of the noise. One method is the Voice Activity Detection technique. Voice Activity Detection (VAD) determines whether a frame of the captured signal represents voiced, unvoiced, or silent data (Haigh and Mason, 1993). Voiced sounds are periodic in nature and tend to contain more energy than unvoiced sounds, while unvoiced sounds are more noise-like and have more energy than silence. Silence has the least amount of energy and is a representation of the background noise of the environment (Renevey and Drygajlo, 2001; Myllymaki and Virtanen, 2008). The Voice Activity Index (VAI) in this work was, however, done by inspection although plans to automate this are to be included in a future project.

The underlying principle relies on the fact that when the newscaster is speaking, the VAI will be greater than zero (VAI>0) indicating that speech energy is present in the broadcast signal, but when the newscaster pauses during broadcast, VAI will be equal to zero (VAI=0), indicating that there is no speech during that broadcast. In this work, pauses (VAI=0), in the broadcast signal were used to determine the statistical properties of the background and channel noise of the environment so as to be able to eliminate it from the noisy signal (Sohn and Kim, 1999). Plans to automate this are to be included in a future project.

2.6.2 The Wiener Filter

The Wiener filter obtains a linear estimate of the original signal (speech) while minimizing the mean-squared error between the original (clean) and enhanced signal (MMSE estimate) (Das, et al, 1986). In true Wiener filtering, both the speech and the noise signal are considered as realizations of stationary stochastic processes (Baher, 1990). It is assumed that the second order statistics of the speech and noise signals are 'a priori' known (Proakis and Manolakis, 1988; Proakis, et al, 1992).

Let $s(t)$ be a signal that is corrupted by an unknown additive noise, $n(t)$. The measured signal $x(t)$ is a sum of $s(t)$ and $n(t)$ (Zadeh and Ragazzini, 1950) :

$$x(t) = s(t) + n(t) \tag{2.6.1}$$

The output, $y(t)$, is determined by means of a filter impulse response, $w(t)$, using the following convolution:

$$y(t) = w(t) * [s(t) + n(t)]$$

$$y(t) = w(t) * x(t) \tag{2.6.2}$$

To implement wiener filtering, the power spectrum of the noisy speech $P_x(e^{jw})$ and the average of the noise power spectrum $P_n(e^{jw})$ is estimated. In this case, the Wiener filter is given by;

$$W(e^{jw}) = \frac{P_s(e^{jw})}{P_x(e^{jw})}$$

$$W(e^{jw}) = \frac{P_x(e^{jw}) - P_n(e^{jw})}{P_x(e^{jw})} \qquad (2.6.3)$$

The Wiener filter minimizes the error between the actual output and the desired output and is one of the tools of choice in removing noise from noisy signal and its implementations always gives excellent results.

2.6.3 The Kalman Filter (Time Domain Approach)

The Kalman Filter is an adaptive least square error filter that provides a computationally efficient recursive solution for estimating a signal in the presence of Gaussian noises (Lynn, 1982; Bozic, 1994).

The implementation of the Kalman filter, which is a time domain technique, assumes that the process and additive noise are uncorrelated and that the noise is a stationary normal random process (Bishop and Welch, 2001; Vaseghi, 2006). The latter assumption is what is referred to as the whiteness character of the noise.

It is also assumed that the speech signal remains stationary during each frame, that is, the AR (auto- regressive) model of speech remains the same across a segment of speech (Mulgrew and Cowan, 1958; Zavarehei, 2002). To fit the one-dimensional speech signal to the state space model of the Kalman filter, a state vector is introduced as:

$$x(k) = [x(k-p+1)\, x(k-p+2)\, x(k-p+3) \ldots x(k)]^T \qquad (2.6.4)$$

Where $x(k)$ is the speech signal at time k.

When the speech signal is contaminated by additive white noise n(k) (Grewal, 2008) , it can be expressed as:

$$y(k) = x(k) + n(t) \qquad (2.6.5)$$

And the speech signal can be modeled as an auto- regressive (AR) process of order p satisfying equation (2.6.7).

$$x(k) = \sum a_i\, x(k-i) + u(k) \;\; i = 1 \ldots p \qquad (2.6.7)$$

Where a_i's are AR linear prediction (LP) coefficients and *u(k)* is the prediction error which is assumed to have a normal distribution approximately equals N(0,Q). Substituting equation 2.6.4 into equation 2.6.7 give:

$$x(k) = Ax(k-1) + Gu(k) \qquad (2.6.8)$$

where,

$$G = [0\ 0 \ldots 0\ 1]^T$$

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ a_p & a_{p-1} & a_{p-2} & \cdots & a_1 \end{bmatrix}$$

G has a length of p (LP order) and the observation equation would be:

$$y(k) = Hx(k) + n(k) \qquad (2.6.9)$$

$H = G^T$

and n(k) has a Gaussian distribution approximately equals to N(0,R) (Paliwal and Basu, 1987; Li and Andersen, 2005).

The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error.

2.6.4 The Spectral Subtraction Approach

This technique operates in the frequency domain and makes the assumption that the spectrum of the input signal can be expressed as the sum of the speech spectrum and the noise spectrum (Malca and Wulich, 1996; Dominic, 2002).

This method suppresses stationary noise from speech by subtracting the spectral noise calculated during non-speech activity.

There have been various speech enhancement (SE) projects that used the spectral subtraction technique. One of such was real time speech enhancement work performed by the Department of Electrical & Electronics Engineering, Imperial College of Science, Technology and Medicine, University of London.

It was assumed that the spectrum of the input signal can be expressed as the sum of the speech and the noise spectra. The spectrum of the background noise was then estimated using a Voice Activity Detector (VAD) to determine periods of silence/pauses when the signal was the channel noise only. The noise spectrum was then subtracted from the speech spectrum (Brookes, 2001).

Another project studied noise reduction and increased VAD accuracy using the spectral subtraction technique.

The work uses the short-term spectral magnitude of the noisy speech and an estimate or reference of the noise signal.

A Voice Activity Detector (VAD) was used to determine periods of silence in order to obtain an accurate noise estimate where the noise was assumed to be short-term stationary so that noise from silent frames can be used to remove noise from speech frames. The spectrum of the speech-free frame was used as an estimate of the noise in the speech frame and it was assumed that the effect of the phase of the enhanced speech was not significant to the auditory sensation.

A perceptual mask threshold algorithm using nonlinear weighting of the gain function was part of the enhancement strategy so as to prevent negative spectral components (Faneuff and Richard, 2003).

All the studied techniques are best suited for digital signals.

Once the speech has been converted into an electrical signal, it can be processed for transmission. In recent times, the analog signal is seldom used. Instead a digital form is preferred.

A signal f (t) is called a continuous-time or an analog signal if it is defined, somehow, for all values of the continuous variable t. If f (t) is defined only at discrete values of t; it is called a discrete-time signal or an analog sampled-data. Suppose that in addition to being discrete-time signal, f (t) can assume only discrete values, and that each value is represented by a code such as the binary code, the resulting signal is said to be a digital signal.

The analog input signal must first be sampled and digitized using an ADC (analog to digital converter) (Porat, 1997).

The resulting binary numbers, representing successive sampled values of the input signal, are transferred to the processor, which carries out numerical calculations on them. These calculations typically involve multiplying the input values by constants and adding the products together. If necessary, the results of these calculations, which now represent sampled values of the filtered signal, are output through a DAC (digital to analog converter) to convert the signal back to analog form (Stearns and Hush, 1990).

The implementation of the above enhancement process depends on being able to carry out different frequency domain operations. This makes the Fast Fourier transform (FFT) to be one of the necessary tools required for the operation.

2.7 The Fast Fourier Transform

The Fast Fourier transform (FFT) is a discrete Fourier transform algorithm which reduces the number of computations needed for N points from $2N^2$ to $2N\log N$ (Brook and Wynne, 1988; Bellanger, 1989; Kamen, 1990). Fast Fourier transform algorithms generally fall into two classes: decimation in time, and decimation in frequency (Shiavi, 1991; Hayes, 1999). The Cooley-Tukey FFT algorithm first rearranges the input elements in bit-reversed order, and then builds the output transform (decimation in time). The basic idea is to break up a transform of length N into two transforms of length N/2 using the identity:

$$\sum_{n=0}^{N-1} a_n e^{-2\pi i n k/N} = \sum_{n=0}^{(N/2)-1} a_{2n} e^{-2\pi i (2n) k/N} + \sum_{n=0}^{(N/2)-1} a_{2n+1} e^{-2\pi i (2n+1) k/N}$$

$$= \sum_{n=0}^{(N/2)-1} a_n^{even} e^{-2\pi i n k/(N/2)} + e^{-2\pi i k/N} \sum_{n=0}^{(N/2)-1} a_n^{odd} e^{-2\pi i n k/(N/2)}$$

The Sande-Tukey algorithm first transforms, then rearranges the output values (decimation in frequency).

FFTs are of great importance to a wide variety of applications, from digital signal processing and solving partial differential equations to algorithms for quick multiplication of large integers.

Furthermore, one of the necessary tools required for the operation of this work is window function.

2.8 WINDOW FUNCTION

A window function is a function that is zero-valued outside of some chosen interval. When another function or a signal (data) is multiplied by a window function, the product is also zero-valued outside the interval (Fante, 1988; Johnson, 1989). Multiplying by a window function (called 'windowing') suppresses glitches and so avoids the broadening of the frequency spectrum caused by the glitches (Morgan, 1994).

Some typical window functions are shown in table 2.2. N represents the width, in samples, of a discrete-time window function while n is an integer, with values $0 \leq n \leq N-1$.

Table 2.2: Window Functions

Window type	w_n
Rectangular	1
Hanning	$0.5\left(1 - \cos\left[{}^{2\pi n}/_{(N+1)}\right]\right)$
Hamming	$0.54 + 0.46\cos\left[{}^{2\pi n}/_{(N-1)}\right]$
Blackman	$0.42 + 0.5\cos\left[{}^{2\pi n}/_{(N+1)}\right] + 0.08\cos\left[{}^{4\pi n}/_{(N+1)}\right]$
Kaiser	$I_0\left(\alpha\sqrt{1 - ({}^{2n}/_{N} - 1)}\right)\Big/_{I_0(\alpha)}$

The function I_o in the Kaiser window function, is a zero order Bessel function of the first kind (Oppenheim and Schafer, 1975). This function can be computed by means of a power series expansion to any required accuracy. The amount of taper of the Kaiser window is determined by the value of the window parameter α. With $\alpha = 0$, the window is a flat, rectangular shape; as α increases, the window becomes more strongly tapered.

The Fast Fourier Transform and window function will now be used to derive the spectral subtraction technique realized in this work.

CHAPTER THREE

METHODOLOGY

3.1 Elements of the Spectral Subtraction Technique

Techniques for the recovery of signals from noise are typically of three classes. These are filter approaches using either the Wiener or the Kalman Filter and Spectral Subtraction Approach. While all three approaches have been used and found to work, this work focuses on the third option – 'Spectral Subtraction Technique'.

Spectral Subtraction (SS) is a technique used to reduce the effect of noise acoustically added to the speech signals. The application here relies on the fact that the spectrum of the input signal can be expressed as the sum of the speech spectrum and the noise spectrum (Halevy, 2002). The noise sources are assumed to be white.

To implement SS, the noise spectrum is estimated from regions that are analyzed as "noise-only" and subtracting it from the rest of the noisy speech signal. It is also assumed that the noise remains relatively constant prior to and during speech activity. Under such a situation, the following paragraphs outline the process involved in removing noise from noisy signal (Boll, 1979). It is noteworthy that the validation of this work will depend on how well the combined noise sources fit the assumptions and this was tested during the work.

The noisy speech signal is windowed, such that the sums of these windowed sequences add up to the original (Ykhlef, et al, 2002). Let s(k) and n(k) be represented by a windowed speech signal and noise signal, respectively. The sum of the two is then denoted by x(k) which can be expressed as follows:

$x(k) = s(k) + n(k).$ (3.1.1)

Taking the Fourier Transform of both sides gives

$$X(e^{jw}) = S(e^{jw}) + N(e^{jw}) \quad (3.1.2)$$

Where

$$x(k) \leftrightarrow X(e^{jw})$$

$$X(e^{jw}) = \sum_{k=0}^{L-1} x(k)e^{-jwk}$$

$$x(k) = \frac{1}{2\pi}\int_{-\pi}^{\pi} X(e^{jw})e^{jwk}\, dw \quad (3.1.3)$$

If the magnitude of $N(e^{jw})$ is found and replaced by its average value $\mu(e^{jw})$ where the latter is the signal taken during the regions estimated as "noise-only" (George, 2005) the phase $\theta_N(e^{jw})$ of $N(e^{jw})$ can be replaced by the phase $\theta_x(e^{jw})$ of $X(e^{jw})$. The spectral subtraction estimator $\hat{S}(e^{jw})$ then becomes:

$$|\hat{S}(e^{jw})|^2 \approx [|X(e^{jw})|^2 - |\mu(e^{jw})|^2]e^{j\theta_x(e^{jw})} \quad (3.1.4)$$

The resulting error from this estimator is:

$$\varepsilon(e^{jw}) = \hat{S}(e^{jw}) - S(e^{jw}) = N(e^{jw}) - \mu(e^{jw})e^{j\theta_x} \quad (3.1.5)$$

$$\hat{S}(e^{jw}) = |\hat{S}(e^{jw})|\angle X(e^{jw}) \quad (3.1.6)$$

$$\hat{S}(k) = F^{-1}\{\hat{S}(e^{jw})\} \quad (3.1.7)$$

The subtraction process can cause some anomalies such as those arising when the resulting spectrum becomes negative. This is usually treated (www.ece.umd.edu) by half-wave rectification which may introduce "musical" tones artifacts in the processed signal. This can be expressed by equation *(3.1.8)*.

$$|\hat{S}(e^{jw})| = \begin{cases} |\hat{S}(e^{jw})|, & if\,|\hat{S}(e^{jw})| \geq 0 \\ 0, & elsewhere \end{cases} \quad (3.1.8)$$

After subtraction of noise spectral and half-wave rectification, the inverse transform is taken for each window and overlap added to reconstitute the output speech sequence (Berouti, et al., (1979). The system block diagram is shown in Fig.3.1.

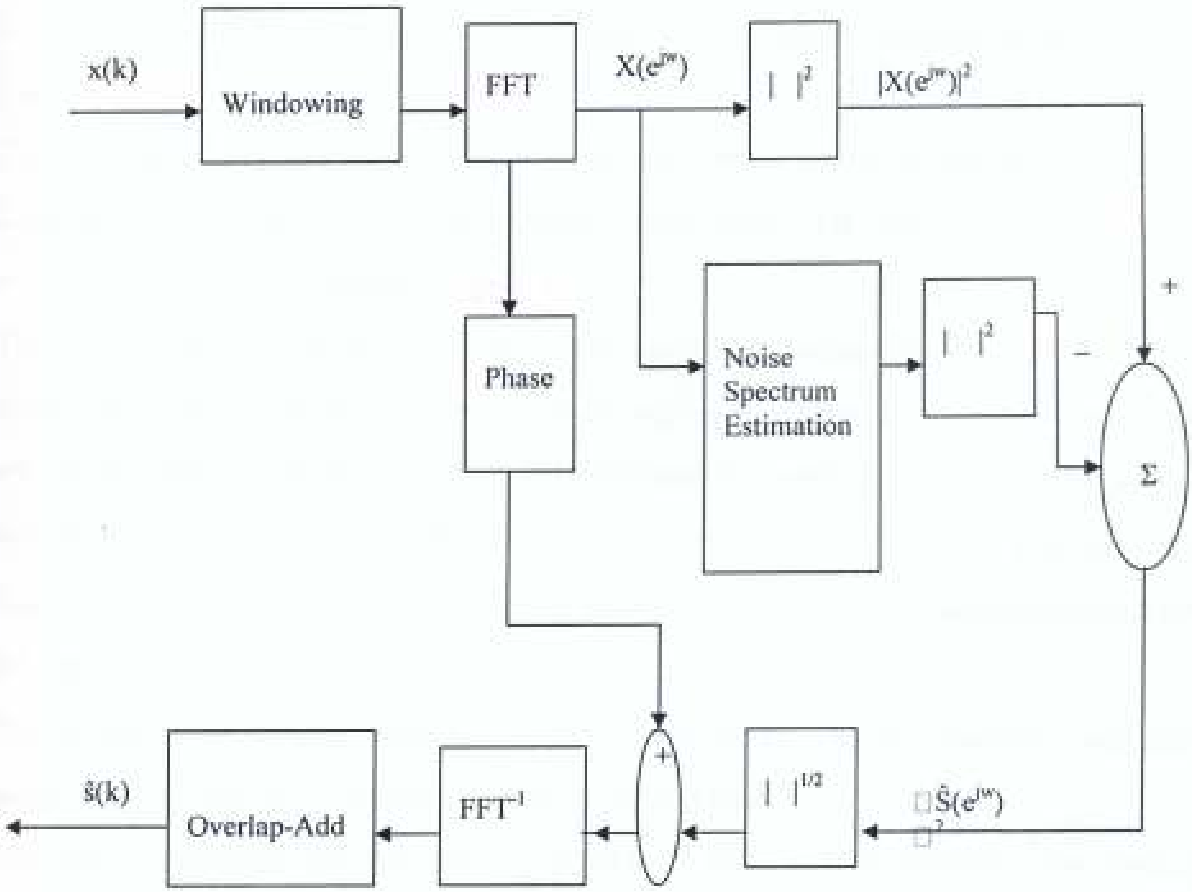


Fig. 3.1: Block Diagram of Spectral Subtraction Technique

3.2 Signal Acquisition and Hardware Setup

As can be seen above, the digital form of the signal is required in order to generate all the necessary components and exploit all the advantages accompanying processing in the digital domain. While it is possible to build hardware Analog to Digital converter, most desktop PC's have an MMX feature which facilitates the acquisition of signals connected to one of the input ports.

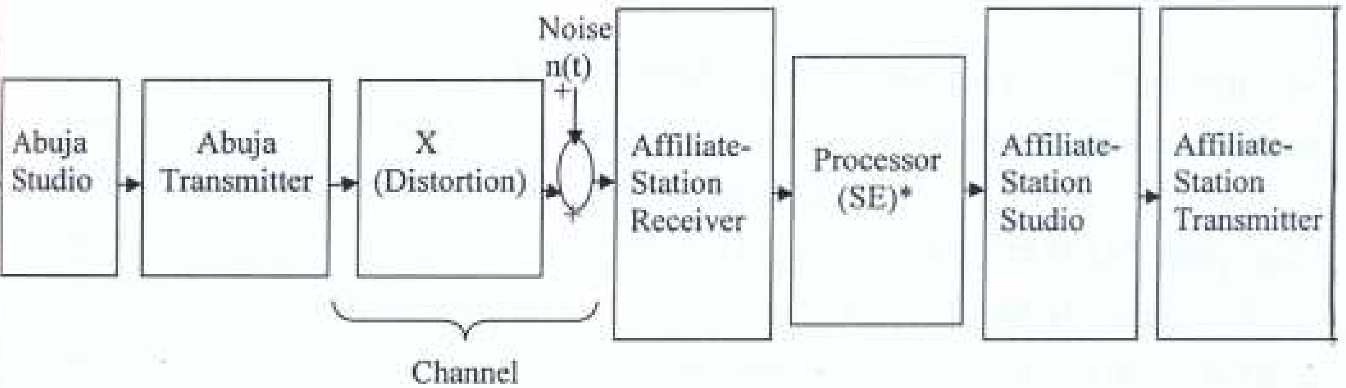
The sampling process can then be controlled through drivers written in Q-basic, Visual basic or using one of the signal processing modules in the MATLAB® software. The arrangement adopted in this work is as shown in figure 3.2.

The first thing was how to use MATLAB's Data Acquisition Toolbox (DAT) to acquire the noisy signal at the affiliate station. The software in the toolbox allows MATLAB® to acquire data from sensors and send out electrical signals that can be used to control or drive external devices. This toolbox can be used with two different pieces of hardware. One is the sound card built into the laptop and another are the microphone and speaker that serve as the data acquisition (and output) devices.

The receiver at the affiliate station was made to communicate with the windows sound card (an analog input device) and a channel was opened for data input.

The required sampling rate was then configured to be 8kHz and the duration of the input signal was set to 60000 samples. Data was acquired when a Start and get-data commands were issued.

Also, MATLAB® software will be installed on the system so as to be able to use MATLAB® signal processing tool box. As shown below, the noisy news broadcast from Abuja National Station received at the affiliate station was fed into the system (processor). The processor then performs some filtering (spectral subtraction) operation that transforms the noisy signals into noise-free or better signals.



E= Signal Enhancer

Fig. 3.2: Block diagram of real time implementation

3.3 Experiments with Channel Noise

Since the success of the signal enhancement requires knowledge of the noise in the background, experiments were conducted to ascertain the channel noise for the FRCN Broadcasts, in particular, when Voice activity Index (VAI) is zero during pauses, the data were acquired and organized in the computer. Voice activity detection (VAD) was not implemented automatically in this study. Instead, pauses in the captured broadcast were identified by inspection and extracted.

Using the MATLAB® histogram feature, the noise distribution was determined. The result is as shown in figure 3.3. The power spectrum which is the Fourier transform of the noise signal squared was similarly determined and is shown in figure 3.3(i).

Two white noise signals -one generated randomly (Taghizadeh, 2000; MATLAB® 2002) while the other was downloaded from the internet, were analyzed. The statistical properties of the signals including their mean and standard deviation were determined and are as shown in Table 3.1.

Table 3.1: Statistical Properties of the Channel Noise Signal

Signal Type	Means	Standard Deviations(σ)
Random Noise	-0.0025	1.012
White Noise from Internet	-0.0025	0.122
Noise when VAI=0	-5.175e-004	0.121

The plot of random noise, white noise from internet, and noise when VAI=0 are shown in figures 3.3a, 3.3d and 3.3g, respectively; figure 3.3b, 3.3e and 3.3h show their histograms, respectively, and figures 3.3c, 3.3f, 3.3i show their spectra. It is also clear from this analysis that their histograms are symmetrical and their spectra have a flat power spectral density over all frequencies of interest. This implies that the channel noise accompanying the broadcast exhibits properties similar to other white noise samples studied. This result justifies the adoption of the Spectral Subtraction technique for the proposed noise reduction.

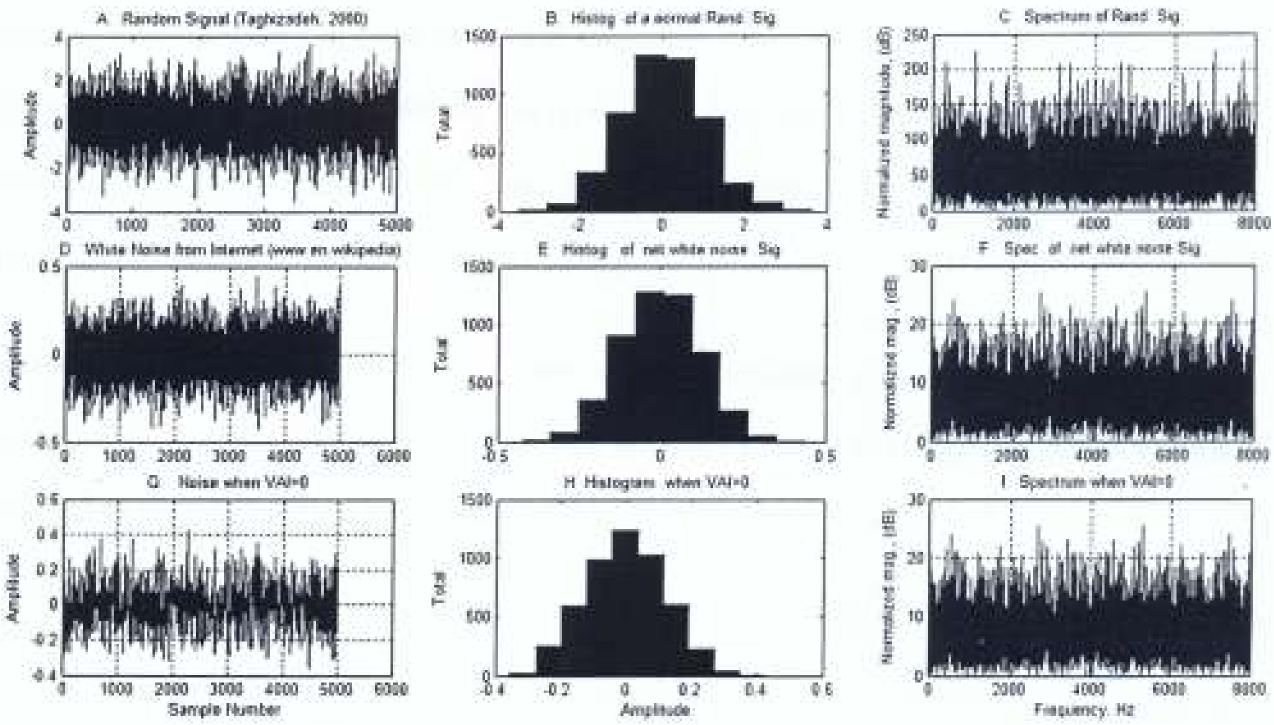


Fig. 3.3: Histogram of the Noise Signals

3.4 Experimental Studies of the Spectral Subtraction Technique for Signal Enhancement.

Given the above properties of the noise, it is imperative to study the spectral subtraction technique (SST) by using known simulated signals with different levels of noise. A set of sinusoidal signals at different frequencies was added to a sample of the channel noise. The resulting sum was then processed using SST realization described in section 3.1.

During the study, three sinusoidal signals (3.4a, 3.4d, 3.4g) were simulated and their properties studied. The autocorrelation (3.4b, 3.4e, 3.4h) and spectra (3.4c, 3.4f, 3.4i) of each were determined. The results are shown in figure 3.4.

The spectrum of each simulated signal shows a mono-frequency spike as expected, occurring at the frequencies of the simulated signals. This provides a test that shows that the MATLAB® based tool accurately reflects what is expected.

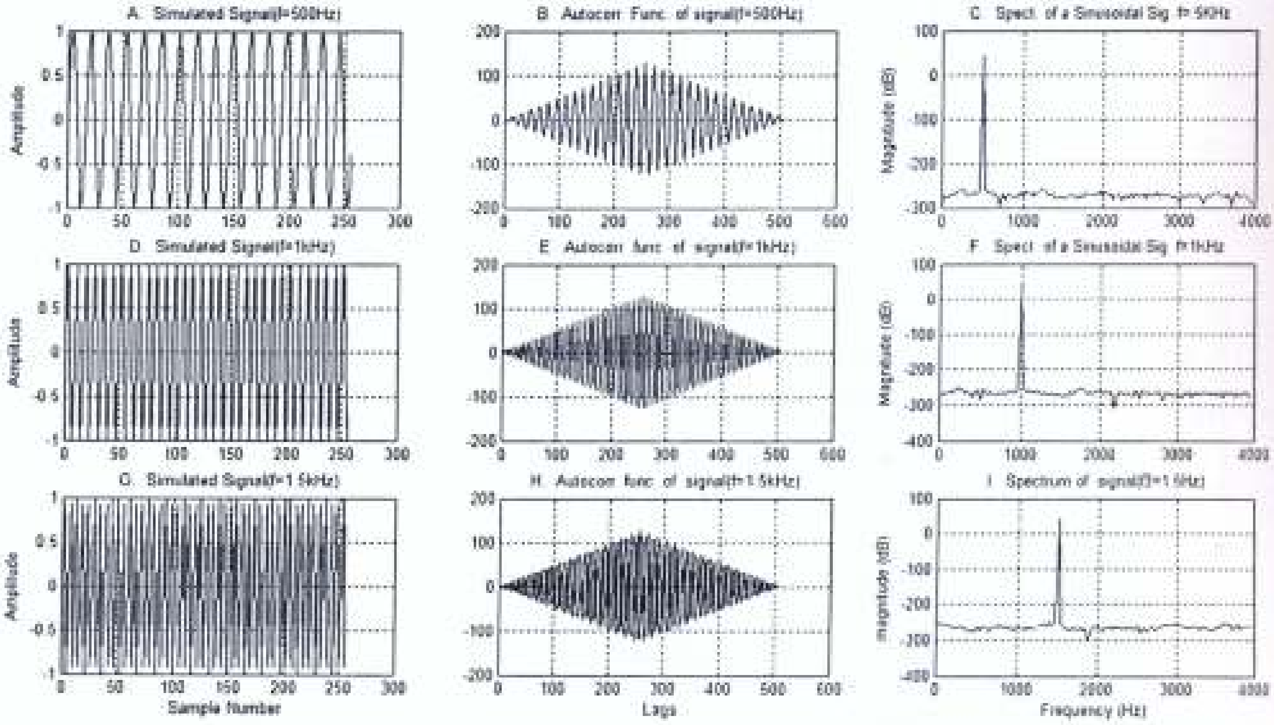


Fig. 3.4: Plots of Autocorrelations and Spectra of the Simulated Signals

The noise signal was added to the simulated signals and the sinusoidal signal amplitude was varied in order to simulate different signal to noise ratio conditions. It was observed that as the signal to noise ratio decreased, the noise in the output increased relative to the signal. The result of different signal to noise ratio is shown in table 3.2 while the plot (3.6a, 3.6c, 3.6e, 3.6g, 3.6i, 3.6k, 3.7a, 3.7c, 3.7e, 3.7g, 3.7i, 3.7k) and spectra (3.6b, 3.6d, 3.6f, 3.6h, 3.6j, 3.6l, 3.7b, 3.7d, 3.7f, 3.7h, 3.7j, 3.7l) of the simulated signals is as shown in figure 3.6 and figure 3.7, respectively.

Table 3.2: Different levels of Simulated Signal

Signal Type	**Signal Means**	**Standard Deviation (σ)**	**Variance (σ^2)**	**Signal to Noise Ratio $(SNR)_{i/p}$ dB**	**Signal to Noise Ratio $(SNR)_{o/p}$ dB**
Noise when VAI=0	-5.1753e-005	0.1212	0.0147	-	-
Simulated Signal(x)	0.0046	1.2261	1.5033	20.0975	35.6355
x/3	0.0015	0.4087	0.1670	10.5551	26.0931
x/6	7.7057e-004	0.2044	0.0418	4.5345	20.0725
x/12	3.8529e-004	0.1022	0.0104	-1.4861	14.0519
x/24	1.9264e-004	0.0511	0.0026	-7.5067	8.0313
x/48	9.6322e-005	0.0255	6.5249e-004	-13.5273	2.0107

Table 3.2 seems to suggest that the technique provides a 15dB improvement in the signal to noise ratio. This is clearly shown graphically in figure 3.5 by the intersection on approximately 15dB point on the Signal to Noise ratio axis. This can be improved but for this study, it corresponds to a significant improvement that ought to make the received signal more intelligible.

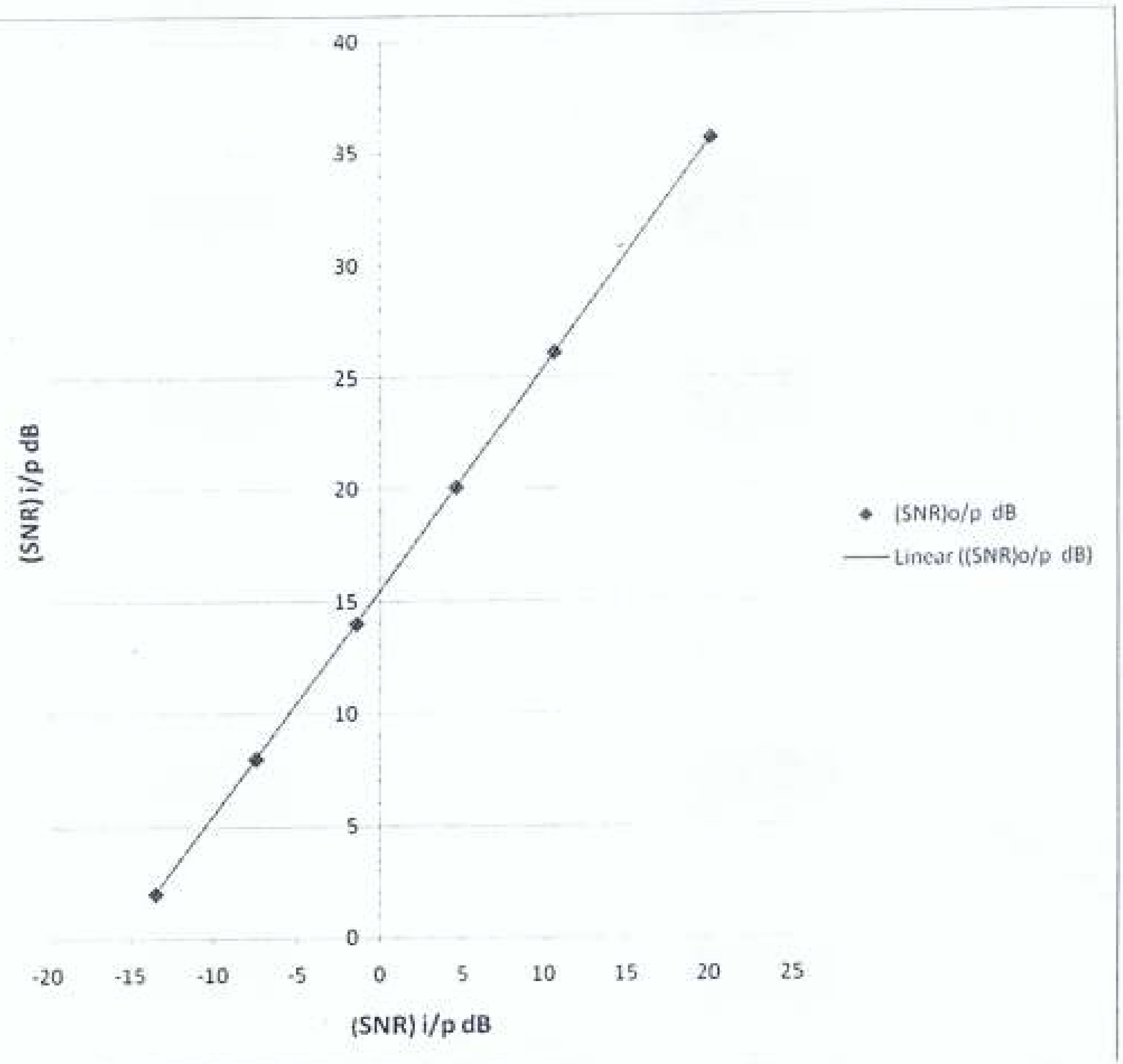


Fig. 3.5: Plots of Signal to Noise Ratio of Clean Signals

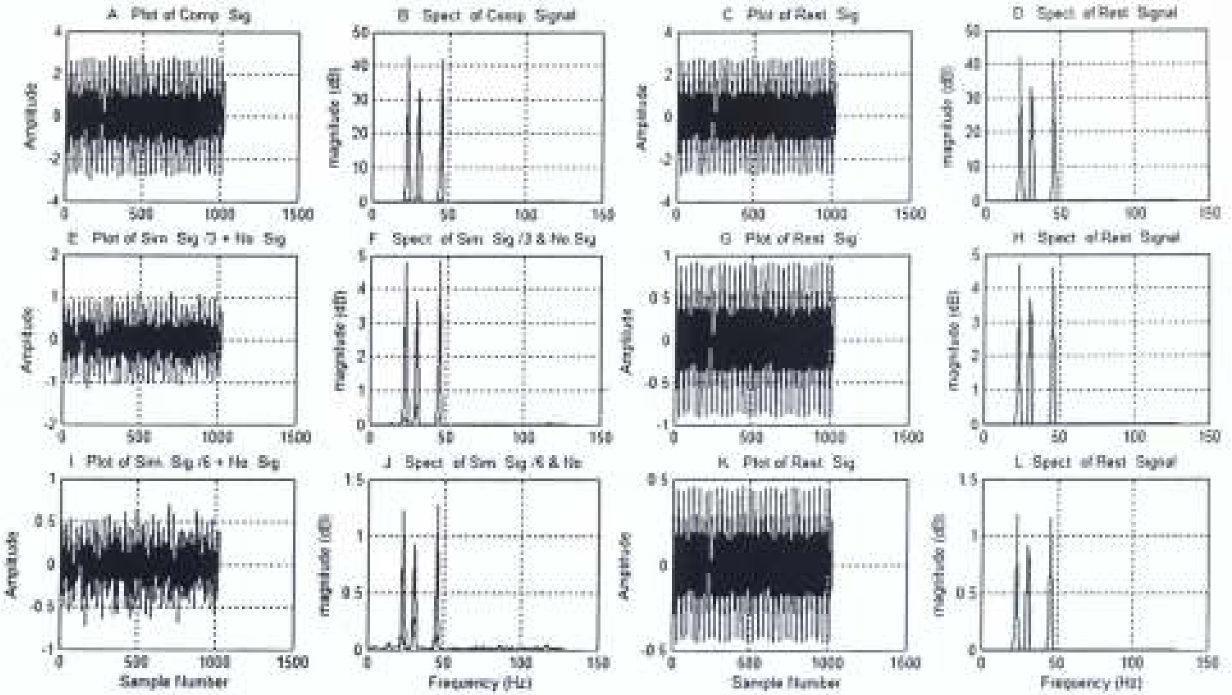


Fig. 3.6: Plots of different levels of the Simulated Signals and Spectra

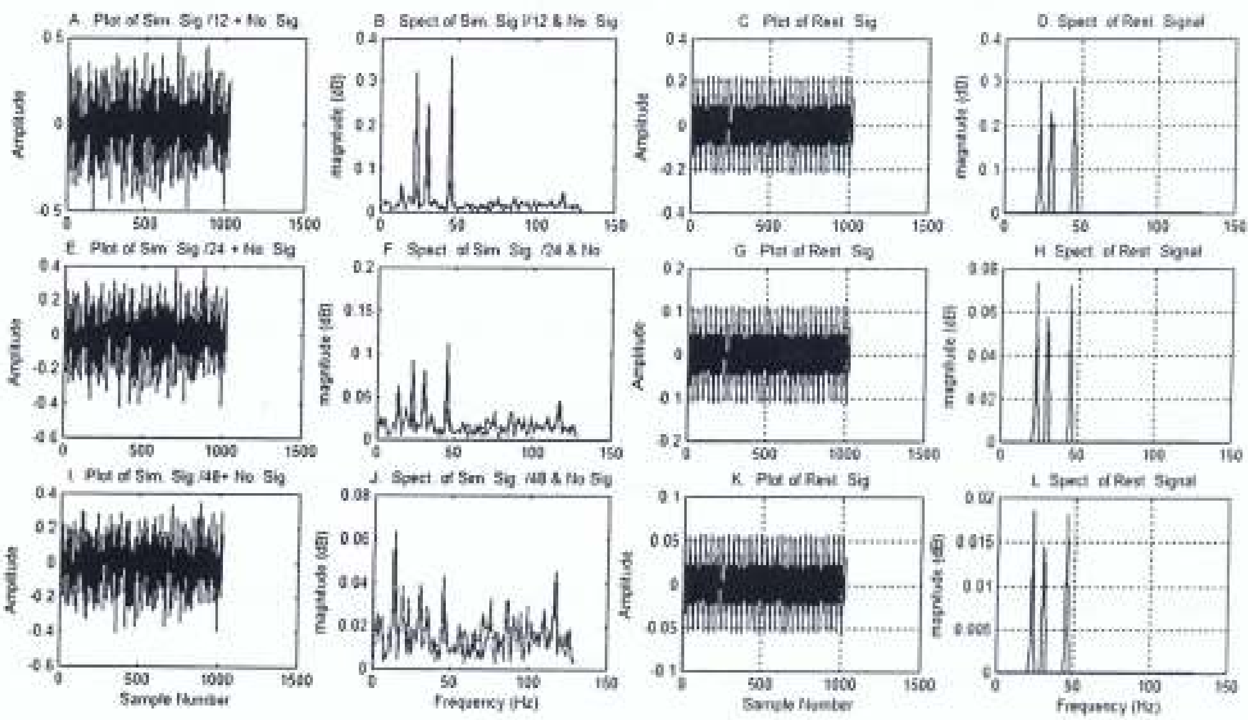


Fig. 3.7: Plots of different levels of Signals to Noise

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Results of Experiments with Clean Audio Signal

To test spectral subtraction technique (SST), a clean speech signal was added to a noise signal (obtained during VAI=0) then captured using the sound card of a Multi Media Extensions (MMX) enabled PC. The results were then imported into the MATLAB® software for study (MATLAB®, 2002).

Their statistical properties were studied and are as shown in table 4.1.

Table 4.1: Statistical Properties of the Clean Signal

Signal Type	Signal Means	Standard Deviations(σ)
Clean Signal	-2.695e-005	0.155
Noise Signal (VAI=0)	-5.175e-005	0.121

Parts of the imported signals were taken for analysis of speech enhancement using spectral subtraction and it was observed that the results conform reasonable well with theoretical results as the statistical properties (mean and standard deviation) of the restored signal were similar to that of the clean test signal as displayed in table 4.2. Figure 4.1 shows plots of noise signal (4.1a), clean signal (4.1b), composite signal (4.1c) and the restored signal (4.1d).

The Autocorrelation function of a clean signal (4.2a) and restored signal (4.2b) were determined and are shown in Figure 4.2. It was observed that they conform with theoretical results. Also Clean Signal and Restored Signal were cross correlated (4.2c) and the result shows that they are correlated.

Table 4.2: Statistical Properties of the Analyzed Clean Signal

Signal Type	Signal Means	Standard Deviations(σ)
Part of Clean Signal	6.5331e-005	0.146
Part of Noise Signal	-7.9750e-004	0.122
Composite Signal	-7.4235e-004	0.189
Restored Signal	5.7518e-005	0.146

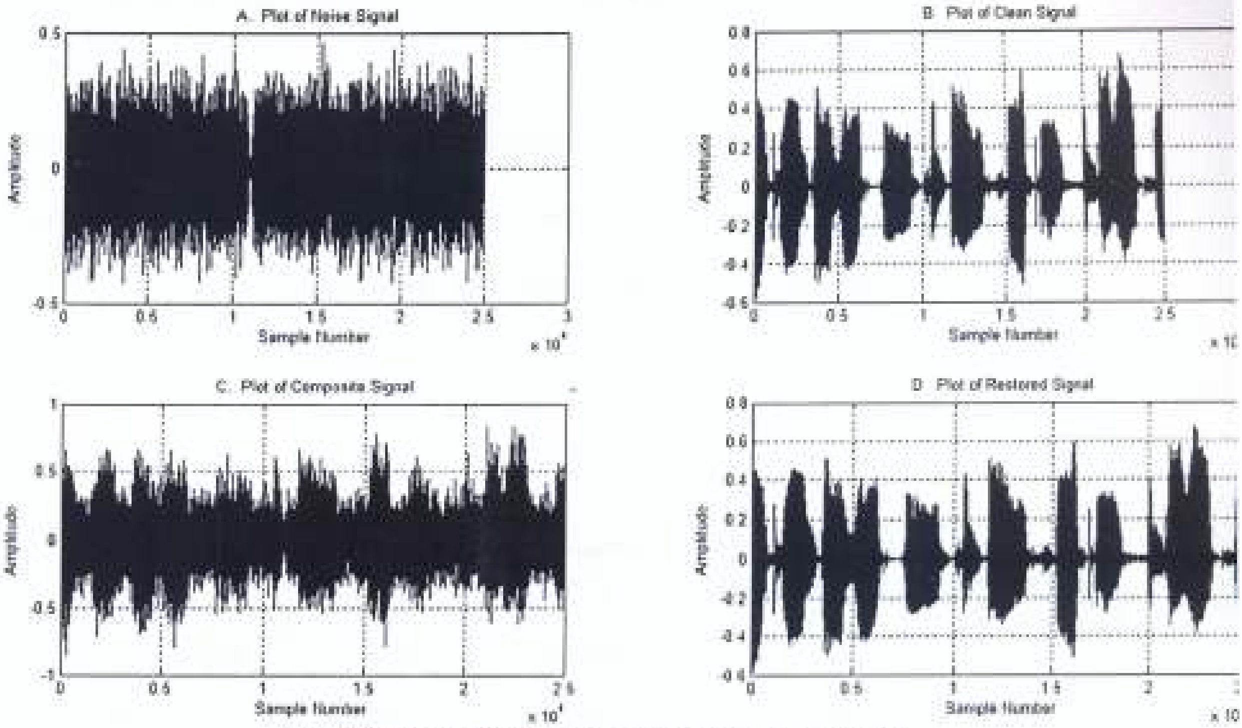


Fig. 4.1: Plots of Clean Signal and Noise Signal

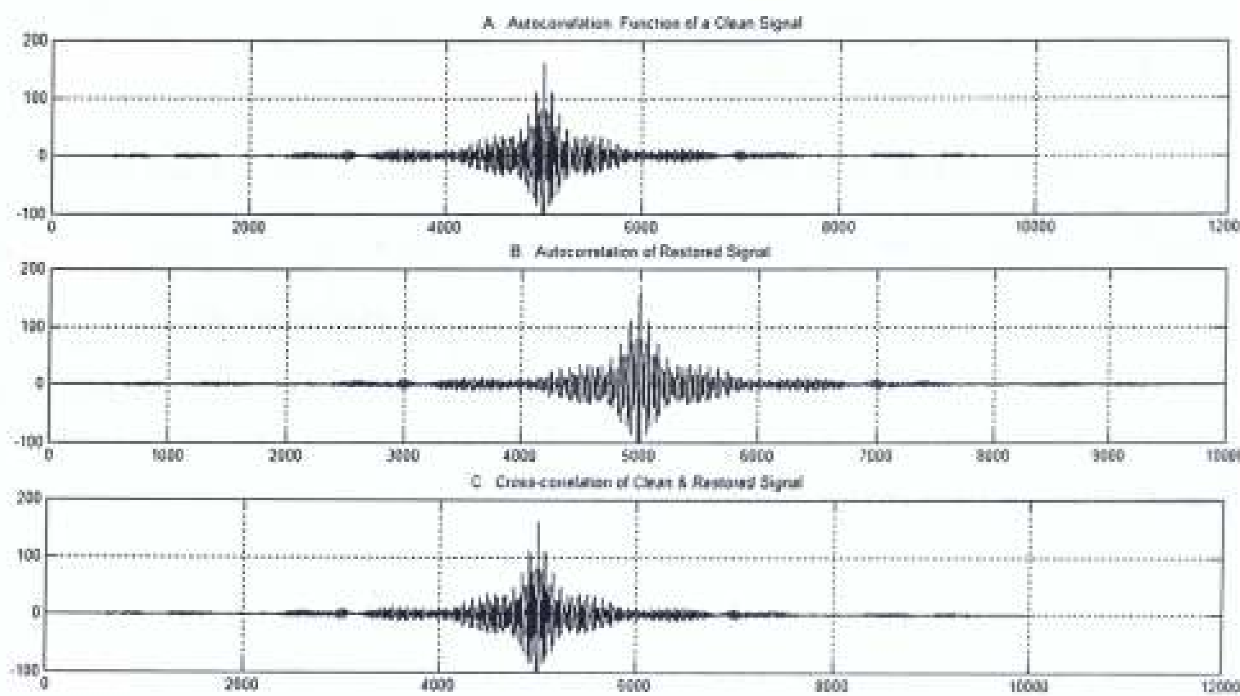


Fig. 4.2: Autocorrelation and Cross-Correlation of Clean Signal and Noise Signal

The noise signal was added to the clean signal and the amplitude of the clean signal was varied in order to simulate different signal to noise ratio conditions and spectra of signals were determined. It was observed that as the signal magnitudes were going down, the noise is becoming very apparent. The results are as shown in table 4.3 while plots (4.4a, 4.4c, 4.4e, 4.4g, 4.5a, 4.5c, 4.5e, 4.5g) and spectra (4.4b, 4.4d, 4.4f, 4.4h, 4.5b, 4.5d, 4.5f, 4.5h) are shown in figure 4.4 and 4.5 respectively.

Table 4.3: Different levels of the Clean Signal

Signal Type	**Signal Mean**	**Standard Deviation (σ)**	**Variance (σ^2)**	**Signal to Noise Ratio $(SNR)_{i/p}$ dB**	**Signal to Noise Ratio $(SNR)_{o/p}$ dB**
Noise when VAI=0	-7.9750e-004	0.1216	0.0148	-	-
Signal (x)	6.5331e-005	0.1456	0.0212	1.5649	15.8109
x/4	1.6333e-005	0.0364	0.0013	-10.4763	3.7697
x/16	4.0832e-006	0.0091	8.2805e-005	-22.5175	-8.2715
x/32	2.0416e-006	0.0045	2.0701e-005	-28.5381	-14.2921

From table 4.3, it implies that if a good noise signal is available, the output of the SST can give an improved signal. The input and output signal to noise ratio in table 4.3 can be represented graphically by figure 4.3. The intersection on the Signal to Noise ratio axis in figure 4.3 represents an improvement of approximately 15dB of the input signal.

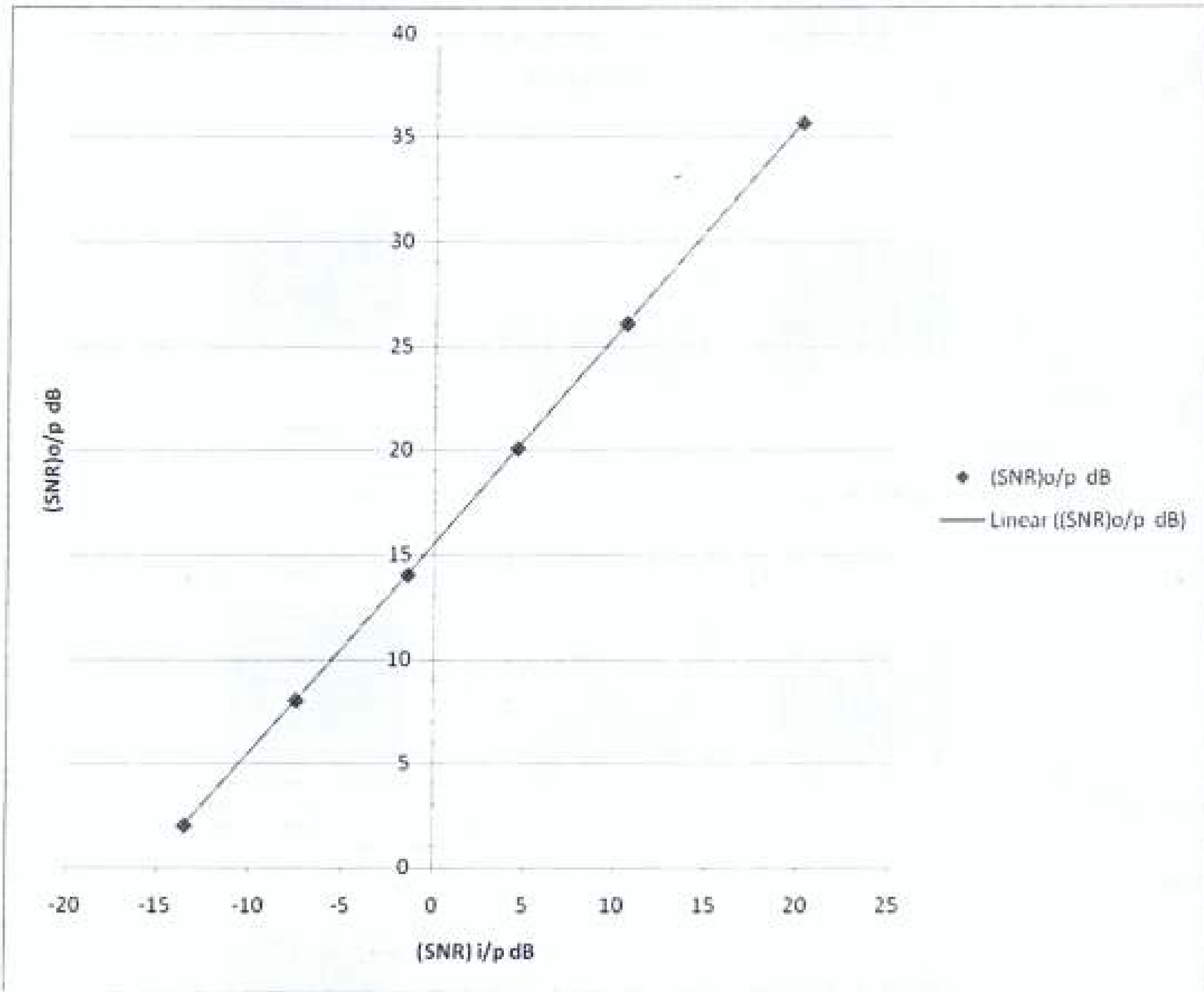


Fig. 4.3: Plots of Signal to Noise Ratio of Clean Signals

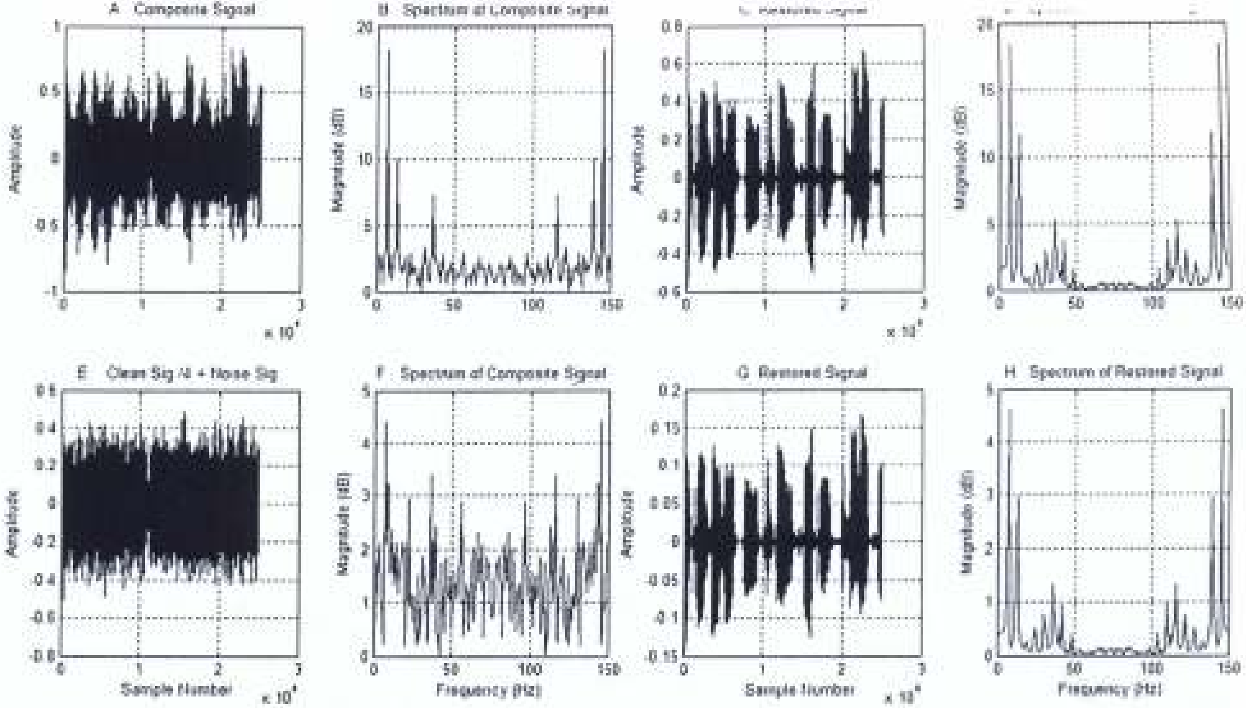


Fig. 4.4: Plots and Spectra of different levels of Composite Signals

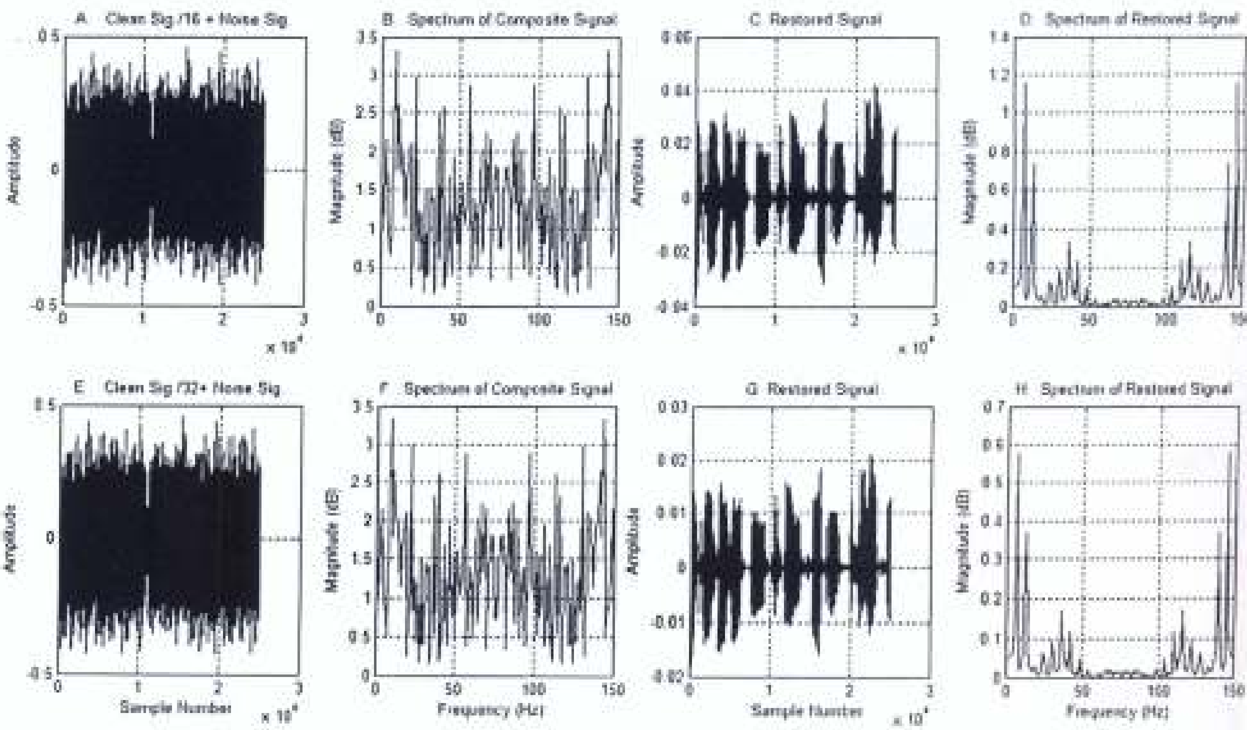


Fig. 4.5: Plots and Spectra of different levels of Signals to Noise

4.2 Realization of Spectral Subtraction Based Broadcast Enhancement

Following the procedure outlined earlier, the spectrum of the input signal was expressed as the sum of the speech spectrum and the noise spectrum. The noise spectrum was estimated from regions that are analyzed as "noise-only" (when VAI=0) and the estimated value was subtracted from the rest of the spectrum of noisy speech signal. Table 4.4 shows the statistical properties of the signal, while the spectrum of noisy speech signal (4.6a) and the spectrum of the noise signal (4.6b) are shown in figure 4.6.

Table 4.4: Statistical properties of the Noisy Broadcast Signal

Signal Type	**Signal Mean**	**Standard Deviation (σ)**	**Variance (σ^2)**	**Signal to Noise Ratio $(SNR)_{i/p}$ dB**	**Signal to Noise Ratio $(SNR)_{o/p}$ dB**
Noise when VAI=0	-0.0023	0.2632	0.0693	-	-
Concatenated Noise	-2.5102e-004	0.1204	0.0145	-	-
Noisy Signal	-6.5832e-004	0.2429	0.0590	4.9854	17.0266

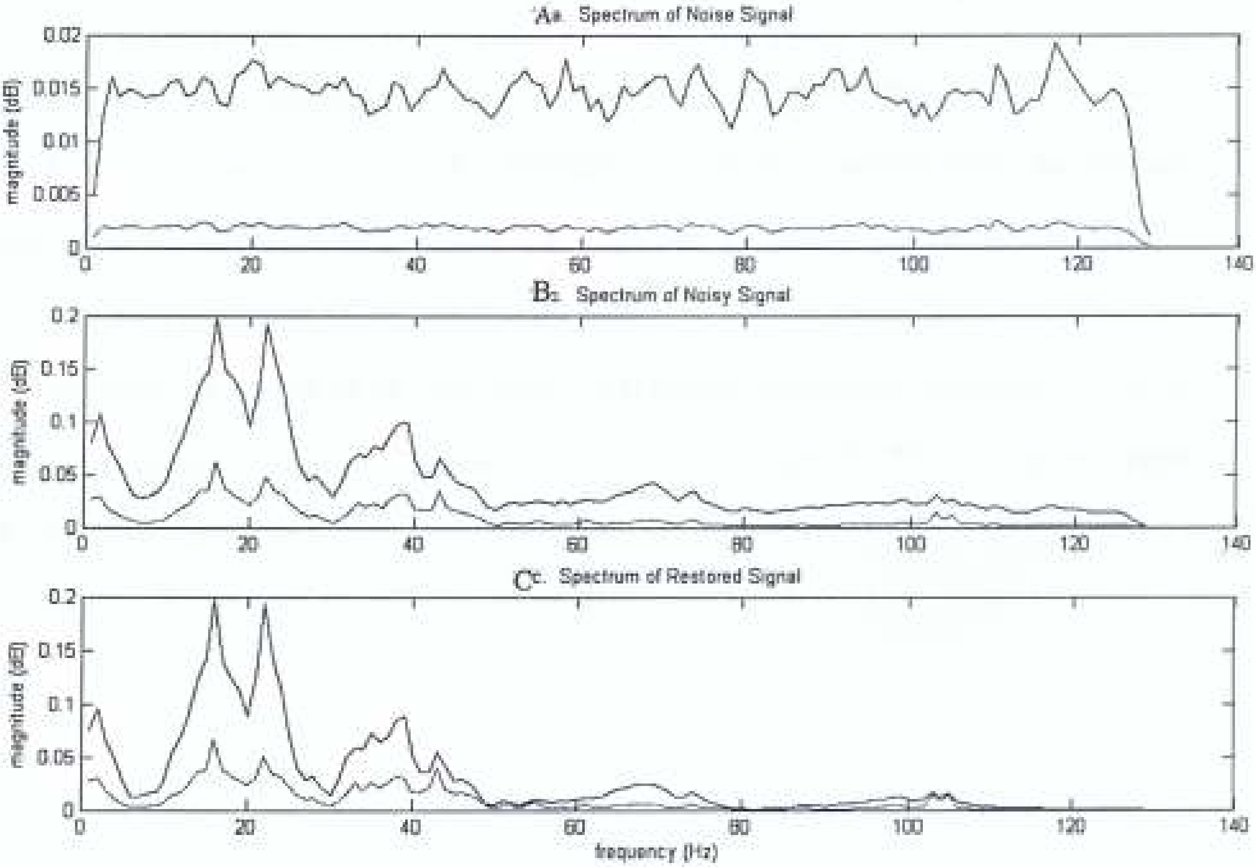


Fig. 4.6: Spectra of the Noisy FRCN News Broadcast Signals

The noisy speech signal broadcast from FRCN Abuja national station was windowed using a Hamming window, such that the sums of these windowed sequences add up to the original. The Fourier Transform of the windowed noisy signal was taken. The spectrum of noisy speech signal (4.7a) and the spectrum of the noise signal (4.7b) when Hamming window was used are as shown in figure 4.7.

The average value of the magnitude of noise signal (when VAI=0) was then subtracted from the magnitude of the noisy signal. To avoid anomalies such as those arising when the spectrum becomes negative, half-wave rectification was employed by taking the absolute values. The results are as shown in figure 4.6 (c) and figure 4.7(c).

The inverse transform was taken for each window and the resulting signal was added to form the output speech sequence. Figure 4.8 shows the plots of noise signal (4.8a), noisy speech signal (4.8b) and restored signal (4.8c).

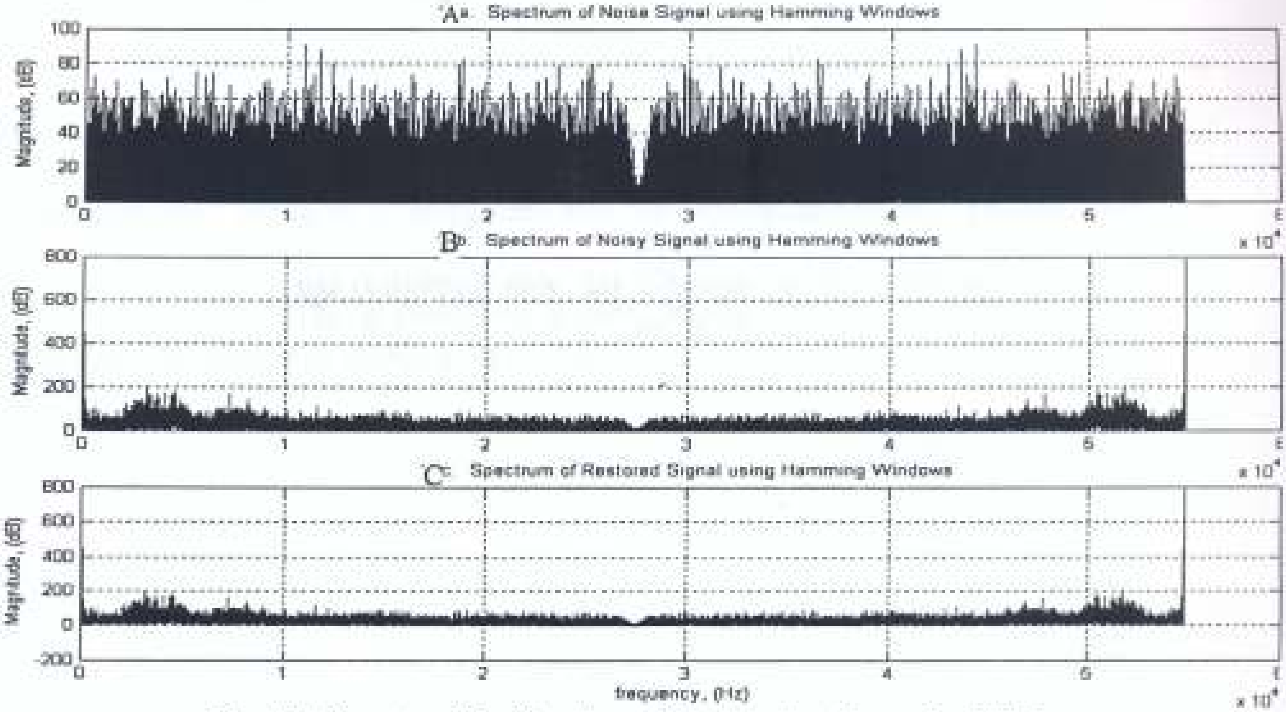


Fig. 4.7: Spectra of the Broadcast Signals using Hamming Window

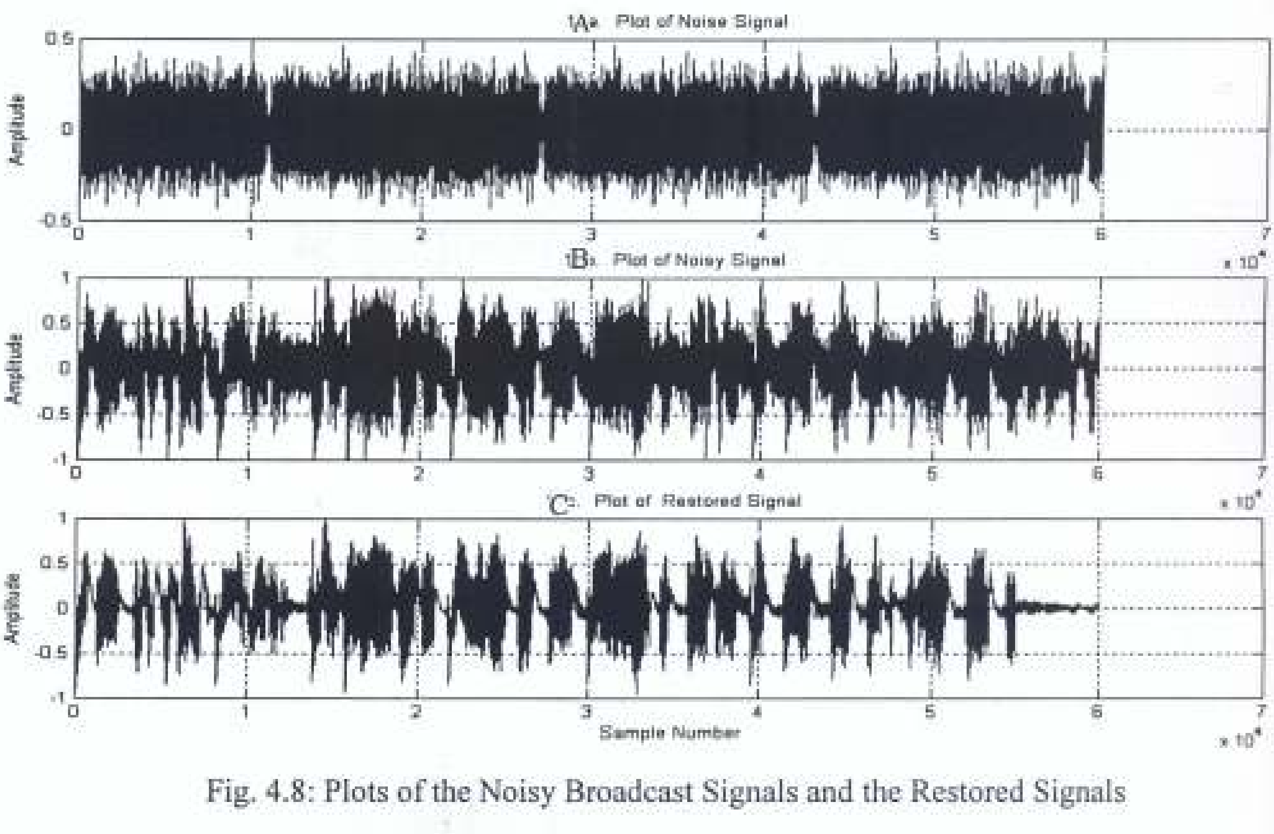


Fig. 4.8: Plots of the Noisy Broadcast Signals and the Restored Signals

The plot of autocorrelation function and cross-correlation function of the signals is as shown in figure 4.9. It was observed from the autocorrelation function of the noisy signal (4.9a) that the presence of spikes at the upper and lower side implies that the actual signal and the noise signal were not correlated which is in agreement with the theoretical results. The autocorrelation function of the restored signal (4.9b) shows that it is correlated. Both signals were cross-correlated and the result is as shown in figure 4.9c.

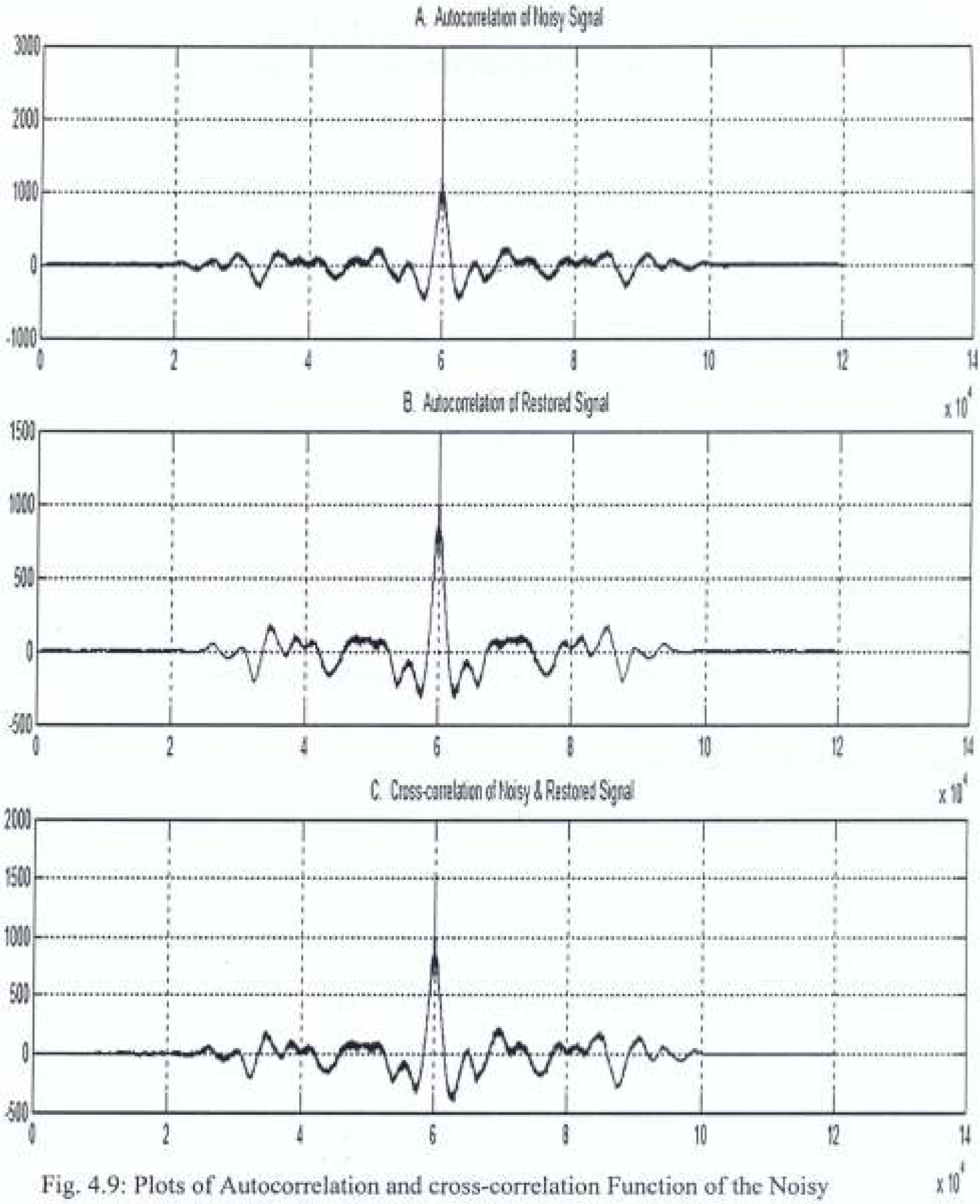


Fig. 4.9: Plots of Autocorrelation and cross-correlation Function of the Noisy Broadcast Signals and the Restored Signals

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATION

5.1 CONCLUSIONS

In this thesis, an implementation of the Spectral Subtraction technique to speech processing has been studied. Speech enhancement refers to the process of estimating 'clean speech' from the observed noisy signal, aided by prior knowledge of the noise statistics. Any algorithm for speech enhancement will require a trade-off between noise reduction (to improve the subjective speech quality) and signal distortion (leading to a decrease in the objectively measurable speech intelligibility).

5.2 RECOMMENDATION

The Voice Activity Detection (VAD) in this work was done by inspection. Since channel properties may change, automation of the process will greatly enhance its effectiveness. Consequently, plans to automate this are to be included in a future project so as to have a system that can automatically detect voice activity- Voice Activity Detection (VAD).

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APPENDIX

MATLAB PROGRAMS

```
% Program: W1 Data Acquisition and Analysis using MATLAB
% Step 1: Create the analog input object to communicate
% with data acquisition device (a windows sound card).
ai = analoginput('winsound');
% Add channel: Add one hardware channel to ai.
addchannel(ai,1);
% Step 2: Configure property values - Configure the sampling
% rate to 8kHz and collect 60 second of
% data (8000 samples) for the channel.
Fs=8000;Duration = 60;set(ai,'SampleRate',Fs);
set(ai,'SamplesPerTrigger',Duration*Fs);
% Step 3: Acquire data - Start the acquisition and retrieve the data.
% When all the data is acquired, ai automatically stops executing.
start(ai);data = getdata(ai);plot(data)
% Step 4: determine the frequency components of the data
xfft=abs(fft(data));mag=20*log10(xfft); mag=mag(1:end/60);plot(mag);
% Step 5: Clean up
delete(ai);clear ai
% Step 6: To save
Wavwrite(ai,fs,'nig.wav')
```

% Program: W2 Statistical properties of signals (Histogram) and Spectrum

```
clf;clear all
% Generates Uniformly Distributed random signal
N=6000; % Define Number of samples
a=randn(1,5000); % Generate Normal Random Numbers
figure(1); % Select the figure
subplot(3,3,1); % Subdivide the figure into 6 quadrants
plot(a); % Plot a in the first quadrant;grid;
title('A.  Random Signal (Taghizadeh, 2000)');ylabel('Amplitude');
subplot(3,3,2); % Select the second quadrant
hist(a); % Plot the histogram of a;grid;
title('B.  Histog. of a normal Rand. Sig.');ylabel('Total');
n1=0.8e4; % number of FFT points
q=abs(fft(a,n1));subplot(3,3,3);plot(q); grid;
ylabel(' Normalized magnitude, (dB)');
title('C.  Spectrum of Rand. Sig. ')
[c,r]=wavread('cignoise.wav'); % read in the signal
b=c(0.5e4:1.0e4); % takes parts of the signal
subplot(3,3,4); % Select the third quadrant
plot(b);grid;title('D.  White Noise from Internet (www.en.wikipedia)');
ylabel('Amplitude');subplot(3,3,5); % Select the 4th quadrant
hist(b); % Plot the histogram of b;grid;
title('E.  Histog.  of  net white noise. Sig.');ylabel('Total');
```

```
q=abs(fft(b,n1));subplot(3,3,6);plot(q); grid;

ylabel(' Normalized mag., (dB)'); title('F.  Spec. of  net white noise Sig.')

 [d,r]=wavread('newsnoise.wav'); % read in the signal

c=d(0.5e4:1.0e4); % takes parts of the signal

subplot(3,3,7); % Select the 5th quadrant

plot(c);grid;title('G.   Noise when VAI=0');

xlabel('Sample Number');ylabel('Amplitude'); subplot(3,3,8); % Select the 6th quadrant

hist(c); % Plot the histogram of c;grid;

title('H. Histogram  when VAI=0 ');xlabel('Amplitude');

ylabel('Total');q=abs(fft(b,n1));subplot(3,3,9);plot(q); grid;

ylabel(' Normalized mag., (dB)');xlabel('Frequency, Hz ');

title('I.  Spectrum when VAI=0.')
```

% Program: W3 Autocorrelations and Spectra of simulated signals

```
clf;clear all

N=256; % Total Number of Samples;

fs=8000; % Sampling frequency set at 1000Hz

f=500;k=0:N-1;

% Now generate the sinusoidal signal

x=sin(2*pi*(f/fs)*k);subplot(3,3,1);plot(x);grid;

ylabel('Amplitude');title('A.  Simulated Signal(f=500Hz)')

Rxx=xcorr(x);subplot(3,3,2);plot(Rxx);grid;

title('B.  Autocorr. Func. of signal(f=500Hz)')
```

```
% Estimate its spectrum using fft command
X=fft(x);magX=abs(X);
% Build up an appropriate frequency axis
fx=0:(N/2)-1; % first make a vector for
%f=0,1,2,...(N/2)-1
fx=(fx*fs)/N; % Now scale it so that it represents
%frequencies in Hz
subplot(3,3,3);plot(fx,20*log10(magX(1:N/2)));
grid;title('C.  Spect. of a Sinusoidal Sig. f=.5KHz');
ylabel('Magnitude (dB)');
f=1000;
x=sin(2*pi*(f/fs)*k);subplot(3,3,4);
plot(x);grid;ylabel('Amplitude');title('D.  Simulated Signal(f=1kHz)')
Rxx=xcorr(x);subplot(3,3,5);plot(Rxx);grid;
title('E.  Autocorr. func. of  signal(f=1kHz)');X=fft(x);magX=abs(X);
subplot(3,3,6);plot(fx,20*log10(magX(1:N/2)));
grid;title('F.  Spect. of a Sinusoidal Sig. f=1KHz');ylabel('Magnitude (dB)');

f=1500;
x=sin(2*pi*(f/fs)*k);subplot(3,3,7);
plot(x);grid;xlabel('Sample Number');
ylabel('Amplitude');title('G.  Simulated Signal(f=1.5kHz)')
Rxx=xcorr(x);subplot(3,3,8);plot(Rxx);grid;
xlabel('Lags');title('H.  Autocorr. func. of  signal(f=1.5kHz)')
```

```
X=fft(x);magX=abs(X);

subplot(3,3,9);plot(fx,20*log10(magX(1:N/2)));

grid;xlabel('frequency (Hz)');ylabel('magnitude (dB)');

title('I.  Spectrum of  signal(f3=1.5Hz)');xlabel('Frequency (Hz)');
```

% Program: W4 Plots of different SNR and Spectra of simulated signals

```
clear  all;clf

[c,r]=wavread('cignoise.wav'); % read in the noise signal

b=c(0.5e4:3.0e4); % takes parts of the noise signal

f1=.75;a1=0.23*f1*pi;f2=1;a2=0.23*f2*pi;f3=1.5;a3=0.23*f3*pi;

for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k));

s(k)=x(k)+b(k);end;subplot(3,4,1);plot(s); grid

ylabel('Amplitude');title('A.  Plot of Comp. Sig.');

for k=1:1:1024;p(k)=s(k)-b(k);

end;subplot(3,4,3);plot(p);grid;title('C.  Plot of Rest. Sig.');

ylabel('Amplitude');rspec3=spectrum(s);

subplot(3,4,2);plot(rspec3); grid;ylabel('magnitude (dB)');

title('B.  Spect. of Comp. Signal');rspec2=spectrum(p);

subplot(3,4,4);plot(rspec2); grid;ylabel('magnitude (dB)');

title('D.  Spect. of Rest. Signal')

for k=1:1:1024

x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/3;s(k)=x(k)+b(k);

end;subplot(3,4,5);plot(s); grid;ylabel('Amplitude');

title('E.  Plot of Sim. Sig./3 + No. Sig.');for k=1:1:1024
```

```
p(k)=s(k)-b(k);end;subplot(3,4,7);plot(p);grid
title('G.  Plot of Rest. Sig.');ylabel('Amplitude');
rspec3=spectrum(s);subplot(3,4,6);plot(rspec3); grid
ylabel('magnitude (dB)');title('F.  Spect. of Sim. Sig./3 & No.Sig.')
rspec2=spectrum(p);subplot(3,4,8);plot(rspec2); grid
ylabel('magnitude (dB)');title('H.  Spect. of Rest. Signal')
for k=1:1:1024
x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/6;
s(k)=x(k)+b(k);end;subplot(3,4,9);plot(s); grid
ylabel('Amplitude');xlabel('Sample Number');
title('I.  Plot of Sim. Sig./6 + No. Sig.');
for k=1:1:1024
p(k)=s(k)-b(k);end;subplot(3,4,11);plot(p);grid
title('K.  Plot of Rest. Sig.');ylabel('Amplitude');
xlabel('Sample Number');rspec3=spectrum(s);
subplot(3,4,10);plot(rspec3); grid
xlabel('Frequency (Hz)');ylabel('magnitude (dB)');
title('J.  Spect. of Sim. Sig./6 & No');rspec2=spectrum(p);
subplot(3,4,12);plot(rspec2); grid
ylabel('magnitude (dB)');xlabel('Frequency (Hz)');
title('L. Spect. of Rest. Signal')
for k=1:1:1024
x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/12;
```

```
s(k)=x(k)+b(k);end;figure(2);subplot(3,4,1);plot(s)
ylabel('Amplitude');title('A.  Plot of Sim. Sig./12 + No. Sig.');
for k=1:1:1024;p(k)=s(k)-b(k);
end;subplot(3,4,3);plot(p);grid;title('C.  Plot of Rest. Sig.');
ylabel('Amplitude');rspec3=spectrum(s);
subplot(3,4,2);plot(rspec3);ylabel('magnitude (dB)');
title('B.  Spect.of Sim. Sig.l/12 & No. Sig.')
rspec2=spectrum(p);subplot(3,4,4);plot(rspec2); grid
ylabel('magnitude (dB)');title('D. Spect. of Rest. Signal')
for k=1:1:1024
x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/24;
s(k)=x(k)+b(k);end;subplot(3,4,5);plot(s)
ylabel('Amplitude');title('E.  Plot of Sim. Sig./24 + No. Sig.');
for k=1:1:1024;p(k)=s(k)-b(k);end;subplot(3,4,7);plot(p);
grid;title('G.  Plot of Rest. Sig.');ylabel('Amplitude');
rspec3=spectrum(s);subplot(3,4,6);plot(rspec3)
ylabel('magnitude (dB)');title('F.  Spect. of Sim. Sig. /24 & No.')
rspec2=spectrum(p);subplot(3,4,8);plot(rspec2); grid
ylabel('magnitude (dB)');title('H. Spect. of Rest. Signal')
for k=1:1:1024
x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/48;
s(k)=x(k)+b(k);end;subplot(3,4,9);plot(s)
ylabel('Amplitude');xlabel('Sample Number');
```

```
title('I.  Plot of Sim. Sig./48+ No. Sig.');

for k=1:1:1024;p(k)=s(k)-b(k);

end;subplot(3,4,11);plot(p);grid

title('K.  Plot of Rest. Sig.');ylabel('Amplitude');

xlabel('Sample Number');rspec3=spectrum(s);

subplot(3,4,10);plot(rspec3);xlabel('Frequency (Hz)');

ylabel('magnitude (dB)');title('J.  Spect. of Sim. Sig. /48 & No.Sig')

rspec2=spectrum(p);subplot(3,4,12);plot(rspec2); grid

xlabel('Frequency (Hz)');ylabel('magnitude (dB)');

title('L. Spect. of Rest. Signal')
```

% Program: W5 Signal Subtraction

```
clf;clear all

[d,r]=wavread('cigar.wav'); % read in the clean signal

[c,r]=wavread('cignoise.wav'); % read in the noise signal

a=d(0.5e4:3.0e4); % takes parts of the clean signal

b=c(0.5e4:3.0e4); % takes parts of the noise signal

subplot(2,2,1);plot(b)

title('A.  Plot of Noise Signal');xlabel('Sample Number');

ylabel('Amplitude');grid;subplot(2,2,2);plot(a)

title('B.  Plot of Clean Signal');xlabel('Sample Number');

ylabel('Amplitude');grid;for k=1:1:2.5e4

s(k)=a(k)+b(k);end;subplot(2,2,3);plot(s);

title('C.  Plot of Composite Signal');xlabel('Sample Number');
```

```
ylabel('Amplitude');grid;for k=1:1:2.5e4
p(k)=s(k)-b(k);end;subplot(2,2,4);plot(p);
grid;title('D.  Plot of Restored Signal');
xlabel('Sample Number');
ylabel('Amplitude');
```

% Program: W6 Autocorrelation and cross-correlation of signals

```
clf;clear all
[d,r]=wavread('cigar.wav'); % read in the clean signal
[c,r]=wavread('cignoise.wav'); % read in the noise signal
a=d(0.5e4:1.0e4); % takes parts of the clean signal
b=c(0.5e4:1.0e4); % takes parts of the noise signal
y=xcorr(a);subplot(3,1,1);plot(y)
title('A.  Autocorrelation. Function of a Clean Signal'); grid
for k=1:1:0.5e4;s(k)=a(k)+b(k);end;
for k=1:1:0.5e4;p(k)=s(k)-b(k);end;
y=xcorr(p);subplot(3,1,2);plot(y)
title('B.  Autocorrelation of Restored Signal');grid;y=xcorr(a,p);
subplot(3,1,3);plot(y)
title('C.  Cross-correlation of Clean & Restored Signal');grid
```

% Program: W7 spectra analysis

```
clf;clear all
[d,r]=wavread('cigar.wav'); % read in the clean signal
[c,r]=wavread('cignoise.wav'); % read in the noise signal
a=d(0.5e4:3.0e4); % takes parts of the clean signal
b=c(0.5e4:3.0e4); % takes parts of the noise signal
for k=1:1:2.5e4  % program instruction
s(k)=a(k)+b(k); % clean signal + noise
end;subplot(2,4,1); % Select the1st quadrant
plot(s); % plot of resultant signal;grid;
title('A.  Composite Signal');ylabel('Amplitude');
n1=1.5e2; % number of FFT points;
q=abs(fft(s,n1)); subplot(2,4,2);plot(q); grid;
title('B.  Spectrum of Composite Signal');ylabel('Magnitude (dB)');
for k=1:1:2.5e4;p(k)=s(k)-b(k); % clean signal - noise
end;subplot(2,4,3); % Select the 2nd quadrant
plot(p); % plot of resultant signal;grid;
title('C. Restored Signal');ylabel('Amplitude');
n1=1.5e2; % number of FFT points;q=abs(fft(p,n1));
subplot(2,4,4);plot(q); grid;title('D.  Spectrum of Restored Signal');
ylabel('Magnitude (dB)');
n=a/4; % clean signal/4
for k=1:1:2.5e4;s(k)=n(k)+b(k);end;subplot(2,4,5);plot(s);grid;
```

```
title('E.   Clean Sig./4 + Noise Sig.');ylabel('Amplitude');
xlabel('Sample Number');n1=1.5e2; % number of FFT points
q=abs(fft(s,n1));subplot(2,4,6);plot(q); grid;
title('F.  Spectrum of Composite Signal');
ylabel('Magnitude (dB)');
xlabel('Frequency (Hz)');
k=1:1:2.5e4;p(k)=s(k)-b(k);
end;subplot(2,4,7);plot(p);grid;title('G. Restored Signal');
xlabel('Sample Number');
ylabel('Amplitude');q=abs(fft(p,n1));
subplot(2,4,8);plot(q);
grid;title('H.  Spectrum of Restored Signal');
ylabel('Magnitude (dB)');xlabel('Frequency (Hz)');
n=a/16; % clean signal/16
for k=1:1:2.5e4;s(k)=n(k)+b(k);end;figure(2);
subplot(2,4,1);plot(s);
grid;title('A.   Clean Sig./16 + Noise Sig.');
ylabel('Amplitude');n1=1.5e2; % number of FFT points
q=abs(fft(s,n1)); subplot(2,4,2)
plot(q); grid;title('B.  Spectrum of Composite Signal');
ylabel('Magnitude (dB)');
for k=1:1:2.5e4;p(k)=s(k)-b(k);end;subplot(2,4,3);plot(p);
grid;title('C. Restored Signal');
```

```
ylabel('Amplitude');
q=abs(fft(p,n1)); subplot(2,4,4);plot(q); grid;
title('D.  Spectrum of Restored Signal');
ylabel('Magnitude (dB)');

n=a/32; % clean signal/32
for k=1:1:2.5e4;s(k)=n(k)+b(k);
end;subplot(2,4,5);plot(s);
grid;title('E.   Clean Sig./32+ Noise Sig.');
xlabel('Sample Number');ylabel('Amplitude');
n1=1.5e2; % number of FFT points
q=abs(fft(s,n1)); subplot(2,4,6)
plot(q); grid;title('F.  Spectrum of Composite Signal');
ylabel('Magnitude (dB)');xlabel('Frequency (Hz)');
for k=1:1:2.5e4;p(k)=s(k)-b(k);
end;subplot(2,4,7);plot(p);grid;
title('G. Restored Signal');xlabel('Sample Number');
ylabel('Amplitude');q=abs(fft(p,n1));
subplot(2,4,8);plot(q); grid;title('H.  Spectrum of Restored Signal');
ylabel('Magnitude (dB)');xlabel('Frequency (Hz)');
```

% Program: W8 SNR

```
clear all
[d,r]=wavread('cignoise.wav'); % read in the noise signal
f1=.75;a1=0.23*f1*pi;f2=1;a2=0.23*f2*pi;f3=1.5;a3=0.23*f3*pi;
for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k));
end;
mean(d)
std(d)
var(d)
mean(x)
std(x)
var(x)
SNR=10*log10(var(x)/var(d))
for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/3;end;
mean(x)
std(x)
var(x)
SNR=10*log10(var(x)/var(d))

for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/6;end;
mean(x)
std(x)
var(x)
```

```
SNR=10*log10(var(x)/var(d))

for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/12;end;

mean(x)

std(x)

var(x)

SNR=10*log10(var(x)/var(d))

for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/24;end;

mean(x)

std(x)

var(x)

SNR=10*log10(var(x)/var(d))

for k=1:1:1024;x(k)=(sin(a1*k)+sin(a2*k)+sin(a3*k))/48;end;

mean(x)

std(x)

var(x)

SNR=10*log10(var(x)/var(d))
```

% Program: W9 Realization

```
clear all;clf

[d,r]= wavread('netnews.wav'); % read in the noisy signal

[c,r]= wavread('newsnoise.wav'); % read in the noise signal

a=d(0.5e4:6.5e4); % takes parts of the noisy signal

b=c(0.5e4:6.5e4); % takes parts of the noise signal
```

```
% spectra

q=spectrum(b); subplot(3,1,1);plot(q)

ylabel('magnitude (dB)');

title('A.  Spectrum of Noise Signal ')

q=spectrum(a); subplot(3,1,2);plot(q)

ylabel('magnitude (dB)');title('B.  Spectrum of Noisy Signal ')

for k=1:1:5.5e4;p(k)=a(k)-b(k);end; q=spectrum(p);

 subplot(3,1,3); plot(q);xlabel('frequency (Hz)');ylabel('magnitude (dB)');

title('C.  Spectrum of Restored Signal ')
```

% Spectral Subtraction

```
n=length(a); % number of samples of a

m=length(b); % number of samples of b

h=hamming(n); % define the hamming samples for a

i=hamming(m); % define the hamming samples for b

n1=5.5e4; % number of FFT points

m1=5.5e4; % number of FFT points

p=a.*h; %window the noisy signal

q=abs(fft(p,n1)); % find the magnitude of the FFT of the windowed noisy signal

figure(2);subplot(3,1,2);plot(q);

grid;ylabel(' Magnitude, (dB)');

title('B.  Spectrum of Noisy Signal using Hamming Windows')

f=b.*i; %window the noise signal
```

```
g=abs(fft(f,m1)); % find the magnitude of the FFT of the windowed noise signal
subplot(3,1,1);plot(g); grid;ylabel(' Magnitude, (dB)');
title('A.  Spectrum of Noise Signal using Hamming Windows')
for k=1:1:5.5e4;r(k)=q(k)-f(k);end;
 subplot(3,1,3); plot(r);grid;
xlabel('frequency, (Hz)');
ylabel(' Magnitude, (dB)');
title('C.  Spectrum of Restored Signal using Hamming Windows')
figure(3);
subplot(3,1,1);plot(b);title('A.  Plot of Noise Signal');
ylabel('Amplitude');grid;subplot(3,1,2);plot(a)
title('B.  Plot of Noisy Signal'); ylabel('Amplitude');grid
for k=1:1:5.5e4
p(k)=a(k)-b(k);end;subplot(3,1,3);
plot(p);grid
title('C.  Plot of  Restored Signal');xlabel('Sample Number');
ylabel('Amplitude');
```

% Correlation Functions

```
figure(4);y=xcorr(a);
subplot(3,1,1);plot(y);title('A.  Autocorrelation of Noisy Signal');grid
y=xcorr(p);subplot(3,1,2);plot(y)
title('B.  Autocorrelation of Restored Signal');grid
```

```
y=xcorr(a,p);subplot(3,1,3);plot(y)
title('C.  Cross-correlation of Noisy & Restored Signal');grid
```

% SNR

```
mean(a)
std(a)
var(a)
mean(b)
std(b)
var(b)
SNR1=10*log10(var(p)/var(b))
n=b/4;
SNR2=10*log10(var(p)/var(n))
s=length(r);n1=s;c=ifft(r,n1);z=abs(c);
plot(z); grid;u=length(z);v=hamming(u);
y= z.*v;
for k=1:1:2.5e4
p(k)=a(k)-b(k);
end;mean(p)
std(p)
var(p)
SNR=10*log10(var(p)/var(b))
```