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Master's Degree in Aeronautics

Option : **CNS/ATM**

THEME

Identification of acoustic impulse responses and noise filtering in the Airbus 320 cabin using adaptive algorithms.

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DEDICATIONS

I would like to express my sincere gratitude to Almighty Allah, the Most Powerful and Merciful, for granting me the courage and the will to overcome the various obstacles I had to face while attempting to complete this humble work.

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DEDICATIONS

I dedicate this modest work To My dearest mother (Sedrati Amel), the jewels of my life, may God keep her.

To my brother Mohamed and my dear sister Linda, for their help and their precious advice.

To my friends, for their sincere friendship (Oussama ,Igmi,Zinou,Salah, ,Nejmou,Akram and Anis).

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To anyone who appreciates me... thank you all .

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Abstract:

In addition to their applications in wireless communication, the use of adaptive algorithms, such as the Normalized Least Mean Squares (NLMS) filter, has become increasingly valuable in mitigating noise interference within aircraft cabins. The E-170 aircraft, in particular, faces challenges related to noise pollution during flight. To ensure clear communication between the pilot and passengers, advanced noise reduction techniques are imperative. In this context, LMS and NLMS filters play a pivotal role. These filters adaptively cancel out unwanted noise and interference, allowing passengers to hear critical announcements more effectively. To assess the effectiveness of such filters, simulations can be conducted in a MATLAB environment that replicates the acoustic properties of an Airbus 320 cabin. By recording and processing pilot announcements in a simulated room with dimensions akin to those of the aircraft, engineers can refine these noise reduction strategies, ultimately improving the in-flight experience for all.

Résumer :

En plus de ses applications dans les communications sans fil, l'utilisation d'algorithmes adaptatifs, tels que le algorithm est devenue de plus en plus précieuse pour atténuer les interférences sonores au sein des cabines d'aéronefs. L'aéronef airbus-320, en particulier, est confronté à des défis liés à la pollution sonore en vol. Afin d'assurer une communication claire entre le pilote et les passagers, des techniques avancées de réduction du bruit sont indispensables. Dans ce contexte, les algorithms LMS et NLMS jouent un rôle essentiel. Ces algorithms éliminent de manière adaptative les bruits indésirables et les interférences, permettant ainsi aux passagers de recevoir de manière plus efficace les annonces cruciales. Pour évaluer l'efficacité de ces algorithms , des simulations peuvent être

effectuées dans un environnement MATLAB reproduisant les propriétés acoustiques de la cabine d'un airbus-320. En enregistrant et en traitant les annonces du pilote dans une salle simulée aux dimensions similaires à celles de l'aéronef, les ingénieurs peuvent affiner ces stratégies de réduction du bruit, améliorant ainsi l'expérience en vol pour tous.

ملخص

بالإضافة إلى تطبيقاتها في الاتصالات اللاسلكية، أصبح استخدام الخوارزميات التكيفية، مثل مرشح المربعات المتوسطة الأقل (NLMS)، ذو قيمة متزايدة في تخفيف تداخل الضوضاء داخل كابينة الطائرات. وتواجه الطائرة E-170، على وجه الخصوص، تحديات تتعلق بالتلوث الضوضائي أثناء الرحلة. ولضمان التواصل الواضح بين الطيار والركاب، تعد التقنيات المتقدمة لتقليل الضوضاء ضرورية. في هذا السياق، تلعب مرشحات LMS و NLMS دورًا أساسيًا. تعمل هذه المرشحات على التخلص من الضوضاء والتداخلات غير المرغوب فيها بشكل تكيفي، مما يسمح للركاب بتلقي الإعلانات المهمة بشكل أكثر كفاءة. لتقييم فعالية هذه المرشحات، يمكن إجراء عمليات المحاكاة في بيئة MATLAB لإعادة إنتاج الخصائص الصوتية لمقصورة الطائرة A320. ومن خلال تسجيل ومعالجة إعلانات الطيارين في غرفة محاكاة ذات أبعاد مماثلة لتلك الخاصة بالطائرة، يمكن للمهندسين تحسين استراتيجيات تقليل الضوضاء هذه، وتحسين تجربة الطيران للجمي

Summary

List of abbreviations:

LMS	Least-mean-square
NLMS	Normalized Least Mean Square
MSE	Mean Square Error
FIR	Finite Impulse Response
MMSE	Minimum Mean Square Error
SNR	Signal to noise ratio
ANC	Active noise cancelling

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Introduction

General Introduction:

In the world of aviation, where speed, precision, and safety reign supreme, there exists a persistent challenge that affects both passengers and crew members alike: noise within the aircraft cabin. The serene experience of soaring above the clouds is often marred by the relentless hum of engines, the whir of air circulation systems, and the ambient sounds of fellow travelers. This acoustic environment, while an inherent aspect of air travel, can be a source of discomfort, distraction, and even stress.

Recognizing the importance of a quieter and more comfortable journey, the aviation industry has embarked on a quest to conquer cabin noise. At the forefront of this endeavor are innovative technologies, and one of the most promising solutions is the application of adaptive filters. These sophisticated digital signal processing tools have the remarkable ability to actively cancel out unwanted noise, transforming the in-flight experience for passengers and optimizing communication for the flight crew.

The noise within the aircraft cabin is not merely an auditory nuisance; it can have physical and psychological ramifications. Prolonged exposure to high noise levels can lead to fatigue, heightened stress levels, and even hearing impairment. Effective communication between passengers and crew members can also be hindered, potentially compromising safety.

In response to these challenges, the aviation industry has turned to adaptive filtering technology. These algorithms, with their adaptability and real-time response capabilities, hold the promise of providing a quieter and more pleasant in-flight environment. Among the standout algorithms in this field are LMS (Least Mean Squares) and NLMS (Normalized Least Mean Squares), which excel at analyzing incoming noise and generating counteracting signals to effectively cancel out undesired sounds.

In this comprehensive exploration, we will uncover the inner workings of cabin noise and unveil the mechanics and applications of LMS and NLMS adaptive filters within the aircraft cabin environment. We will delve into the theory behind these algorithms, explore their practical implementations, and assess their performance in the dynamic context of aviation.

As we embark on this journey, we aim to illuminate the synergy between aviation and advanced signal processing, demonstrating how adaptive filters are poised to elevate the flying experience, making air travel not only efficient but also quieter and more comfortable for all aboard.

CHAPTER 01

GENERALITIES ON ACOUSTICS

I.1. Introduction:

Modern aircraft design aims to provide comfort and safety, and addressing noise reduction and sound propagation becomes crucial in achieving this goal. The abstract highlights the diverse sources of sound and noise within the cabin, emphasizing the need to minimize their impact on passenger comfort. Techniques like innovative sound insulation materials, optimized interior design, and active noise control are utilized to mitigate these challenges. Ultimately, the abstract underscores the importance of creating a peaceful and enjoyable environment for passengers during air travel.

I.2. The acoustic signal:

An acoustic signal refers to a sound wave or pressure fluctuation in the air (or another medium) that is perceived as sound by the human ear or a detection device. Acoustic signals are produced by sound sources such as musical instruments, human voices, moving machinery, and so on.

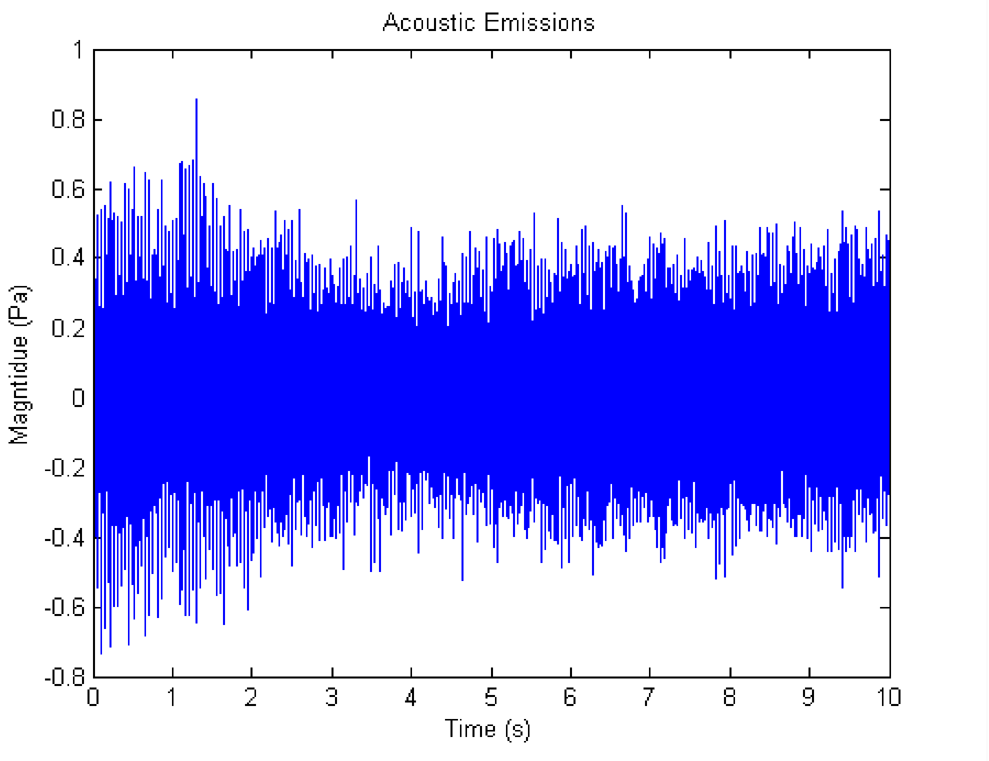

Figure 1.1: signal emission

I.3. Characteristics of Sound:

I.3.1. Frequency:

This is the number of complete cycles of oscillation of a sound wave per unit of time. Frequency is measured in Hertz (Hz) and determines the perceived pitch of the sound, whether it's low-frequency (low pitch) or high-frequency (high pitch).

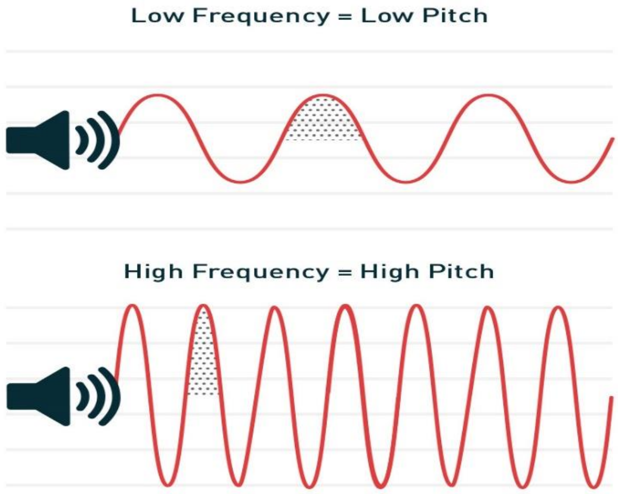

Figure I.2: signal low and high frequency.

I.3.2. Amplitude:

In the context of sound, amplitude refers to the peak value of a sound wave. It represents the strength of the sound or the amount of energy carried by the wave. Amplitude is directly related to the loudness of the sound we hear; higher amplitude corresponds to louder and more intense sound, while lower amplitude corresponds to softer and weaker sound. Amplitude is typically measured in decibels (dB).Duration: The duration of the signal indicates the period of time it is present. It can range from very short (like a finger snap) to very long (like thunder).

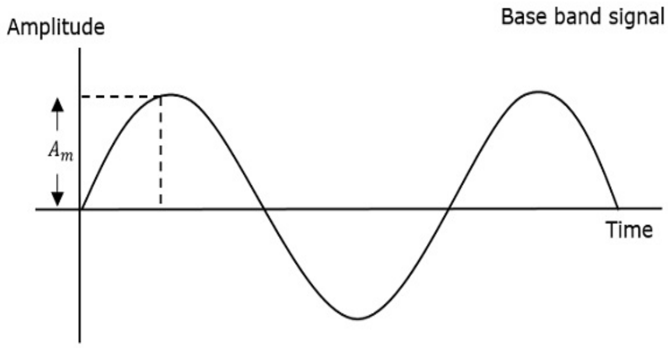

Figure I.3: The Amplitude of signal

I.3.3. the intensity of sound:

Sound Level in Decibels:

$$L_{(dB)}=10*\log_{10}(I / I_0) \tag{1.1}$$

Where:

I : is the intensity of the sound in question.

I_0 : is a reference intensity (often the intensity of human auditory threshold at a specific frequency, typically 10–12 W/m²).

This formula shows that the sound level in decibels depends on the ratio between the intensity of the sound being considered and the reference intensity. This allows for expressing a wide range of sound intensities on a logarithmic scale that is more convenient and meaningful.

In summary, the greater the amplitude of sound vibrations, the higher the sound intensity, which translates to a louder sound. This relationship is quantified in decibels to take into account the wide dynamic range of sound levels we encounter in our auditory environment

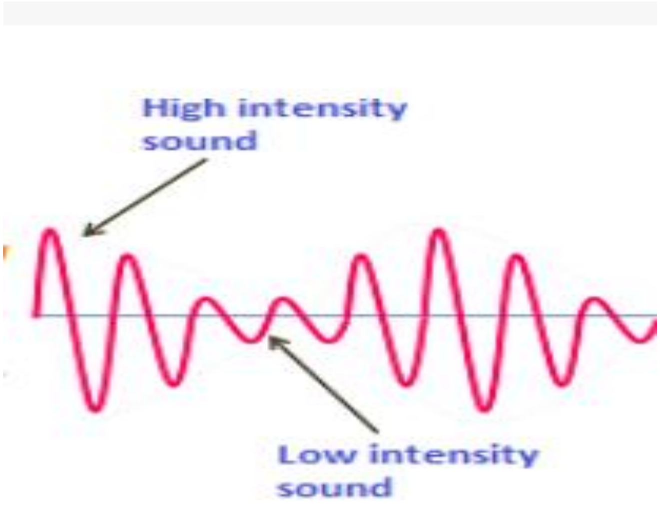

Figure I.4: high and low intensity.

I.3.4. Wave propagation speed:

Acoustic waves propagate through the air at 340 m/s, through water at 1500 m/s, and even faster in denser materials (3500 m/s in bone and up to 6000 m/s in steel!). In a vacuum, devoid of matter, no sound can propagate.

For example, if a sound source is placed under a bell jar, the sound is audible. However, if a vacuum is created under the bell; the sound disappears since there are no air molecules present. Other factors such as humidity and temperature also influence the propagation speed of the wave.

I.3.5. Impedance:

Impedance is a measure of the resistance of a material or medium to the passage of a wave, such as a sound or electromagnetic wave. It's a combination of resistance and reactance (the reactive component of opposition to the wave's passage).

In the context of acoustics, acoustic impedance generally refers to the resistance that a sound wave encounters when transitioning from one medium to another, such as from air to water or to a solid material. Differences in impedance between mediums can lead to reflection, transmission, or absorption of the sound wave at the interfaces between these mediums.

Impedance can vary based on the frequency of the wave, the material, and properties of the medium. In summary, impedance is a property that measures how a medium resists the passage of a wave and can play a crucial role in understanding the propagation of sound

waves and interactions with different mediums. [1]

I.4. Other Properties Related to Sound Propagation:

When a sound wave is emitted, it tends to be modified by parameters such as distance or potential obstacles.

I.4.1. Attenuation:

In free field, meaning in a space where no obstacle disrupts the propagation of

the sound wave, its acoustic intensity decreases as one moves away from the sound source.

$$I = (I_0 / r^2) \qquad (1.2)$$

Where :

i is the sound intensity at a distance r from the sound source,

i_0 is the sound intensity at a reference distance from the sound source (usually at a close distance where attenuation is negligible),

r is the distance between the point where the sound intensity is measured and the sound source.

I.4.2. Reflexion :

When a sound wave encounters an obstacle like a room wall, a certain amount of energy is reflected and returns to the room. This phenomenon is called reflection. Successive

reflections contribute to reverberation.

I.4.3. Transmission:

Some of the energy is transmitted to the neighboring room through the wall, which acts as a secondary sound source.

I.5. Sound propagation:

Sound propagation refers to the way sound waves travel through a medium, usually air, but also other materials such as water, metals, or wood. Sound is essentially a series of pressure variations that propagate through the particles of the medium, thus creating a sound wave.

I.6. Acoustic channels :

Acoustic channels refer to the pathways through which sound or audio is transmitted.

In the realm of communication, an acoustic channel is a means by which sound is conveyed from a source to a receiver. Acoustic channels find use in various contexts such as communication systems, audio recordings, sound broadcasting, and more.

For instance, in telephone communication, the acoustic channel is the conduit through which one caller's voice is transmitted to the other caller. In signal processing systems, analyzing and designing acoustic channels is important to ensure the quality and clarity of audio transmission.

Acoustic channels can be influenced by various factors, such as the distance between the source and the receiver, physical obstacles, sound absorption and reflection, as well as other environmental conditions. Understanding the characteristics of acoustic channels is essential for optimizing sound transmission quality and for developing signal processing technologies suited for different scenarios.

I.7. The Noise:

Noise is when vibrations in the air create sound that we hear. Sometimes, this sound can be annoying, bothersome, or even dangerous. When we work with signals (like sounds or data), we use the term "noise" to talk about random and complicated parts that we can't really understand easily. We look at how often the vibrations happen, how strong they are, and how long they last.

The way we feel about noise can change depending on how often we hear it, if it keeps happening, and if we can't do anything to stop it. Other things, like where the noise is coming from, when it happens, and who's hearing it, can also affect how we feel.

To figure out how loud the noise really is for our ears, we use a special way of measuring called "weighted decibels," written as dB. This helps us understand how much our ears are sensitive to different sounds and gives us a better idea of how loud the noise actually is.

I.8. Source of Noise in an aircraft cabin:

Noise within an aircraft cabin is a significant concern that can impact the comfort of both passengers and the flight crew. Several sources contribute to the noise experienced inside the aircraft cabin:

•**Engines:** Jet engines produce a considerable amount of noise, particularly during takeoff and landing Engine noise can transmit through the aircraft's structure and into the cabin.

•**Aerodynamics**: Aerodynamic forces during flight, such as turbulence and air pressure, can also generate noise that is transmitted into the cabin.

• **Auxiliary Systems:** Systems like air conditioning, ventilation, and onboard generators can contribute to cabin noise levels.

• **Air Conditioning:** The noise from the air conditioning system, including compressors and fans, can add to the overall cabin noise.

•**Vibrations:** Vibrations from the aircraft's structure caused by various sources can translate into audible noise within the cabin

•**Air brakes and Landing Gear:** Deploying and retracting air brakes and landing gear can also produce noticeable noises.

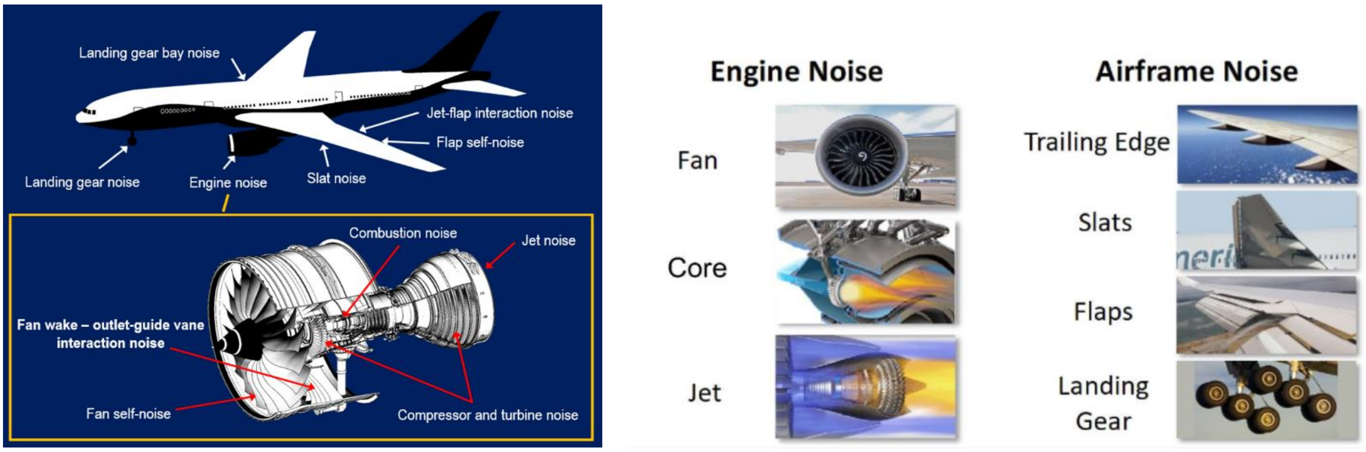

Figure I.5: the sources of noise within an aircraft cabin.

I.9. Type of noise:

❖ 1.9.1 White noise:

White noise" is a type of noise that has a uniform distribution of energy across the entire sound spectrum. This means that all frequencies are present with the same energy ratio. In other words, each frequency carries the same amount of energy.

White noise has a distinctive sound that can be described as a constant and continuous "shhhhh." It's often compared to the sound of a radio or television that's not properly tuned to a station. Due to its even distribution of energy across all frequencies, white noise has the same amount of energy in low frequencies as it does in high frequencies.

❖ 1.9.2 Pink noise:

Pink noise is another type of random sound, but it's characterized by having equal energy in each octave of frequency. This means that each octave (a doubling or halving of frequency) carries the same amount of energy. Pink noise sounds more balanced to the human ear compared to white noise. It is often used in audio testing, sound masking, and other applications where a more natural and soothing sound is desired.

❖ 1.9.3 Brown noise:

Brown noise, also known as red noise or Brownian noise, is a type of sound characterized by its unique frequency spectrum. It belongs to the category of "colored noise," with a specific power distribution across frequencies. Unlike white noise, brown noise exhibits a gradual decrease in power density as frequency increases, resulting in a deeper, rumbling quality. Often used for relaxation, sleep, and masking background sounds, its potential benefits are subjective and not widely substantiated by scientific research. Online recordings and generators provide access to brown noise for various purposes.

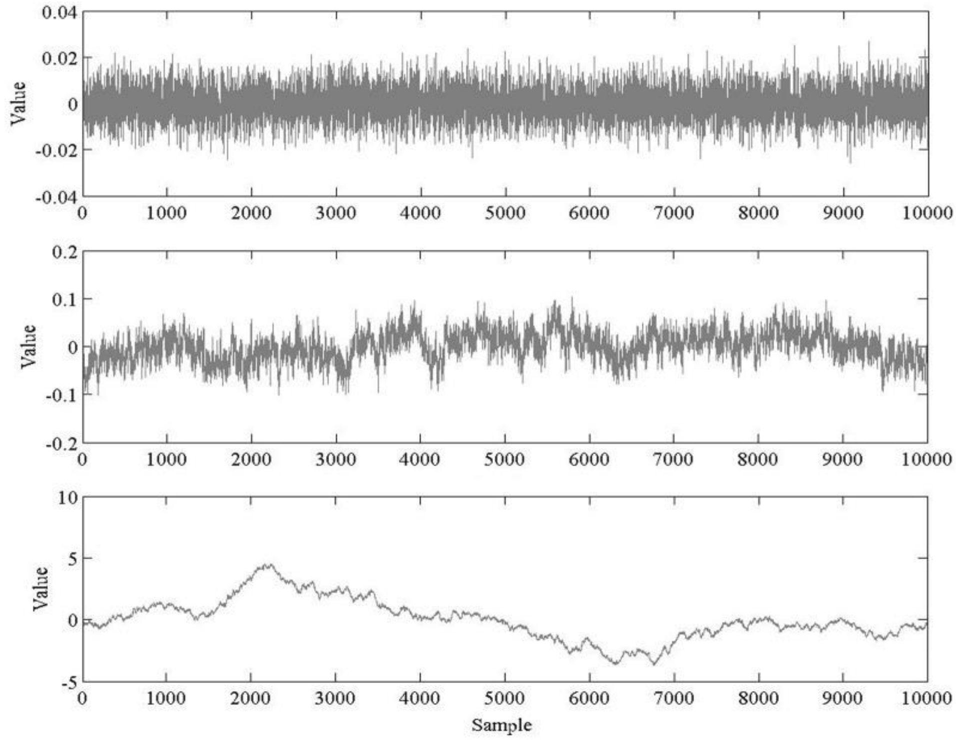

Figure I.6: Sample time series of white (top), pink (middle), and brown (bottom) noise.

I.10. Active noise cancelling ANC :

Is a technology used to reduce or eliminate unwanted sounds by generating sound waves with Opposite phase. The main goal of this technology is to reduce ambient noise and create a Quieter and more pleasant sound experience for the user. [2]

Here's how Active Noise Cancelling generally works in aircraft cabin :0

❖ **1.10.1 Microphones:**

Multiple microphones are strategically placed throughout the aircraft cabin to pick up ambient noise and engine vibrations.

❖ **1.10.2 Noise Analysis:**

The captured noise data is analyzed in real-time by a dedicated ANC system onboard the aircraft.

❖ 1.10.3 Anti-Phase Sound Waves:

Based on the noise analysis, the ANC system generates anti-phase sound waves. These are sound waves that have the same amplitude as the incoming noise but are 180 degrees out of phase, meaning they have the opposite phase.

❖ 1.10.4 Speaker Playback:

These anti-phase sound waves are then played back through the cabin's speakers, typically located in the headrests or ceiling. When the anti-phase sound waves meet

the incoming noise, they interfere destructively, effectively canceling out the noise

❖ 1.10.5 Continuous Adjustment:

The ANC system continuously adjusts the anti-phase sound waves as the noise environment changes. This ensures that the cabin remains quiet even as the aircraft's noise profile shifts during flight Active Noise Cancelling is commonly used in earphones, headphones, and other audio .

figure . bombardier Q400 aircraft

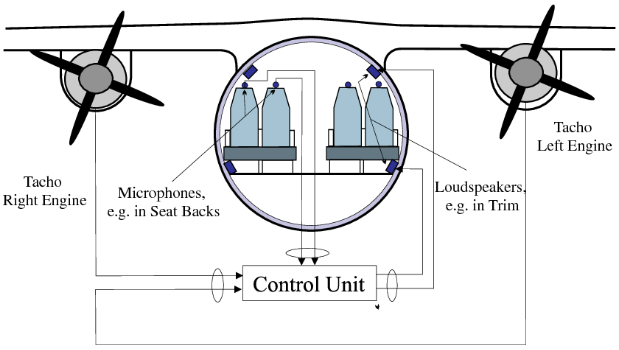

Figure .active noise cancelling in bombardier Q400 aircraft

Active noise cancellation is particularly effective at reducing low-frequency noise, such as the engine noise and airframe vibrations commonly encountered on aircraft. It significantly contributes to passenger comfort by providing a quieter and more relaxing travel experience.

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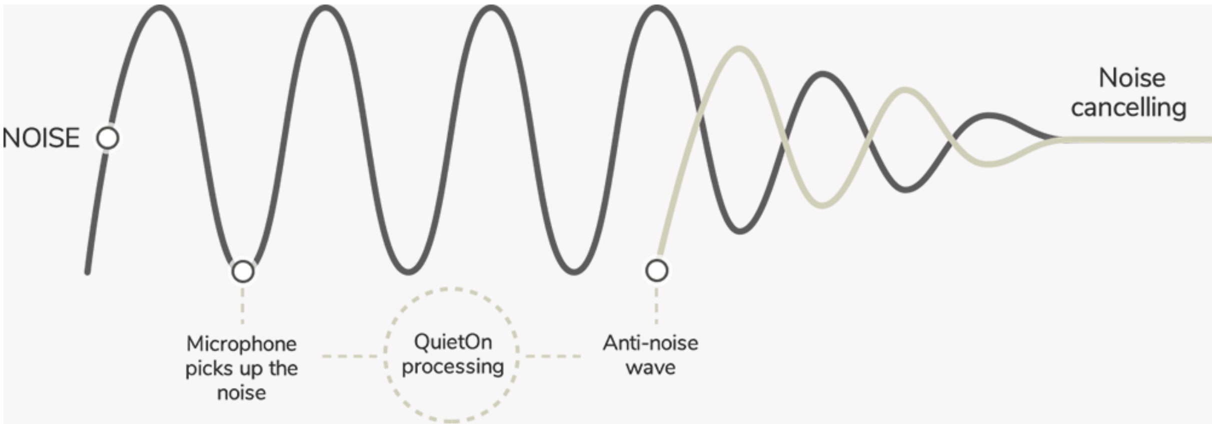

Figure 1.7: ANC Active Noise Cancelling.

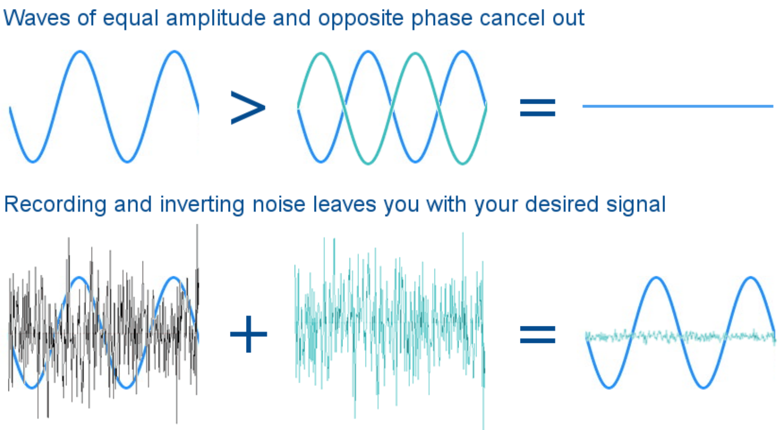

Figure 1.8: Principle of ANC.

I.11. The problem of ANC with The Noise Inside the Aircraft Cabin:

In the realm of air travel, the aircraft cabin presents a distinctive environment brimming with a diverse array of sounds, ranging from the roar of engines to the hushed conversations of passengers. This amalgamation of multi-sourced sounds under one roof poses a formidable challenge to the effectiveness of active noise cancellation (ANC) technology.

Active noise cancellation technology typically analyzes and senses the surrounding sounds to generate counteractive signals that cancel out those noises. However, several challenges loom large in this context:

- **Sound Diversity :** The aircraft cabin offers multiple sources of noise, making the precise identification and isolation of these sources a complex endeavor.

- **Changings Conditions :** The sounds within the aircraft cabin are in a constant state of flux due to factors like altitude, speed, and weather conditions. This perpetual alteration amplifies the difficulty of primitively generating counteractive signals for the noise.

- **Sound Interplay:** Various sounds intertwine within the confined space ,rendering it challenging for the technology to discern the specific sounds to target for cancellation.

- **Time Delay :**
  Time delays between the noise signal and the cancellation signal might lead to less than optimal performance.

Sounds in our surroundings can be intricate and consist of multiple frequencies, such as urban noises, park sounds, transportation sounds, office environments, airports, public places, and more. These sounds may involve overlapping noises from various sources, and it can be difficult for an ANC system to effectively distinguish and cancel out all of these sounds. "Complexity of sounds" refers to the diversity and multiplicity of environmental and ambient sounds that active noise cancellation (ANC) technology must address. It signifies that the acoustic environment includes a wide range of sounds with different frequencies and amplitudes, adding to the challenge faced by ANC systems.

So we should use Advanced Algorithms that algorithms can accurately analyze and predict complex sound patterns

algorithms are adaptive in nature, which means they continuously adjust the filter coefficients based on the changing characteristics of the noise environment. These algorithms are widely used in ANC systems to dynamically counteract noise and improve the overall noise reduction performance.

I.12. Acoustic Echo :

"echo" in acoustics refers to the reflection of sound waves off surfaces, resulting in a delayed repetition of the original sound. This phenomenon occurs when sound waves encounter a surface and bounce back towards the source or another receiver. The reflected sound reaches the receiver after a short time delay, typically noticeable when there is a significant distance between the source and the reflective surface ,[3].

I.13. The principle of acoustic echo cancellation:

The principle of acoustic echo cancellation involves reducing or eliminating the unwanted echo that occurs when a portion of an audio signal is reflected and returned to the sender after being transmitted through a communication path, such as a room or a telephone line. This echo can make communication difficult to understand and disrupt the audio quality. To cancel acoustic echo, adaptive filtering techniques are often employed. Here's how it generally works:

Capture of Echo Signal: The echo signal is captured at the point where it occurs, for example, at the microphone of a phone, before it gets mixed with the original signal.

Channel Modeling: A model of the transmission channel is used to estimate how the echo signal propagates and reflects in the environment. This model might include room characteristics, obstacles, delays, etc.

Adaptation of Filters: Adaptive filters, such as the Least Mean Squares algorithm, are used to adjust the coefficients of a signal processing filter. These filters seek to minimize the difference between the captured echo signal and the predicted echo signal based on the channel model, aiming to attenuate or eliminate the echo.

Echo Reduction: The coefficients of the adaptive filter are iteratively adjusted based on the difference between the captured echo signal and the predicted echo signal. This ongoing adaptation gradually reduces the presence of the echo in the signal.

Echo-Free Communication: Once the adaptive filter has appropriately adjusted the coefficients, the echo signal is effectively attenuated or removed, allowing for clearer and higher-quality communication.

In summary, the principle of acoustic echo cancellation is based on modeling the transmission channel and using adaptive filters to reduce or eliminate echo, thereby improving the quality of audio communication.

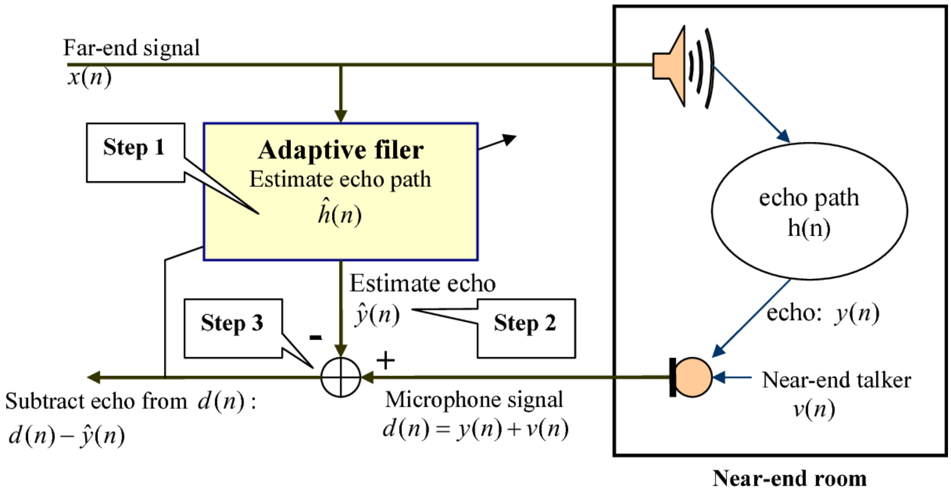

Figure 1.9: The principle of acoustic echo cancellation.

I.14. Conclusion :

In this chapter, we discussed sound and its components, and noise, particularly the noise present within the aircraft cabin, and its sources,

we discussed and lastly acoustic echo , Active Noise cancelling technique for reducing this noise, and the challenges it poses within the cabin.

CHAPTER 02 :

Signal processing applied to aircraft cabin acoustics

Chapitre II.

II.1. Introduction :

This section presents an adaptive approach in the context of signal processing applications.

We present digital and adaptive filters algorithms

Filtering is performed adaptively, if the coefficients are adjusted, according to a given

once a new signal value is available. These modifications

must keep pace with the evolution of systems in their environment as quickly as possible. The

adaptive filters adjust themselves, according to external signals, to suppress disturbances

in the frequency range of the desired signal at any given moment

II.2. Digital filtering :

Digital filtering is a technique used in signal processing to manipulate digital signals through mathematical algorithms. The purpose of digital filtering is to enhance or attenuate specific components of the signal's frequency spectrum, as well as to remove noise and extract important information from digital data streams. It is widely used in various applications to improve signal quality and extract relevant information from digital data streams.

A digital filter F is a calculation algorithm by which a sequence of numbers x(n), called the input sequence, is transformed into another sequence of number sequence y(n) called output sequence. [4] .

General formulation:

$$y(n) = \sum_{i=0}^{M}(b_i \mathrm{x}(\mathrm{n}-\mathrm{i})) + \sum_{j=0}^{N}\left(a_j \mathrm{y}(\mathrm{n}-\mathrm{j})\right) \qquad (2.1)$$

II.3. Impulse Response of a Filter:

In signal processing, filters are systems that modify the characteristics of a signal. The impulse response of a filter represents how the filter responds to a unit impulse in terms of amplitude and time. It helps understand how the filter will affect different frequencies or components of the input signal.

In summary, impulse responses are fundamental concepts for understanding the behavior of linear systems and filters in the fields of mathematics, physics, and engineering. They allow

us to analyze how a system responds to specific inputs and how it modifies signals that pass through it.

II.3.1. Finite Impulse Response (FIR) Filters:

FIR filters have a finite impulse response, which means that their output is only influenced by a finite number of past input samples. The output of an FIR filter is calculated by convolving the input signal with a set of coefficients (also known as taps) that define the filter's behavior.

Coefficients (h[n]): These are the filter's impulse response coefficients that define how the filter processes the input signal.

Delay elements: These elements store the previous input samples for convolution with the coefficients.

Multiplier (or Adder): Used to compute the weighted sum of the delayed input samples and coefficients

The output of an FIR filter y[n] at time instant n is calculated using the convolution operation:

$$y[n] = \sum_{k=0}^{N-1} h[k] \cdot x[n-k] \qquad (2.2)$$

y[n] is the output at time

x[n−k] represents the delayed input samples.

h[k] represents the filter coefficients (taps) at index k

N is the number of filter taps.

The equation above calculates the weighted sum of the delayed input samples x[n−k] with the filter coefficients h[k].

Now, let's move on to IIR filters:

II.3.2. Infinite Impulse Response (IIR) Filters:

IIR filters have an infinite impulse response, meaning that their output is influenced by an infinite number of past input samples as well as past output samples. The output of an IIR filter is calculated based on recursive relationships between the input, output, and filter coefficients.

$$y[n] = \sum_{k=0}^{M} b[k] \cdot x[n-k] - \sum_{k=1}^{N} a[k] \cdot y[n-k] \tag{2.3}$$

x[n−k] represents the delayed input samples.

b[k] represents the feedforward (numerator) coefficients at index k

a[k] represents the feedback (denominator) coefficients at index k

M is the order of the numerator (number of feedforward coefficients).

N is the order of the denominator (number of feedback coefficients).

This equation calculates the output y[n] based on a combination of the current and past input samples x[n−k] and the past output samples y[n−k], weighted by the coefficients b[k] and a[k].

II.4. The need for adaptation :

Room acoustics has made rapid progress in the understanding of physical phenomena and in the mastery of precision and control methods, thanks to digital methods that provide access to computer simulations and signal processing.

The new audio terminals developed by the telecommunications industry are characterized by the broadcasting of speech over a loudspeaker and the recording of sound by one or more microphones at a distance from the user. As a result, unlike conventional telephones equipped with a handset, these new handsets interact intensively with the user. These new handsets interact strongly with the acoustic environment.

The new problems encountered call for specific sound recording treatments. The aim is to minimize the power of the interfering signals for the user, without degrading the speech signal.

To achieve this, we need to take into account the specific properties of the acoustic channels to be processed. This response has a complex temporal structure (set of reflections depending on room geometry, obstacles present, etc.) and admits of no simple model.

We therefore need to use adaptive identification algorithms (since the acoustic channels are unknown and evolve over time) that are robust to output

output disturbances.

II.5. Adaptive filtering :

II.5.1. Definition :

Adaptive filtering is a signal processing method that adjusts filter parameters to enhance signal quality in response to signal or environmental changes. Its aim is to reduce unwanted noise and preserve desired components by continuously updating filter coefficients based on the input signal and reference signal. This technique is valuable for extracting information from noisy signals in fields like telecommunications, audio, and image processing, ultimately improving signal processing system performance.

II.5.2. Principle of adaptive filtering :

Adapt processing tools to the statistical properties of signals and systems, as well as adapt to their fluctuations over time. This involves a well-balanced mixture of stationary and non-stationary.

Stationary maintains statistical properties over time, through which purely random fluctuations are eliminated or at least reduced. Non-stationary refers to the slow or rapid variation over time in statistical properties, without which there would be no need for adaptation.

In the absence of signal and system fluctuations, the optimal filter could be computed once.

Filters can be classified as linear or nonlinear.

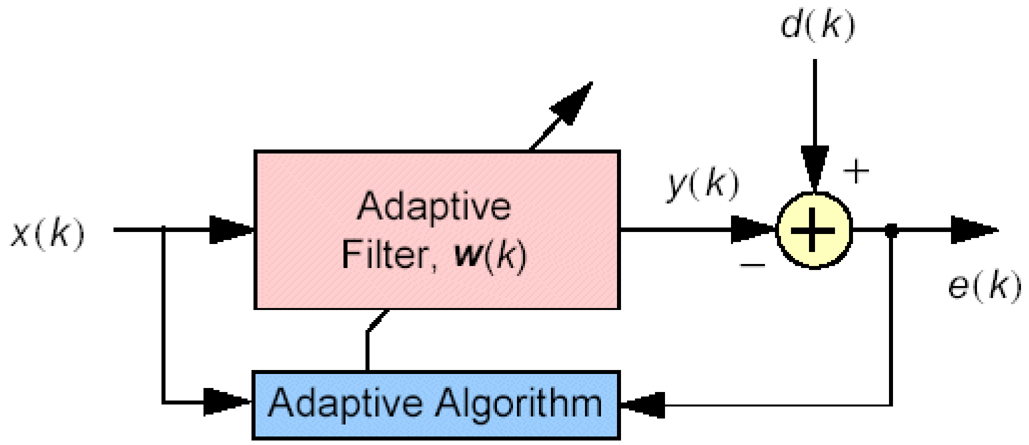

Figure II.3: adaptive filter.

The various signals used in adaptive filtering are:

- x(k): the input signal of the filter.
- w(k): the filter coefficients.
- y(k): the output signal of the filter.
- d(k): the reference signal.
- e(k): the error signal, which represents the difference between d(k) and y(k), and is used for controlling the values of the filter coefficients.

II.5.3. Applications of adaptive filtering :

Adaptive filtering is a versatile technique widely used in various fields such as signal processing, digital communications, and automatic control. Its power lies in its ability to adjust and optimize filter parameters automatically based on changing input conditions. This helps in enhancing signal quality, reducing noise, mitigating interference, and achieving desired system performance .The essential differences between applications come from how the desired response d(n) is

defined. Four major classes of applications can be distinguished. [5] .

a/ System identification

System identification is the process of determining a filter that best models the behavior of an unknown system. The filter is estimated based on the difference between the output of the process and its estimation at the output of the filter. Here, d(n) represents the output of the system being identified.

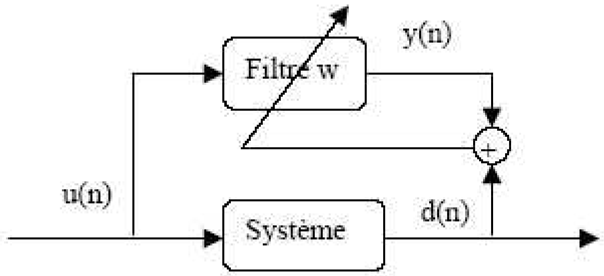

Figure II.4: principle of system identification.

b/ prediction

Linear prediction is a mathematical technique used to forecast or estimate future values of a signal based on its past values. It assumes that there is a linear relationship between the current value of the signal and its previous values. In other words, it tries to find a linear combination of past values that best approximates the current value.

"d(n)" represents the signal at time "n", and "y(n)" is the predicted signal based on the previous time instances.

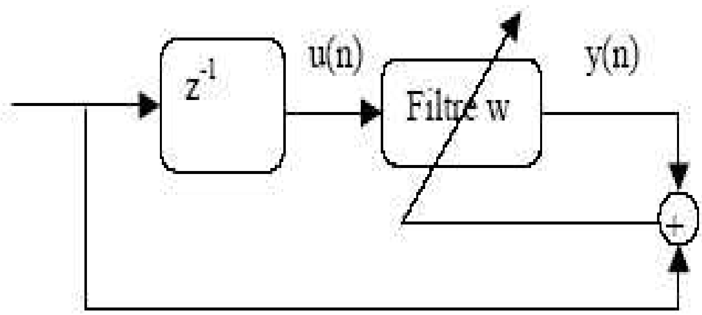

Figure II.5: principle of prediction.

C/ Inverse system identification

This involves reconstructing a reference signal that has been distorted by an unknown process, and this issue is referred to as the equalization problem. Here, d(n) is the (delayed) input to the system that one seeks to "reverse" or "invert."

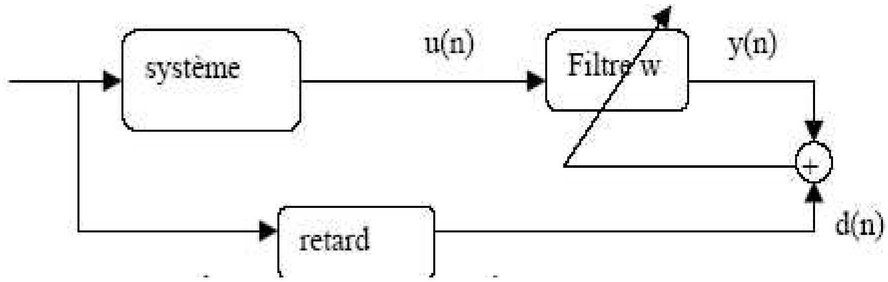

Figure II.6: Inverse system identification.

D/ Noise cancelling :

The input signal is correlated with a reference signal.

d(n) is a primary signal containing interference to be canceled.

x(n) is the reference signal devoid (or nearly devoid) of information and obtained from a sensor close to the one providing d(n). [6]

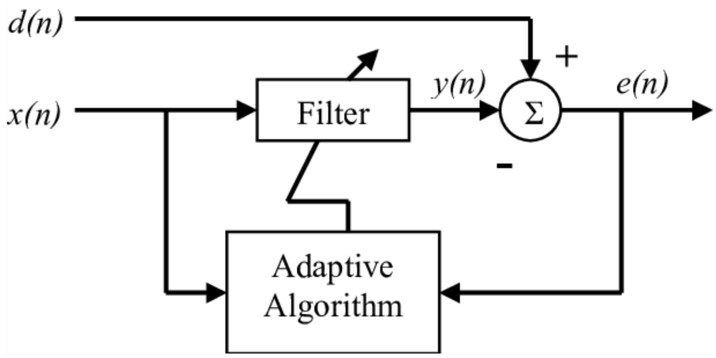

Figure II.7: Noise cancellation.

II.6. Performance criteria for an adaptive filter:

The specific performance criteria that matter most will depend on the application and the goals you want to achieve with the adaptive filter.

Here are some commonly used performance criteria for evaluating an adaptive filter:

1/ Mean squared Error (MSE) : measures the average squared difference between the actual output of the adaptive filter and the expected value. A low MSE indicates that the filter is successful in minimizing the gap between the desired output and the actual output.

2/Convergence Speed: This criterion evaluates how quickly the adaptive filter can reach a stable solution. Faster convergence is often desirable, especially in real-time applications where quick adaptation to changing environments is necessary..

3/Robustness: An adaptive filter should be able to handle noisy or corrupted input data without drastically degrading its performance. Robustness to outliers and noise is an important criterion, especially in real-world scenarios.

4/Stability: The adaptive filter should remain stable during operation. Instabilities can lead to divergence, making the filter's output unpredictable and potentially unusable.

The specific performance criteria that matter most will depend on the application and the goals you want to achieve with the adaptive filter. Balancing these criteria is often a trade-off, and the design of the adaptive filter involves making decisions based on the specific requirements of the problem at hand.

II.1. Conclusion :

In this chapter, we discussed identification and adaptive filters, their types, working mechanisms, and the necessity of having an adaptive algorithm for their functioning. Therefore, in the next chapter, we will delve into these adaptive algorithms and present the Algorithms.

Chapter 03

Description of the algorithms used for the identification of impulse responses.

Chapitre III.

III.1. Introduction :

The principle property of an adaptive filter is its time-varying, self-adjusting characteristics. An adaptive filter usually takes on the form of an FIR filter structure, with an adaptive algorithm that continually updates the filter coefficients, such that an error signal is minimised according to some criterion. The error signal is derived in some way from the signal flow diagram of the application, so that it is a measure of how close the filter is to the optimum. Most adaptive algorithms can be regarded as approximations to the Wiener filter, which is therefore central to the understanding of adaptive filters.

III.2. Wiener Filter Theory:

The starting point for deriving the equations for the adaptive filter, is to define very clearly what we mean by an optimum filter. The Wiener filter is probably the most common definition in use, and it relates to the configuration depicted in **Figure (3.1)**. The kth sample of signal y, yk, consists of two components: the principal signal sk, and a noise component nk which is correlated with xk. The Wiener filter provides an optimal estimate of nk, known as $\hat{\mathbf{n}}_{\mathbf{k}}$. [7] .

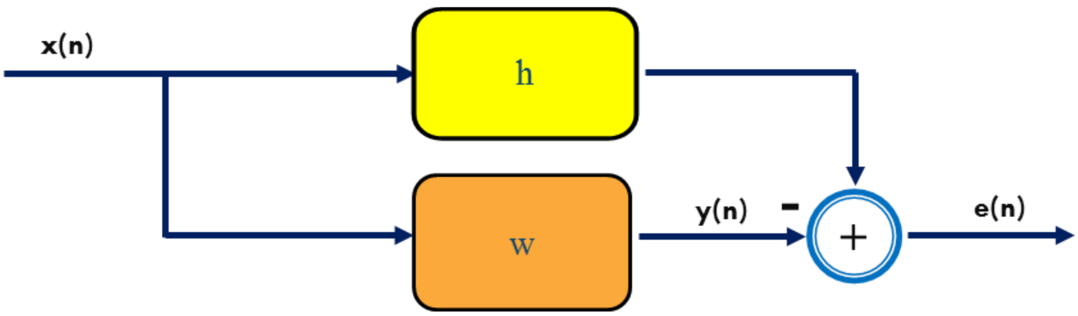

Figure 3.1 : shema of Wiener filter.

Now let us suppose that the Wiener filter is an FIR filter with *N* coefficients, the estimated error signal e_k is found by from the input signal y_k, this is mathematically defined by the equation below:

$$\mathbf{e_k = y_k - \hat{n}_k = y_k - \sum_{i=0}^{N-1} w(i) \cdot x_{k-i}} \qquad (3.1)$$

where $w(i)$ is the i^{th} coefficient of the Wiener filter. Since we are dealing with discrete values, the input signal and Wiener filter coefficients can be represented in matrix notation. Such that:

$$\mathbf{X_k} = \begin{bmatrix} \mathbf{x_k} \\ \mathbf{x_{k-1}} \\ \vdots \\ \mathbf{x_{k-(N-1)}} \end{bmatrix} \mathbf{W} = \begin{bmatrix} \mathbf{w(0)} \\ \mathbf{w(1)} \\ \vdots \\ \mathbf{w(N-1)} \end{bmatrix} \tag{3.2}$$

By substituting for the matrix notation into Equation (3.2), it is possible to represent the estimated error signal by equation (3.3) below:

$$\mathbf{e_k} = \mathbf{y_k} - \mathbf{W^T X_k} = \mathbf{y_k} - \mathbf{X_k^T W} \tag{3.3}$$

The instantaneous squared error of the signal can be found by squaring Equation (3.3) such that it can be represented as the following equation :

$$\mathrm{e_k^2} = \mathrm{y_k^2} - 2\mathrm{W^T}(\mathrm{y_k X_k}) + \mathrm{W^T X_k X_k^T W} \tag{3.4}$$

The mean square error (MSE), is defined by the "expectation" of the squared error, from Equation (3.4) Hence the MSE can be represented by Equation (3.5) below :

$$\xi = \mathrm{E}\left[\mathrm{e_k^2}\right] = \mathrm{E}\left[\mathrm{y_k^2}\right] - 2\mathrm{W^T E}[\mathrm{y_k X_k}] + \mathrm{W^T E}\left[\mathrm{X_k X_k^T}\right]\mathrm{W} \tag{3.5}$$

3.2.1 Optimize the Filter Coefficients:

To find the optimal filter coefficients, take the derivative of the MSE with respect to W and set it to zero:

$$\frac{\partial \xi}{\partial W} = 0 \tag{3.6}$$

This leads to a set of equations that can be solved for the optimal filter coefficients W

Autocorrelation matrix : This matrix captures the autocorrelation of the input signal $\mathrm{X_k}$

$$R_{XX} = E[X_k X_k^T] \tag{3.7}$$

Cross-correlation matrix: This matrix captures the cross-correlation between the observed signal $\mathrm{y_k}$ and input signal $\mathrm{X_k}$

$$R_{yX} = E[y_k X_k] \qquad (3.8)$$

3.2.2 Solution for Optimal Filter Coefficients:

The solution for the optimal filter coefficients W is typically obtained by solving the following equation:

$$W = R_{XX}^{-1} R_{yX} \qquad (3.9)$$

In practice, matrix inversion may be replaced by solving a system of linear equations to find W efficiently.

The solution for W using the Wiener filter approach is based on statistical properties and signal characteristics. It aims to adjust the filter coefficients in such a way that the desired signal is estimated while minimizing the impact of noise, resulting in an optimal filtered signal. The solution depends on the autocorrelation and cross-correlation information, which should be estimated from the available data.

III.3. LMS Algorithm:

The Least Mean Square (LMS) algorithm, first introduced by Widrow and Hoff in 1959, is the most widely used adaptive algorithm. It is based on the gradient descent method, which calculates and updates the filter coefficients recursively.

The basic idea behind the LMS filter is to approximate the optimal filter coefficients by iteratively updating these coefficients to converge towards the optimal filter coefficients. In most cases, the algorithm starts with an initialization vector that is set to zero, and at each step, the coefficients are adjusted by calculating the gradient of the Mean Square Error (MSE). This method involves two fundamental steps.

III.3.1. Filtering Step:

Involves the computation of the output data from a transversal filter based on an initial choice of weights.

$y(k) = \boldsymbol{h}^T(k) * \boldsymbol{x}(k)$……4.1 (3.10)

And then, the estimation of the error by comparing the filter output with the desired output:

e(k) = d(k) - y(k)……… (3.11)

Adaptation Step:

Involves updating the filter weights based on the error estimate. The equation for updating the coefficients is:

(k + **1**) = (k) + µ(k)***e***(k)

The values of future coefficients are calculated based on the current values of these same coefficients and the error. The convergence speed and stability depend on the adaptation step size, which must be chosen small enough for the algorithm to converge and large enough for the algorithm to be adaptive and reach its optimal value as quickly as possible. The primary advantages of LMS algorithms are their simplicity and performance. However, their convergence can be slower compared to other algorithms. Among the many variations of the standard LMS algorithm, some notable ones include. [10].

III.3.2. Implementation of LMS :

The computational steps for the LMS algorithm are as follows:

- Initialize the filter coefficients $\mathbf{w_k(i)}$ to zero.
- At each sampling period:

$a -$ Compute the filter output: $\hat{n}_k = \sum_{i=0}^{N-1} w_k(i) \cdot x_{k-i}$

b − Calculate the error estimate: $e_k = y_k - \hat{n}_k$

C −Update the new filter weights:

$$\mathbf{w_{k+1}(i) = w_k(i) + 2\mu e_k x_{k-i},\ for\ i = 0\ to\ N - 1}$$

In matrix form this can be expressed as:

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu e_k \mathbf{X}_k$$

III.3.3. LMS Algorithm (Batch Gradient Descent):

In the standard batch gradient descent version of the LMS algorithm, you calculate the gradient of the cost function with respect to the model parameters using the entire dataset. Then, you update the model parameters in the direction of the negative gradient to minimize the cost function. [11].

The update rule for the LMS algorithm is given by

$$w(t+1) = w(t) - \mu \star \nabla J(w(t)) \qquad (3.12)$$

where:

w(t) is the model parameter vector at time step t.

α is the learning rate.

∇J(w(t)) is the gradient of the cost function with respect to w(t). [12].

$$\hat{\boldsymbol{\nabla}}_{\mathbf{k}} = \begin{bmatrix} \frac{\partial \mathbf{e}_{\mathbf{k}}^2}{\partial \mathbf{w}(\mathbf{0})} \\ \frac{\partial \mathbf{e}_{\mathbf{k}}^2}{\partial \mathbf{w}(\mathbf{1})} \\ \vdots \\ \frac{\partial \mathbf{e}_{\mathbf{k}}^2}{\partial \mathbf{w}(\mathbf{N-1})} \end{bmatrix} = \mathbf{2e_k} \begin{bmatrix} \frac{\partial \mathbf{e}_{\mathbf{k}}}{\partial \mathbf{w}(\mathbf{0})} \\ \frac{\partial \mathbf{e}_{\mathbf{k}}}{\partial \mathbf{w}(\mathbf{1})} \\ \vdots \\ \frac{\partial \mathbf{e}_{\mathbf{k}}}{\partial \mathbf{w}(\mathbf{N-1})} \end{bmatrix} = -\mathbf{2e_k X_k} \qquad (3.13)$$

III.3.4. Stochastic Gradient Descent (SGD) Variant:

In the stochastic variant of the LMS algorithm, you update the model parameters after processing each individual training example. This results in faster updates and can be more computationally efficient, especially when dealing with large datasets. [13].

The update rule for stochastic LMS (SGD) is given by:

$$w(t+1) = w(t) - \mu \star \nabla J(w(t), x\_i, y\_i) \qquad (3.14)$$

where:

x_i is an individual input example.

y_i is the corresponding target output.

∇J(w(t), x_i, y_i) is the gradient of the cost function with respect to w(t) for the specific example (x_i, y_i).

In each iteration, you randomly select a training example and update the model parameters based on that example's gradient. This randomness introduces noise into the optimization process, which can help escape local minima and explore the parameter space more effectively.

SGD is widely used for training machine learning models, especially deep neural networks, as it allows for efficient and scalable optimization. The learning rate and the order in which training examples are processed can affect the convergence and performance of the algorithm. [14].

III.4. Normalized LMS (NLMS) Algorithm:

The implementation of the NLMS algorithm follows the same steps and equations as the LMS algorithm. The difference lies in the weight update step, which is formulated as follows:

$$h(t+1) = h(t) + \mu_{\mathrm{NLMS}} \frac{x(t)}{\lambda + ||x(t)||\hat{}2} e(t) \qquad (3.15)$$

where:

h(t) is the model parameter vector at time step t.

μ_{NLMS} is the learning rate (a constant factor).

e(t) is the error or the difference between the desired output and the predicted output at time t.

x(t) is the input signal or feature vector at time t.

λ is a small positive constant (sometimes called the regularization parameter).

III.4.1. Normalization:

The key aspect of NLMS is the normalization term in the denominator: $\lambda + ||x\ (t)||^2$. This term scales the learning rate based on the magnitude of the input signal. When the input signal is small, the learning rate increases, and when the input signal is large, the learning rate decreases. [15] .

III.5. Algorithm Selection:

The choice of the algorithm will be based on the following criteria:

• Convergence speed, which is the number of iterations required to converge "sufficiently close" to the optimal Wiener solution in the stationary case.

• Measurement of the "closeness" between this optimal solution and the obtained solution.

• Ability to track variations (non-stationarities) in the process. We will examine which algorithms are truly adaptive. [16].

• Robustness to noise.

• Complexity

• Structure

III.6. Comparison criteria :

In order to be able to compare the discussed adaptive filtering algorithms against each other in terms of the efficiency of noise cancelling, some characteristics must be defined which can be evaluated for each algorithm. For the comparison of the chosen algorithms discussed in the previous subchapters, the following performance criteria are used: the rate of convergence, the performance of the mean-square error MSE and the signal-to-noise ratio SNR after filtering.

Each algorithm works on different methods for noise cancellation and reaches system stability in different ways. In order to find the best adaptive filtering algorithm for noise cancellation, a trade-off between the three performance criteria must be considered. The performance characteristics of the LMS, NLMS algorithms are studied by taking the criteria such as convergence speed and mean-square error into consideration along with the number of iterations.

III.6.1. Rate of convergence :

The rate of convergence is defined as the number of adaptation cycles required for the algorithm to converge from some initial condition to its steady-state or close enough to an optimum, like the optimum Wiener solution in the mean-square error sense .The rate of convergence can be found out by using a learning curve, which shows the averaged mean-square error MSE or least squares error LSE performances as a function of the number of iterations. Depending on each algorithm, the rate of convergence is influenced by different factors.

III.6.2. Error performance :

Adaptive filters attempt to optimize the performance by minimizing the error signal between the output of the adaptive filter and the desired signal according to some criterion. A large error value indicates that the adaptive filter cannot accurately track the desired signal. A minimal error value ensures that the adaptive filter is optimal. The different adaptive filtering algorithms are highly dependent on the optimization criterion.

Minimum mean-square error MMSE:

The criterion of the LMS and NLMS algorithm is the minimum mean-square of the error signal. The MSE is defined as the ensemble average of the squared error sequence, denoted as:

$$\xi(n) = E\{|e(n)|^2\} \qquad (3.16)$$

The so-called maladjustment is another performance measure for algorithms that use the minimum MSE criterion. The maladjustment M is the ratio of the steady- state excess mean-square error to the minimum mean-square error, which can be mathematically described as:

$$\mathcal{M} = \frac{\xi_{\mathrm{ex}}(\infty)}{\xi_{min}} \qquad (3.17)$$

A trade-off between a low rate of convergence and a small mean-square error or maladjustment is necessary, because when the step-size μ increases, the rate of convergence decreases, but the MSE increases.

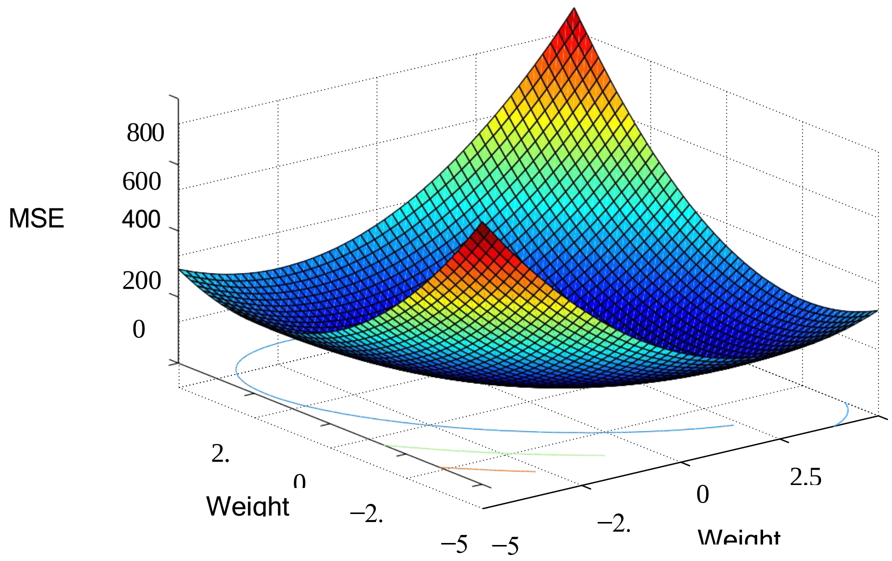

Figure 3.2: MSE surface for 2-D case.

III.6.3. Signal-to-noise ratio SNR :

The signal-to-noise ratio SNR is another important performance criterion in adaptive noise cancellation and describes the relationship between the strength of the input signal and the noise signal.

The SNR is defined in (3.27) by the ratio of the signal power to the noise power and is often expressed in decibel.

[17]

$$\mathbf{SNR_{dB} = 10log_{10}\frac{S}{N}} \qquad (3.18)$$

In order to compare the different adaptive filtering algorithms in the efficiency of noise cancellation,

the so-called improvement SNR level in (3.19) is used, which is the difference between the input and output SNR .

Therefore, the SNR is calculated before and after applying the adaptive filter. The signal-to-

noise ratio SNR in decibels is computed by the ratio of the summed squared magnitude of

the signal to that of the noise. The input SNR is the ratio between the power of input signal and power of noise at the input

$$\mathbf{SNR_{in}} = \mathbf{10log_{10}} \frac{\sum_n \mathbf{x(n)^2}}{\sum_n \mathbf{v_1(n)^2}} \quad (3.19)$$

where x(n) is the noise-corrupted signal and v1 is the noise sequence. As there is no

information about the noise signal, it is not possible to calculate exactly the input SNR, it can

only be estimated from the sinusoid.

The output SNR has to be higher than the input SNR, which indicates the success of noise

removal. A lower value of the output SNR compared with the input SNR means that the filtering process introduces more noise instead of reducing noise. The output SNR is the ratio between the power of the filtered signal and power of the noise at output

$$\boldsymbol{SNR}_{\mathbf{out}} = \mathbf{10log_{10}} \frac{\sum_n \boldsymbol{y(n)^2}}{\sum_n \boldsymbol{e(n)^2}} \quad (3.20)$$

where y(n) is the output signal of the adaptive filter and e(n) is the noise signal. A large value of the output SNR is desirable, which indicates that the adaptive filter can remove a large amount of noise and is able to produce an accurate estimate of the desired signal. The signal-to-noise ratio increases when the output noise power decreases. Minimizing the output power causes the filtered signal to be perfectly noise-free.

III.7. Conclusion :

In this chapter we are looking how work wiener filter and adaptive algorithm LMS and NLMS in noise cancellation.

the next chapter we will compare between this two algorithm with using matlab and real recording correlated with noise.

CHAPTER 04 :

Simulation and Results

IV.1. Introduction :

In this chapter, we first present the signals used in this work, impulse response ,speech signal and noise. Then we move on to the simulation of the LMS and NLMS algorithms, using MATLAB software, and the evaluation of signal to noise ratio with the different cases.

IV.2. Description of acoustic environment :

We conducted our experiment in a room with the same dimensions as the The Embraer 170 cabin, with a length of 20 meters, a width of 3 meters, and a height of 2.5 meters

the image below for the room in which we conducted the experiment.

Figure 4.01: A study hall similar to A320 cabin.

The airbus 320 is a regional jet aircraft developed by the Brazilian aerospace company Embraer. It is a part of the E-Jet family, which also includes the airbus 330, airbus 340, and airbus 350. The airbus family is known for its efficiency, comfort, and advanced avionics.

Figure 4.02: AIRBUS 320 CABIN.

DIMENSIONS :

Cabin Width: Approximately 2.74 meters.

Cabin Height: Approximately 2.13 meters.

Cabin Length: typically around 23 meters for the standard

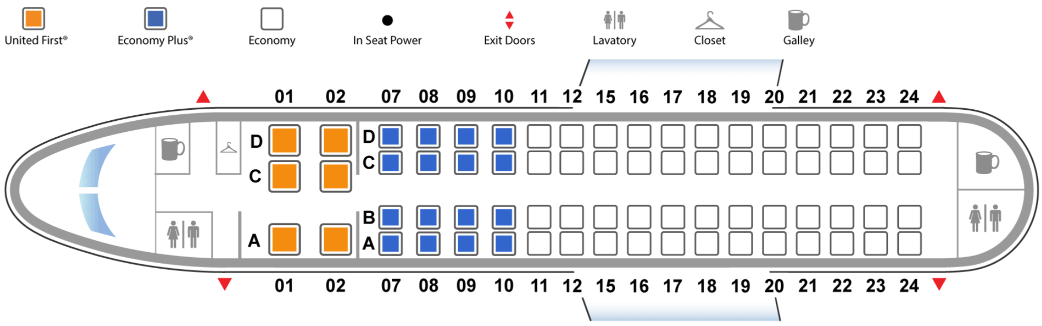

Figure 4.02: structure of airbus 320 CABIN.

Room Impulse Response :

In this study, the echo path is the acoustic coupling between a loudspeaker and a microphone in our room. The impulse response modeling the latter is shown in Figure(4.03)

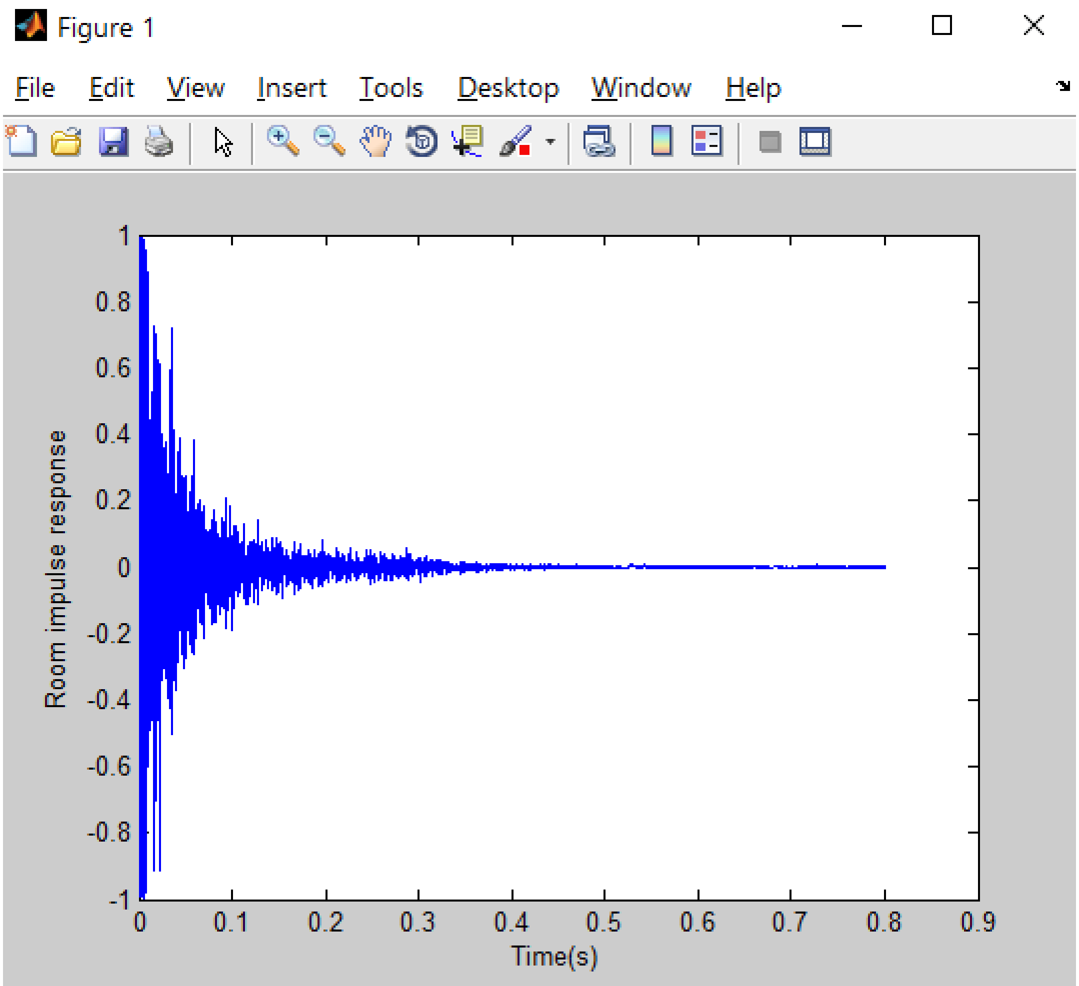

Figure 4.03: Room Impulse Response .

IV.3. Description of test signals :

The following signals were used in the simulations:

3.1 Speech signal :

The speech signal uttered by a male speaker, lasting 33 seconds, sampled at a frequency of 48 kHz and coded on 32 bits :

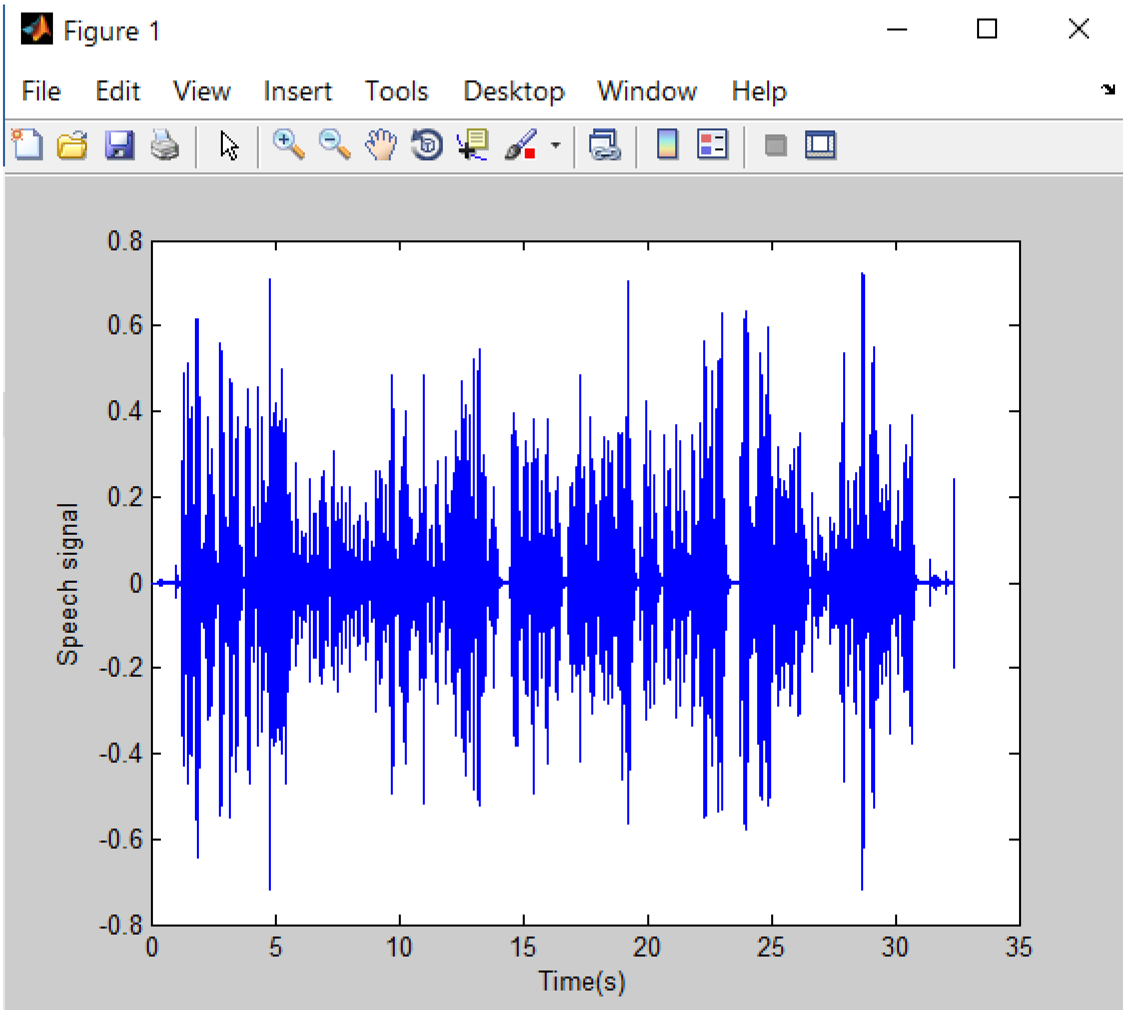

Figure 4.04: Speech signal .

3.2 White noise signal :

The white noise , lasting 33 seconds, magnitude is 0.1 , sampled at a frequency of 48 kHz and coded on 32 bits :

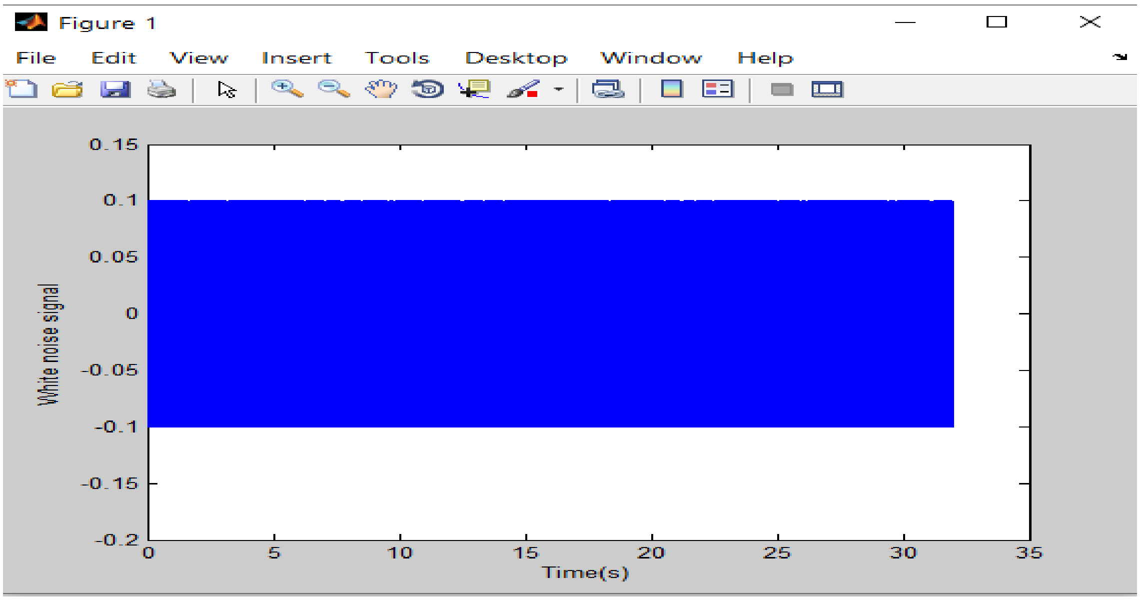

Figure 4.05: White noise signal .

3.3 Pink noise signal :

the speech signal uttered by a male speaker, lasting 33 seconds, magnitude is 0.1 , sampled at a frequency of 48 kHz and coded on 32 bits :

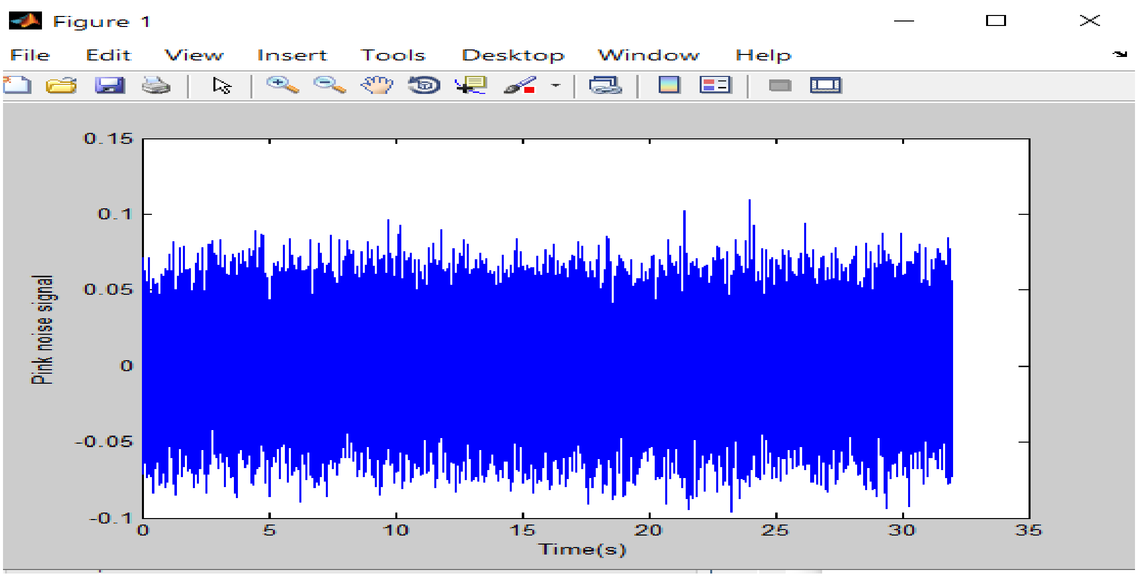

Figure 4.06: Pink noise signal .

IV.4. Simulation and results :

IV.4.1. Distance influence :

In this experiment, we evaluated the effect of the distance "D" between the loudspeaker and the microphone on the measurement.

Filter length =100 , step size = 0.1

Table 4.1: distance effect on the measure.

	SNR(db)	
Distance(m)	**LMS**	**NLMS**
7	**28.41**	**42.85**
14	**23.84**	**41.16**
20	**19.40**	**39.62**

The table (4.01) shows that the SNR of both LMS and NLMS algorithms decreases with distance but the NLMS algorithm outperforms the LMS algorithm in terms of SNR at all three distances. However, NLMS algorithms are more effective at canceling noise at long distances than LMS algorithms.

The SNR values in the table are quite high, which indicates that both the LMS and NLMS algorithms are able to effectively remove noise from the signal

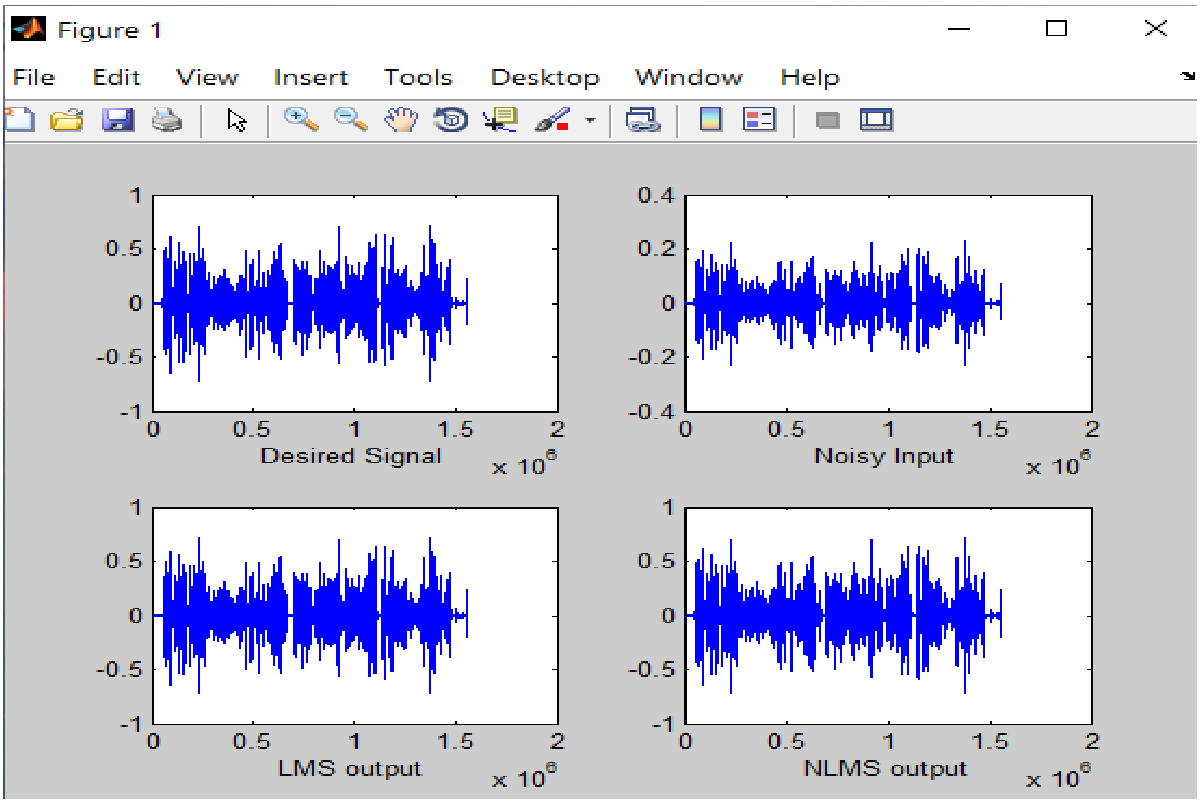

Figure 4.07: distance effect (D=7m).

IV.4.2. Sample frequency influence :

In this experiment, we evaluated the effect of the Sample frequency on the measurement.

D=14m , Filter length =100 , step size = 0.1

Table 4.2: Sample frequency effect on the measure.

	SNR(db)	
Sample frequency (hz)	**LMS**	**NLMS**
32000	**21.56**	**38.71**
48000	**23.84**	**41.16**
88200	**27.51**	**41.72**

The table(4.02) shows that the NLMS algorithm outperforms the LMS algorithm in terms of SNR at all three sample frequencies (32kHz, 48kHz, and 88.2kHz). The improvement in SNR provided by the NLMS algorithm is greater at higher sample frequencies. This is because the NLMS algorithm is better at adapting to the noise statistics, which can vary with sample frequency.

In summary, the NLMS algorithm is a superior choice for noise cancellation over the LMS algorithm, especially at higher sample frequencies

IV.4.3. Step size influence :

In this experiment, we evaluated the effect of the step size on the measurement.

D=14m , Filter length = 100 .

Table 4.3: Step size effect on the measure.

Step size	SNR(db) LMS	SNR(db) NLMS
0.1	23.84	41.16
0.5	30.23	43.38
1	32.97	41.91

The table (4.3) shows that the NLMS algorithm outperforms the LMS algorithm in terms of SNR (signal-to-noise ratio) at all three step sizes (0.1, 0.5, and 1). The improvement in SNR provided by the NLMS algorithm is greater at smaller step sizes. This is because the NLMS algorithm is able to better adapt to the noise statistics at smaller step sizes.

both LMS and NLMS algorithms are sensitive to the step size. A smaller step size results in slower convergence, but it also reduces the risk of instability. A larger step size results in faster convergence, but it also increases the risk of instability.

It is important to choose the step size carefully to balance the convergence speed, stability, and noise cancellation performance.

IV.4.4. Filter length influence :

In this experiment, we evaluated the effect of the filter length on the measurement.

D=14m , step size = 0.1

Table 4.4: Filter length effect on the measure.

Filter length	SNR(db) LMS	SNR(db) NLMS
50	23.78	43.56
100	23.84	41.16
150	23.87	39.72

The table (4.4) the NLMS algorithm outperforms the LMS algorithm in terms of SNR at all three filter lengths (50, 100, and 150). However, the improvement in SNR provided by the NLMS algorithm is greatest at shorter filter lengths. This is because the NLMS algorithm is able to better adapt to the noise statistics at shorter filter lengths , while the LMS was not affected by the filter length. Therefore, it is important to choose the filter length carefully to balance the noise cancellation performance, computational complexity, and the risk of overfitting.

IV.4.5. White noise influence :

In this experiment, we evaluated the effect of white noise signal on the measurement.

D=7m , Filter length =100 , step size = 0.1

Table 4.5: white noise effect on the measure.

	SNR(db)	
Magnitude	**LMS**	**NLMS**
0.1	**8.14**	**8.33**
0.5	**1.16**	**2.46**
0.9	**Nan**	**1.16**

The table(4.5) shows that white noise has a significant negative impact on the performance of both LMS and NLMS algorithms. As the magnitude of the white noise increases, the SNR decreases. This is because the white noise adds noise to the signal, making it more difficult for the algorithms to distinguish the desired signal from the noise, however the NLMS algorithm is more robust to white noise than the LMS algorithm.

We observe in Figure 4.09 When the magnitude of the white noise increases to 0.9, the LMS algorithm becomes unstable and the SNR becomes NaN (not a number). This is because the LMS algorithm updates its filter coefficients based on the error between the desired signal and the filtered output. However, when the noise is too high, the error signal becomes too noisy and the LMS algorithm is no longer able to update its filter coefficients accurately. As a result, the filter becomes unstable and the SNR becomes NaN.

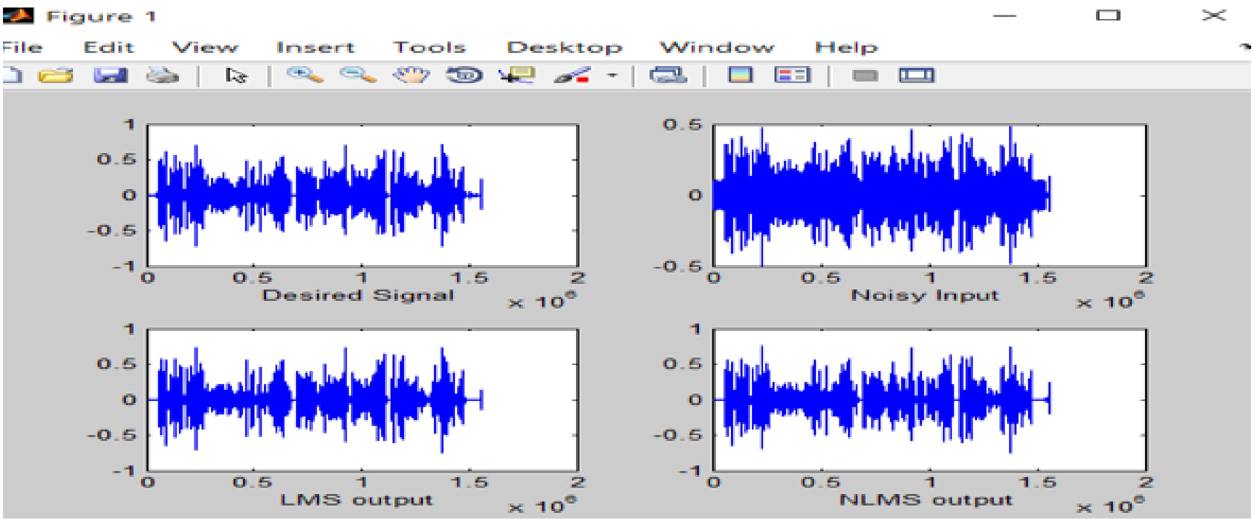

Figure 4.08: white noise effect (magnitude=0.1) .

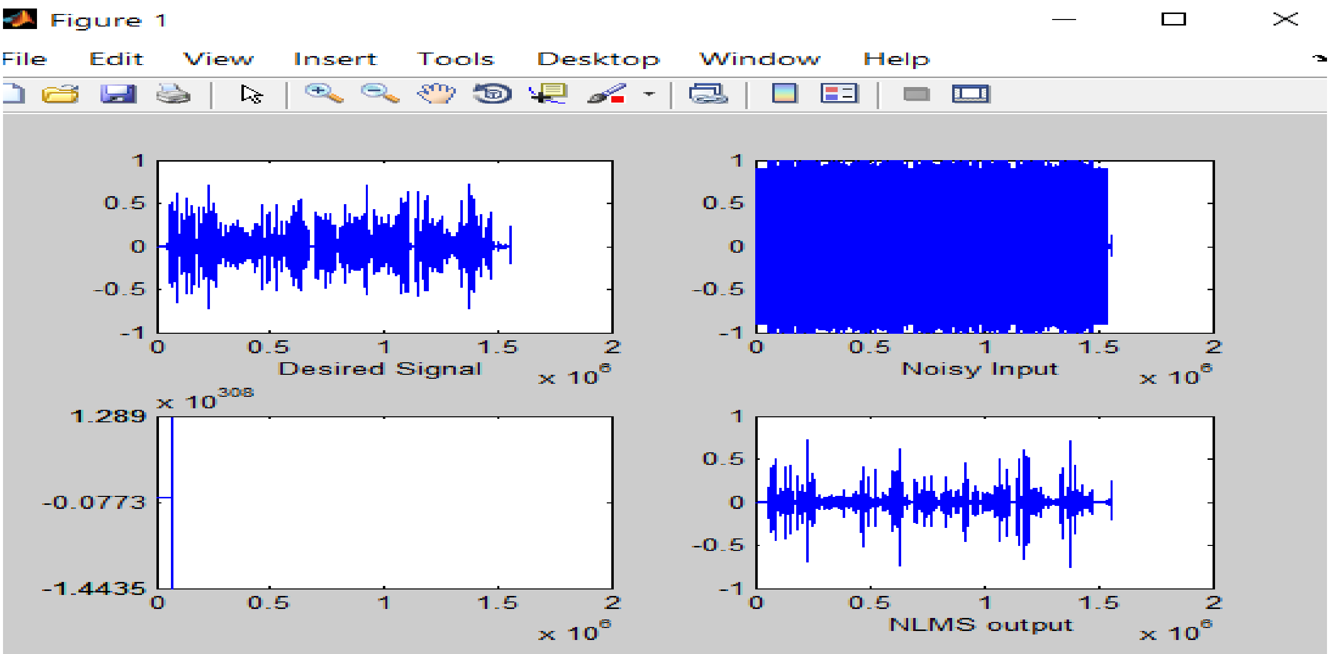

Figure 4.09: white noise effect (magnitude=0.9) .

IV.4.6. Pink noise influence :

In this experiment, we evaluated the effect of pink noise signal on the measurement.

D=7m , Filter length =100 , step size = 0.1

Table 4.6: Pink noise effect on the measure.

Magnitude	SNR(db) LMS	SNR(db) NLMS
0.1	11.26	12.30
0.5	6.10	5.30
0.9	-2850	3.51

The table (4.6) shows that pink noise has a negative impact on the performance of both LMS and NLMS algorithms, but the effect is more severe for the LMS algorithm. As the magnitude of the pink noise increases, the SNR (signal-to-noise ratio) decreases.

The NLMS algorithm is more robust to pink noise than the LMS algorithm.

NLMS algorithm is better at adapting to the noise statistics, which can change with the magnitude of the pink noise.

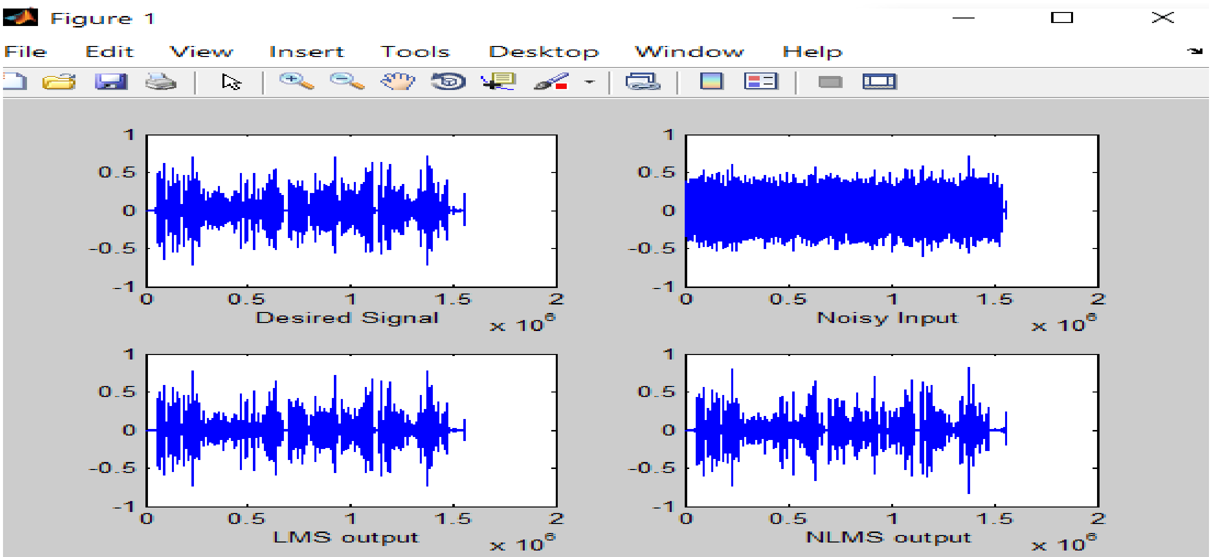

Figure 4.10: Pink noise effect (magnitude=0.5) .

IV.4.7. Type of noise influence :

In this experiment, we evaluated the effect of the type of noise on the measurement.

D=7m , Filter length =100 , step size = 0.1

Magnitude of noise = 0.1

Table 4.7: type of noise effect on the measure.

Noise Type	SNR(db) LMS	SNR(db) NLMS
Pink	**11.26**	**12.30**
White	**8.14**	**8.33**
Pink +White	**7.74**	**7.87**

The table (4.7) shows that the type of noise has a significant impact on the performance of both LMS and NLMS algorithms. Pink noise has the least negative impact on the performance of both algorithms, followed by white noise, and then pink noise + white noise.

At a pink noise magnitude of 0.1, the NLMS algorithm provides a 1.04 dB improvement in SNR over the LMS algorithm. At a white noise magnitude of 0.1, the NLMS algorithm provides a 0.19 dB improvement in SNR over the LMS algorithm. At a pink noise + white noise magnitude of 0.1, the NLMS algorithm provides a 0.13 dB improvement in SNR over the LMS algorithm ,

The NLMS algorithm is more robust to all types of noise than the LMS algorithm. NLMS algorithm is better at adapting to the noise statistics, which can vary with the type of noise.

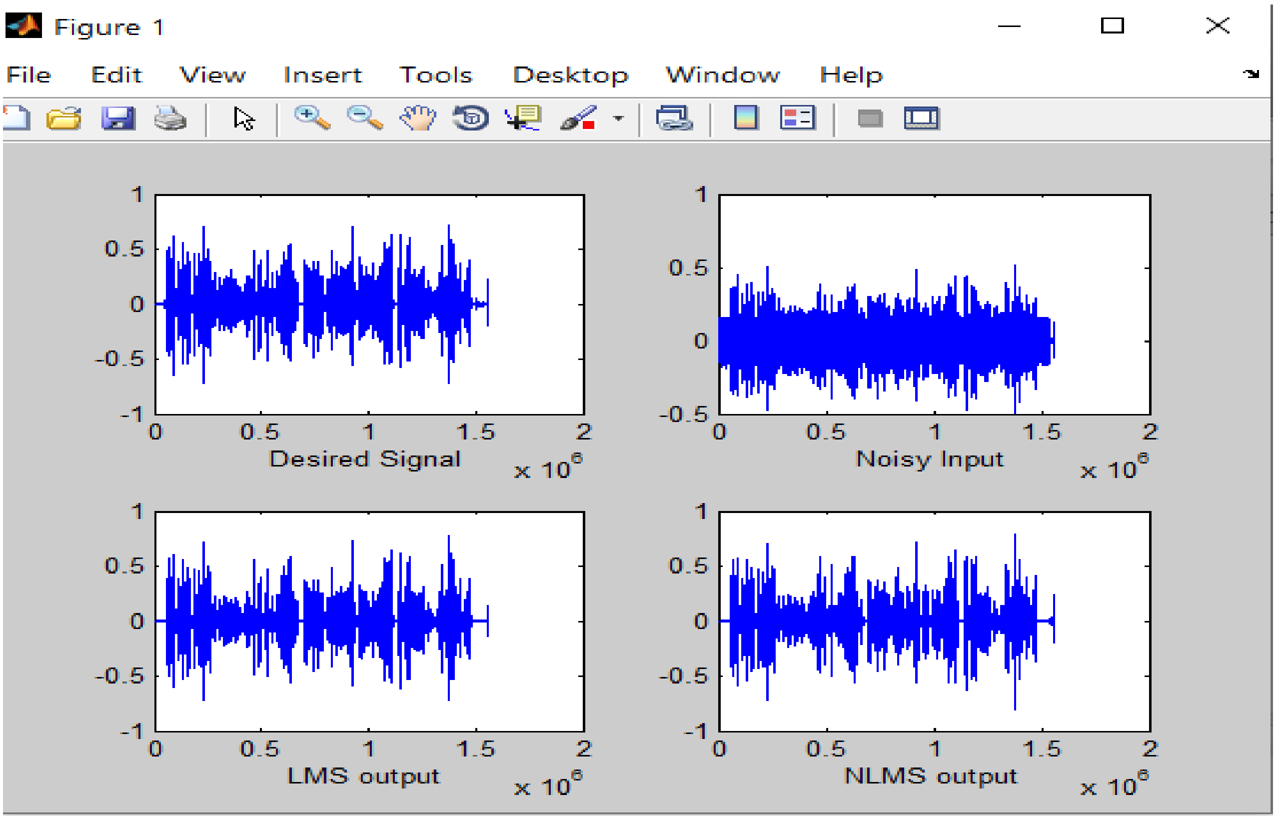

Figure 4.11: (White + pink) noise effect .

IV.4.8. Persons influence :

In this experiment, we evaluated the effect of persons on the measurement.

D=8m , Filter length =100 , step size = 0.1

Table 4.8: persons effect on the measure.

	SNR(db)	
Number of persons	**LMS**	**NLMS**
1	**13.82**	**14.52**
3	**9.32**	**9.34**
5	**Nan**	**6.55**

The table (4.8) shows that the number of persons has a significant impact on the performance of the LMS algorithm, but a relatively small impact on the performance of the NLMS algorithm.

For the LMS algorithm, the SNR decreases as the number of persons increases. This is because the LMS algorithm is more sensitive to the number of noise sources. The more noise sources there are, the more difficult it is for the LMS algorithm to distinguish the desired signal from the noise.

For the NLMS algorithm, the SNR also decreases as the number of persons increases, but the decrease is less pronounced. This is because the NLMS algorithm is better at adapting to the noise statistics, even when there are multiple noise sources.

At a number of persons of 5, the NLMS algorithm still achieves an SNR of 6.55 dB, while the LMS algorithm fails to converge. This shows that the NLMS algorithm is a better choice for noise cancellation applications where the number of noise sources is high

And in figure 4.12 we find the snr of lms in the case of 5 person effect NAN This instability is likely due to the increased complexity of the speech signal, which makes it more difficult for the LMS algorithm to accurately estimate the desired signal.

The NLMS algorithm is able to handle the increased complexity of the speech signal and maintains stability even with 5 persons making conversation. This is because the NLMS algorithm normalizes the step size by the power of the input signal, which helps to reduce the impact of noise and interference on the filter coefficients. As a result, the NLMS algorithm is able to better track the desired signal and provide a higher SNR even in challenging scenarios.

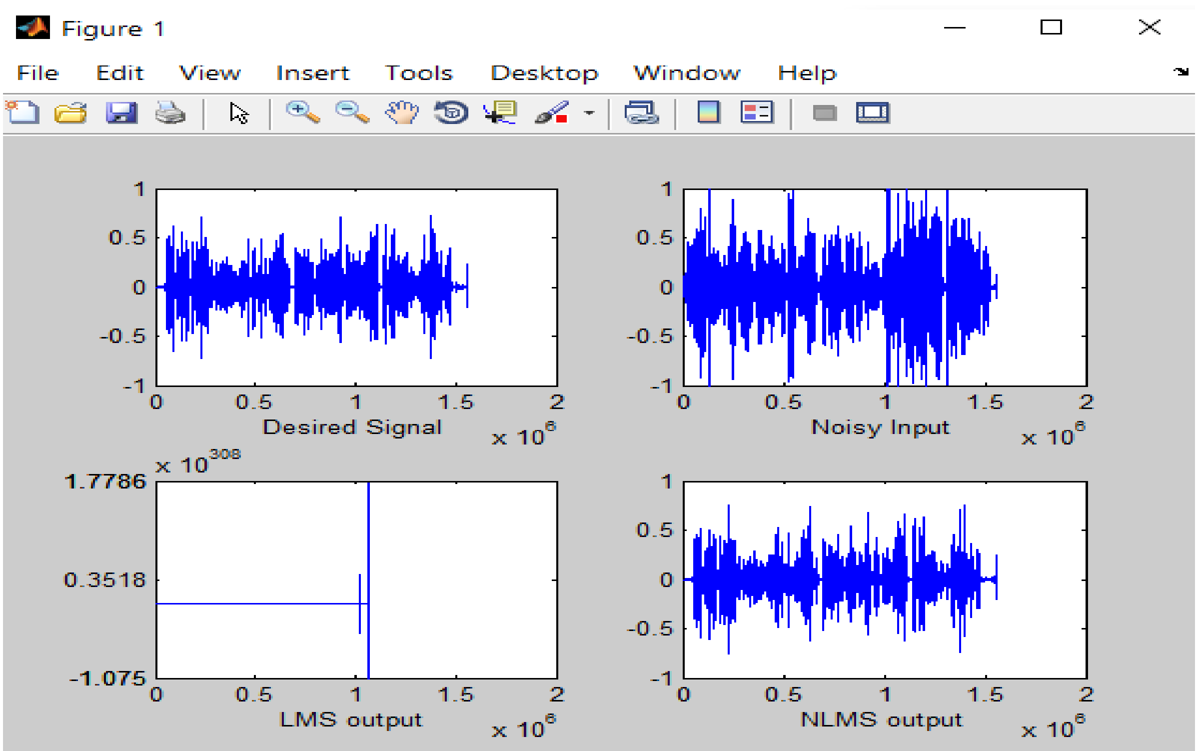

Figure 4.12: persons effect (5 persons).

IV.4.9. Input signal influence:

In this experiment, we evaluated the effect of persons plus noise on the measurement.

D=8m , Filter length =100 , step size = 0.1 , noise magnitude = 0.1 , 3P = 3 person

Table 4.9: Input signal effect on the measure.

	SNR(db)	
Input signal	**LMS**	**NLMS**
3P +white noise	**7.28**	**7.88**
3P +pink noise	**8.54**	**9.52**
3P +white +pink	**7.08**	**7.64**

The table (4.9) shows how the composition of the input signal, which includes the presence of three persons and different types of noise (white noise, pink noise, and a combination of both), affects the performance of two algorithms, LMS and NLMS .

3 Persons + White Noise: NLMS has a slightly higher SNR (7.88 dB) compared to LMS (7.28 dB), indicating that NLMS performs slightly better.

3 Persons + Pink Noise: The performance NlMS algorithm is better with an SNR of 9.52 dB. while LMS at 8.54 dB .

3 Persons + White Noise + Pink Noise: NLMS performs slightly better with an SNR of 7.64 dB, while LMS achieves an SNR of 6.64 dB.

Overall, the NLMS algorithm is better than the LMS in the 3 cases .

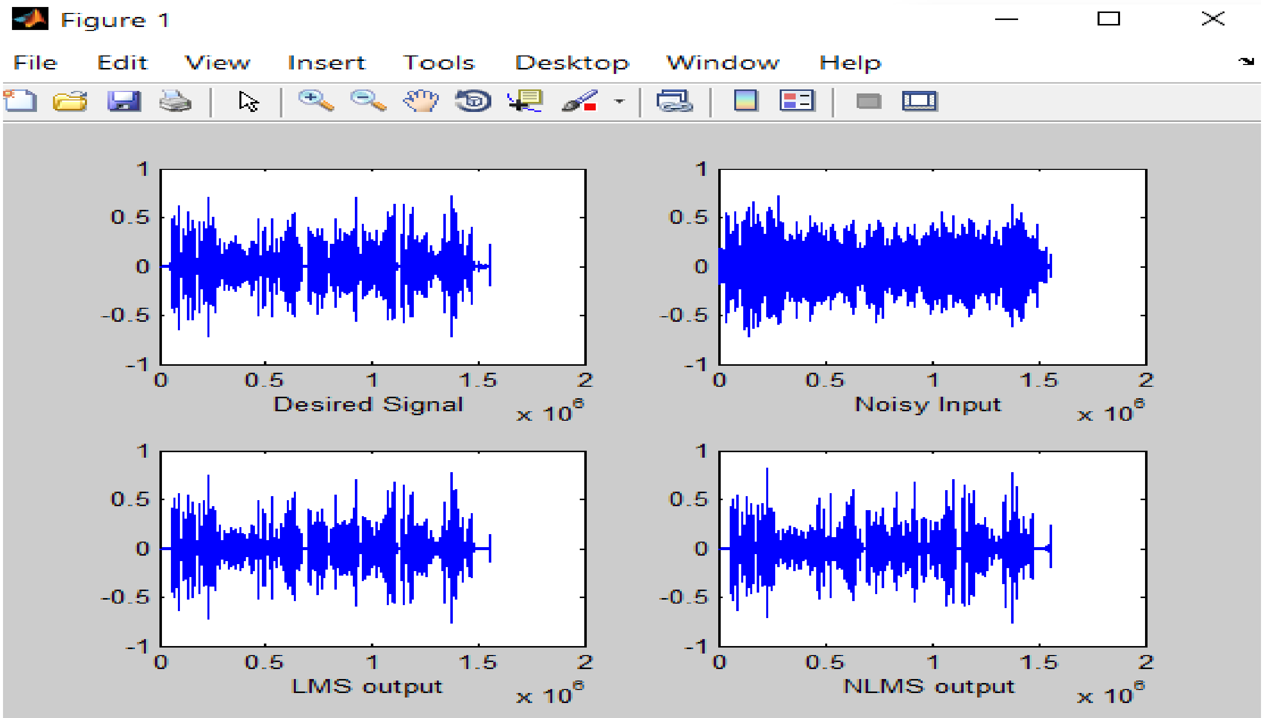

Figure 4.12: 3 persons + (white + pink) noise .

Conclusion :

In general, the NLMS algorithm is preferred over the LMS algorithm for noise reduction applications where the noise level is not constant or where there are sudden changes in the signal characteristics.

However, the LMS algorithm is still widely used due to its simplicity and computational efficiency. The choice between LMS and NLMS depends on the specific application requirements and constraints. If noise reduction is critical and the signal characteristics are variable, NLMS is the better choice. However, if simplicity and computational efficiency are paramount, LMS may be a suitable option.

General Conclusion :

Acoustic noise cancellation is a problem that arises in aircraft. The main difficulties encountered are linked, on the one hand, to the duration of the impulse responses of the acoustic channels to be identified and, on the other hand, to the nature of the signals to be processed.

In this thesis, we have cited the various classical adaptive algorithms frequently applied in the field of acoustic noise cancellation, i.e. algorithms based on the stochastic gradient method (Least Mean Squares) LMS and NLMS, and as our research objective is the cancellation of acoustic noise in the cockpit that bothers users and reduces the quality of communication.

Our work is based on the study and simulation of the NLMS and LMS stochastic gradient-type adaptive algorithm, in order to evaluate its capabilities in terms of noise cancellation and its convergence speed with different input signals. In the simulation part using MATLAB software, the results obtained showed that the adaptive algorithm studied (NLMS and LMS) succeeded in attenuating the noise contained in the useful signal, and gave good performances such as convergence speed and minimum distortion of the useful signal at the output of the processing.

We find that the NLMS algorithm is better than LMS algorithm in our different cases of measure.

We also found that the main drawback of this algorithm is its dependence on the nature of the input signal, since the degradation in performance of the NLMS and LMS algorithms is due to non-stationarities in the speech signal.

Future work which may follow on from this is to improve other, more precise algorithms such as RLS or the non-parametric variable-step NLMS algorithm.

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