Resolution Test Chart Labels:

- 1.0
- 1.1
- 1.25
- 1.4
- 1.6
- 1.8
- 2.0
- 2.2
- 2.5
- 2.8
- 3.0
- 3.2
- 3.6
- 4.0

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Background Acoustic Noise Suppression In Mobile Telephony

**by
Robert Hebert, B. Eng. (Electrical)**

**A thesis submitted to the
Faculty of Graduate Studies and Research
in partial fulfillment of the requirements
for the degree of
Master of Engineering**

**Ottawa-Carleton Institute for Electrical Engineering
Faculty of Engineering
Department of Systems and Computer Engineering
Carleton University
Ottawa, Ontario
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The undersigned recommend to the Faculty of
Graduate Studies and Research acceptance of the thesis

**“Background Acoustic Noise
Suppression In Mobile Telephony”**

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in partial fulfillment of the requirements
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Abstract

This thesis investigates the background acoustic noise suppression in mobile telephony. Experimental background acoustic noise is obtained using a medium size car. Various driving conditions representing the normal use of a medium size car provides a good variety of noise samples for an in depth analysis. A wide variety of samples are obtained by strategically locating each microphone in the car. The problem's solution aims at analyzing a hands free telephony system where the speaker is away from the microphone.

A qualitative noise model is developed for ease of system's optimization. Based on the model, an in depth noise analysis is carried through in both the time and frequency domain. It shows under specific driving conditions how the various locations interact with the speaker's microphone (primary).

As a result of the background acoustic noise analysis, a 2 microphone adaptive noise canceller (ANC) is introduced using sub-band adaptation. Offering at least 11 dB signal to noise ratio (SNR) improvement for all driving conditions. This one solves the "part band" noise enhancement problem associated with existing ANC. In light of these results, the investigation towards a more efficient ANC structure goes further. Two 4 microphone ANC structures are proposed using a beamformer (BF) like approach. Each respective structure offers 12 dB and 15 dB SNR improvement without yielding any part band noise enhancement. Concluding results are obtained from experimental car background acoustic noise throughout the thesis. These emphasize the validity and the efficiency of the proposed structures.

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List of Acronyms

ANC : adaptive noise canceller
A/D : analog to digital converter
BLS : block least square
BF : beamformer
cm : centimeter
dB : decibel
DC/AC : direct current to alternative current
ef : efficiency factor
EM : estimate maximize
FIR : finite impulse response
Hz : hertz
K : kilo
KHz : kilohertz
KLT : Karhunen-Loeve Transform
Km/hr : kilometer per hour
LMS : least mean square
LPC : linear predictive coder
LS : least square
mic : microphone
MIMO : multiple input multiple output
nmse : minimum mean square error
mse : mean square error
msec : millisecond
PSD : power spectrum density
RLS : recursive least square

SNR : signal to noise ratio

Chapter 1 Introduction

1.1 Background.

In mobile telephony, background acoustic noise degrades the performance of voice communications. The major sources contributing to background acoustic noise are shown in figure 1.1. They consist of street noise, road noise, engine, fan motor, air flow, vibration and man made noise [1,2].

Figure 1.1 Major Sources of Background Acoustic Noise in a Car

The background acoustic noise is also a major problem in voice/data integrated systems [1,2,29,31]. The problem is more serious in a hands-free telephony system where the distance between the speaker and the microphone is relatively large [2,20,26].

1.2 Proposed Solutions.

Many approaches have been proposed for reducing the background acoustic noise. A noise suppression system may include one or several of these methods. The most common solutions are described in the following subsections.

1.2.1 Types of Microphone Used.

In mobile telephony, background acoustic noise comes from all directions while the noise, the speech comes from a specific area. An omnidirectional microphone picks up the speech as well as most of the background acoustic noise. The use of unidirectional microphones limits the capture of background acoustic noise to the area to which the microphone is pointing. It has been shown that, in some cases the use of these microphones can provide up to 4.8 dB signal to noise ratio (SNR) improvement over the omnidirectional family [26].

1.2.2 Speech Estimation.

Given a noisy speech signal, one can discriminate between the speech and the noise by making use of a speech model. The model is based on the quasi stationarity property of speech. The aim is to extract the speech parameters from the corrupted signal using only one microphone. The system then attempts to reconstruct the speech signal free of noise. An example of this approach is the well known Linear Predictive Coder (LPC). In this case, the system first estimates the pitch period. Then it estimates the speech

vocal tract characteristics [3,8,13,14,18,64]. This technique has shown a signal to noise ratio (SNR) improvement of up to 7 dB in a 0 dB environment [45].

This approach has proved suitable in removing the cocktail party effect [27]. In this case, the aim is to isolate one speaker out of many. This is done by evaluating the pitch of the desired person. Then, the speech parameters pertaining to the pitch of interest are extracted.

1.2.3 Noise Estimation.

Another approach is to make use of a noise model. The technique is composed of two steps. First, it estimates the noise, then subtract the estimated noise from the noisy signal. Many techniques stem from this approach. They can be divided in two categories:

- (i) a single microphone system; and
- (ii) a multiple microphones systems.

The following methods make use of the noise model:

1.2.3.1 Single Microphone. This method works only if the noise is stationary i.e. its characteristics do not vary with time. During speechless periods, the system evaluates the background acoustic noise. When the speech becomes active, the estimated noise is subtracted from the noisy speech. In most cases, the noise is composed of specific frequency components. The aim of the system is to find these frequency components. The system then places some nulls at their frequency locations.

As mentioned in [31], the problem associated with this technique is the result of an annoying musical tone effect. Obviously, this technique is not suitable for rapid time variant noise. Hence, it does not seem to be adequate for a mobile telephony system.

1.2.3.2 Use of Multiple Microphones For Uncorrelated Noise Removal. It is a well known fact that there exist some uncorrelated background acoustic noise in a mobile telephony system. In [26], a solution for removing the uncorrelated noise is proposed. A system consisting of an array of microphones disposed around the speech source is shown in figure 1.2. The concept is simple. By knowing the exact location of the speaker with respect to each microphone, delays are inserted at each microphone so that the various speech samples are added coherently. Since every noise sample is uncorrelated with one another, adding N samples and dividing the results by N should average out the noise. By inspection, it is clear that this method tends to limit the noise level to its mean without affecting the speech. For a zero mean background acoustic noise process, the technique can be very effective. As indicated in [26], it provides some background noise attenuation and it seems efficient for reducing the uncorrelated noise. However, the problem lies in accurately estimating the speaker position with respect to each microphone.

1.2.3.3 Use of Multiple Microphone For Correlated Noise Removal. Another approach makes use of the noise correlation. This approach is the back bone of this thesis research. It is discussed well in the literature [2,4,26,69]. Figure 1.3 shows the configuration process. This technique compares background acoustic noise ($n_r(t)$) observed at the reference locations with that observed at the primary location ($n_p(t)$). Using $n_r(t)$ it tries to estimate a transfer function $\underline{W}(t)$ which would best reproduce the noise at the primary $n_p(t)$. The transfer function $\underline{W}(t)$ is then optimized using the error $e(t)$ i.e. the difference between the actual noise at the primary $n_p(t)$ and its estimate $\hat{n}_p(t)$.

Experimental results were obtained from tests performed on a medium size car [2,69]. In general, the ANC provides good noise attenuation in the lower end of the acoustic band to the detriment of the upper acoustic band [2,26,69]. Figure 1.4 shows

Figure 1.2 Noise Canceller Using an Array of Microphones

the result of a 2 microphone ANC. Note that the lower band noise (below 1.5 KHz) is suppressed considerably. However the upper band noise is enhanced. As mentioned earlier, this is true for every ANC used in mobile telephony [2,26,69].

Sub-band adaptation partially overcome this problem [2,28,69]. The acoustic band is split in two bands: the lower (below 1.5 KHz) and the upper (above 1.5 KHz). Figures 1.5 and 1.6 show the existence of a certain degree of correlation between the two points

Figure 1.3 Adaptive Noise Canceller Using Correlated Noise

of observation. This indicates that adaptation can be performed independently over each band. Hence, two adaptive noise cancellers are needed, one for each band.

Figure 1.7 shows the result of lower band adaptation. Obviously good noise cancellation is achieved in the lower band without affecting the upper band. Figure 1.8 shows the result of upper band adaptation. Here, noise suppression takes place in the upper band without affecting the lower band. Figure 1.9 shows the combined effect of upper and lower band adaptation.

1.3 Thesis' Aim

The aim of the thesis is to investigate the use of two or more microphones for cancelling the background acoustic noise in a medium size car. This must be achieved without enhancing the background acoustic noise of any part of the acoustic band. The basic concept makes use of the correlated noise which exists between various locations in a car environment.

Car Speed 60 Km/hr, Fan Off, Microphone # 2 (Under the Steering Wheel)

Figure 1.4 Adaptation Using a Two Microphone ANC; Filtered Output :-+-

1.4 Thesis Organization

The thesis is organized in 7 chapters. Chapter 2 proposes a qualitative noise model which theoretically supports any adaptive noise canceller (ANC) system. Chapter 3 covers the recording setup and testing conditions under which the data was acquired. Chapter 4 deals with the data analysis. Chapter 5 covers the use of a two microphone noise cancellation system. Chapter 6 proposes a parallel approach for the use of more than 2 microphone ANC. Some structures as well as their results are presented. Chapter 7 concludes with a discussion of the results, and further research.

Car Speed 60 Km/hr, Fan Off, Microphone # 2 (Under the Steering Wheel)

Figure 1.5 Lower Band Cross-Correlation Between Location # 2 and the Primary Location (at the Steering Wheel)

Car Speed 60 Km/hr, Fan Off, Microphone # 2 (Under the Steering Wheel)

Figure 1.6 Upper Band Cross-Correlation Between Location # 2 and the Primary Location (at the Steering Wheel)

Car Speed 60 Km/hr, Fan Off, Microphone # 2 (Under the Steering Wheel)

Figure 1.7 Lower Band Adaptation Using a 2 Microphone ANC; Filtered Output :-+-

Car Speed 60 Km/hr, Fan Off, Microphone # 2 (Under the Steering Wheel)

Figure 1.8 Upper Band Adaptation Using a 2 Microphone ANC; Filtered Output :-+-

Car Speed 60 Km/hr, Fan Off, Microphone # 2 (Under the Steering Wheel)

Figure 1.9 Lower and Upper Band Adaptation
Using a 2 Microphone ANC; Filtered Output :-+

Chapter 2 Noise Model

2.1 Introduction

Background acoustic noise in cars is composed of many noise sources. The sources originate from outside and within the car cabin [1,2,69]. They can be classified as localized or distributed processes. The major outside noise processes come from the air flow, the street, the engine, the road and, the fan motor. The interior noise come from the fan air blowing, the echo, the vibration and, the passenger.

Unfortunately, each noise process has particular characteristics (or properties) [1,2,10,21]. Let's consider a noise source and two arbitrary observation points in the car. There are three transfer functions governing the propagation of noise from the source to the two observation point as shown in figure 2.1. They are as followed:

$A(z)$: from the source to the primary observation point;

$H(z)$: from the source to the secondary observation point; and

$HA(z)$: from the secondary to the primary.

δ_1 and δ_2 are the propagation delays from the source to the primary and secondary point, respectively.

The model shown in figure 2.1 can be generalized to a multi-noise sources model; but, because of the noise characteristics complexity, the noise model can only be a

Figure 2.1 Transfer Functions Existing Between 2 Locations

qualitative representation of the actual system. However, it does provide some insights with regard to system's optimization.

This chapter is divided in 3 parts. The first part discusses the different types of noises and some of their properties. The second part establishes the concept of multi-noise processes interacting within the car system, and, the third part shows what minimum constraints on the model must be met in order for the noise cancellation to be feasible.

2.2 Type of Noise Sources and Their Properties.

The noise processes can be classified as being localized or distributed [1,2,69]. A localized noise source is generated from a specific area. It can be seen as a point source. As shown in figure 2.2 a simple transfer function separates the noise source from an

localized noise

Figure 2.2 Localized Noise Configuration

observation point. This function depends on the distance and the media located between the two points.

A distributed noise source comes from a wide area. An example of this is the air flow on and around the car. As shown in figure 2.3, it can be represented by many transfer functions linking all the point sources to the observation point. This explains the complexity associated with this type of noise.

In general, the complexity of the transfer function linking two points increases with the distance and the type of material separating them. Therefore in a multi-noise source system (or in the presence of distributed noise), the microphones should be located close to each other for the model to be valid

2.3 Generalized Noise Model

In this section, the aim is to establish a general mathematical noise model which qualitatively represents the car background acoustic noise. This model will then help in finding ways for optimizing any ANC. The proposed model consists of k noise sources, m reference microphones, a speech source and a primary microphone as shown in figure 2.4 [20,21].

distributed noise

Figure 2.3 Distributed Noise Configuration

It is assumed that every transfer function can be approximated by a finite impulse responses (FIRs) of length N . This allows the use of linear regression for estimating the transfer functions [58–62]. In figure 2.4., the speech goes through a transfer function $\underline{A}(t)$ before reaching the primary. Simultaneously, the speech goes through m transfer functions ($\underline{B}_i(t)$; $i=1$ to m) prior to reaching the m references. The k noise sources go through k transfer functions $\underline{C}_j(t)$ prior to reaching the primary. These same k noise sources go through k different transfer function ($\underline{D}_{ij}(t)$) prior to reaching each of the m references. At the primary $e(t)$ and $e_j(t)$ at the j^{th} reference, are errors added which compensate for any unaccounted process and for the non-linearity part of the noise processes.

One must remember that the ANC aim is to estimate the noise at the primary using the observed noise at the reference microphones. As a logical step, the observed processes at the primary and at the references should be defined in term of the noise sources. Hence, as shown in figure 2.4. the primary output is composed of transformed speech and noise processes.

$$\mathbf{x}(t) = \underline{\mathbf{s}}^T(t) \underline{\mathbf{A}}(t) + \underline{\mathbf{n}}^T(t) \underline{\mathbf{C}}^T(t) + \mathbf{e}_x(t) \quad (2.1)$$

Figure 2.4 Multiple Input Multiple Output Noise System Configuration

where $\underline{s}(t)$ is a $N \times 1$ vector composed of the N last speech samples

$$\underline{s}(t) = [s(t) \ s(t-1) \ \dots \ s(t-N+1)]^T \quad (2.2)$$

$\underline{A}(t)$ is a transfer function of length N . It transforms the speech prior to its capture by the primary.

$$\underline{A}(t) = [a(t) \ a(t-1) \ \dots \ a(t-N+1)]^T \quad (2.3)$$

$\underline{n}(t)$ represents the k noise vectors of size $(N \times 1)$ consecutively disposed in a $kN \times 1$ vector. Each $N \times 1$ noise vector is composed of the last N observations of each noise source.

$$\underline{n}(t) = \begin{bmatrix} \underline{n}_1(t) \\ \underline{n}_2(t) \\ \cdot \\ \cdot \\ \cdot \\ \underline{n}_k(t) \end{bmatrix} \quad (2.4)$$

where

$$\underline{n}_i(t) = [n_i(t) \ n_i(t-1) \dots n_i(t-N+1)]^T \quad (2.5)$$

$\underline{C}(t)$ is $kN \times 1$ vector. It is composed of k vectors (FIR) of dimension $N \times 1$ each. The i^{th} $N \times 1$ vector $\underline{C}_i(t)$, transforms the i^{th} noise source vector $\underline{n}_i(t)$

$$\underline{C}(t) = \begin{bmatrix} \underline{C}_1(t) \\ \underline{C}_2(t) \\ \cdot \\ \cdot \\ \cdot \\ \underline{C}_k(t) \end{bmatrix} \quad (2.6)$$

where

$$\underline{C}_i(t) = [C_i(t) \ C_i(t-1) \dots C_i(t-N+1)]^T \quad (2.7)$$

The observed signal at the j^{th} reference is given by

$$y_j(t) = \underline{s}^T(t) \underline{B}_j(t) + \underline{n}^T(t) \underline{D}_j^T(t) + e_{yj}(t) \quad (2.8)$$

where $\underline{s}(t)$ has been previously defined, $\underline{B}_j(t)$ is $N \times 1$ FIR vector. It transforms the speech sequence prior to its capture by the j^{th} reference microphone.

$$\underline{B}_j(t) = [b_j(t) \ b_j(t-1) \ \dots \ b_j(t-N+1)]^T \quad (2.9)$$

$\underline{D}_j(t)$ is a $kN \times 1$ vector composed of k FIRs of length N sequentially disposed. This vector transforms the k noise source sequences disposed in $\underline{n}(t)$ prior to their capture by the j^{th} reference microphone.

$$\underline{D}_j(t) = \begin{bmatrix} \underline{d}_{1j}(t) \\ \underline{d}_{2j}(t) \\ \cdot \\ \cdot \\ \cdot \\ \underline{d}_{kj}(t) \end{bmatrix} \quad (2.10)$$

where $\underline{d}_{ij}(t)$ is a $N \times 1$ FIR vector. It transforms the i^{th} noise source sequence $\underline{n}_i(t)$ prior to its capture by the j^{th} reference microphone.

$$\underline{d}_{ij}(t) = [d_{ij}(t) \ d_{ij}(t-1) \ \dots \ d_{ij}(t-N+1)]^T \quad (2.11)$$

The ANC uses a sequence of N observations from each reference microphone. It then compares it with the primary signal. Therefore, a $N \times 1$ vector representing a sequence of N observations is defined for each reference. Hence for the j^{th} reference microphone

$$\underline{y}_j(t) = [y_j(t) \ y_j(t-1) \ \dots \ y_j(t-N+1)]^T \quad (2.12)$$

Further, it is more convenient to define an observation matrix of dimension $N \times m$ which is represented by

$$\mathbf{Y}(t) = [\underline{y}_1(t) \ \underline{y}_2(t) \ \dots \ \underline{y}_m(t)] \quad (2.13)$$

In order to clearly define the system's limitations and to ease analytical derivations, only one reference microphone is considered. Also, it is assumed that the ANC adapts during speechless period only. This was suggested in [5]. Therefore, the system's equations are simplified. At the primary, the observed noise process is obtained using equation (2.1) by setting $\underline{s}(t) = 0$.

$$\mathbf{x}(t) = \underline{\mathbf{n}}^T(t) \underline{\mathbf{C}}^T(t) + \mathbf{e}_x(t) \quad (2.14)$$

at the reference, the N sample sequence of the noise process is obtained using (2.8) in (2.12)

$$\underline{\mathbf{y}}(t) = \begin{bmatrix} \underline{\mathbf{n}}^T(t) \underline{\mathbf{D}} \\ \underline{\mathbf{n}}^T(t-1) \underline{\mathbf{D}} \\ \vdots \\ \vdots \\ \underline{\mathbf{n}}^T(t-N+1) \underline{\mathbf{D}} \end{bmatrix} + \underline{\mathbf{e}}_y(t) \quad (2.15)$$

$$= \underline{\mathbf{N}}(t) + \underline{\mathbf{e}}_y(t) \quad (2.16)$$

where

$$\underline{N}(t) = \begin{bmatrix} \underline{n}^T(t) \underline{D} \\ \underline{n}^T(t-1) \underline{D} \\ \vdots \\ \vdots \\ \vdots \\ \underline{n}^T(t-N+1) \underline{D} \end{bmatrix} \quad (2.17)$$

and $\underline{e}_y(t)$ is a $N \times 1$ sequence of the N last approximation errors of $y(t)$. This error is assumed to be an independent random process with zero mean and variance σ_{ey}^2 .

The linear regression concept states that there exists a linear combination of the N last observations at the reference microphone such that it can reproduce $x(t)$, the observed noise process at the primary. For doing so, a $N \times 1$ vector $\underline{W}(t)$ is defined. Hence the desired signal estimation (the primary signal) is

$$\tilde{x}(t) = \underline{y}^T(t) \underline{W}(t) \quad (2.18)$$

the estimation error is the difference between the actual signal $x(t)$ and its estimate $\tilde{x}(t)$

$$e(t) = x(t) - \tilde{x}(t) \quad (2.19)$$

The aim of linear regression is to minimize the estimation error in a mean square sense. This is done with respect to the transfer function coefficients $\underline{W}(t)$. Hence the mean square error (mse) is obtained by squaring (2.19) and by taking the expectation on both side of the resulting equation.

$$\text{mse} = E[e^2(t)] = E[x^2(t) - 2x(t) \tilde{x}(t) + \tilde{x}^2(t)] \quad (2.20)$$

$$= E[x^2(t)] - 2E[x(t)\hat{x}(t)] + E[\hat{x}^2(t)] \quad (2.21)$$

For ease of analysis, it is assumed that every transfer function are constant over the period of observation. Hence the transfer functions are independent of time and are not affected by the expectation operator. Substituting (2.14), (2.16) and, (2.18) in (2.21), the mse is now expressed in term of the noise processes.

$$\begin{aligned} \text{mse} = & \underline{C}^T E[\underline{n}(t) \underline{n}^T(t)] \underline{C} + 2\underline{C}^T E[\underline{n}(t) \underline{e}_x(t)] + E[e_x^2(t)] \\ & - 2\underline{C}^T E[\underline{n}(t) \underline{N}^T(t)] \underline{W} - 2E[e_x(t) \underline{N}^T(t)] \underline{W} \\ & - 2E[e_x(t) \underline{e}_y(t)] \underline{W} + \underline{W}^T(t) E[\underline{N}(t) \underline{N}^T(t)] \underline{W} \\ & + 2\underline{W}^T E[\underline{e}_y(t) \underline{N}^T(t)] \underline{W} + \underline{W}^T E[\underline{e}_y(t) \underline{e}_y^T(t)] \underline{W} \end{aligned} \quad (2.22)$$

As stated earlier, $e_x(t)$ and $e_y(t)$ are independent random processes with zero mean and respective variance σ_{ex}^2 and σ_{ey}^2 . Hence the mse becomes

$$\begin{aligned} \text{mse} = & \underline{C}^T E[\underline{n}(t) \underline{n}^T(t)] \underline{C} + \sigma_{ex}^2 - 2 \underline{C}^T E[\underline{n}(t) \underline{N}^T(t)] \underline{W} \\ & + \underline{W}^T(t) E[\underline{N}(t) \underline{N}^T(t)] \underline{W} + \underline{W}^T E[\underline{e}_y(t) \underline{e}_y^T(t)] \underline{W} \end{aligned} \quad (2.23)$$

where $E[\underline{n}(t) \underline{n}^T(t)]$ is the autocorrelation of the noise processes vector. Assuming that each noise process has zero mean and that they are independent from one another, the autocorrelation of the noise becomes

$$E[\underline{n}(t) \underline{n}^T(t)] = R_n(0) = \begin{bmatrix} R_{n_1}(0) & 0 & . & . & . & 0 \\ 0 & R_{n_2}(0) & & & & . \\ . & & . & & & . \\ . & & & . & & . \\ . & & & & . & 0 \\ 0 & . & . & . & 0 & R_{n_k}(0) \end{bmatrix} \quad (2.24)$$

where

$$\mathbf{R}_{n_i}(0) = \begin{bmatrix} \mathbf{E}[n_i^2(t)] & \mathbf{E}[n_i(t) n_i(t-1)] & \dots & \mathbf{E}[n_i(t) n_i(t-N+1)] \\ \mathbf{E}[n_i(t-1) n_i(t)] & \mathbf{E}[n_i^2(t-1)] & & \cdot \\ \cdot & & \cdot & \cdot \\ \cdot & & \cdot & \cdot \\ \mathbf{E}[n_i(t-N+1) n_i(t)] & & \cdot & \mathbf{E}[n_i^2(t-N+1)] \end{bmatrix} \quad (2.25)$$

$\mathbf{E}[\underline{\mathbf{N}}(t)\underline{\mathbf{N}}^T(t)]$ is the autocorrelation of the noise process observed at the reference.

$$\mathbf{R} = \mathbf{E}[\underline{\mathbf{N}}(t) \underline{\mathbf{N}}^T(t)] = \mathbf{E} \left\{ \begin{bmatrix} \underline{\mathbf{D}}^T(t) \underline{\mathbf{n}}(t) \\ \underline{\mathbf{D}}^T(t) \underline{\mathbf{n}}(t-1) \\ \cdot \\ \cdot \\ \underline{\mathbf{D}}^T(t) \underline{\mathbf{n}}(t-N+1) \end{bmatrix} \begin{bmatrix} \underline{\mathbf{n}}^T(t) \underline{\mathbf{D}} & \underline{\mathbf{n}}^T(t-1) \underline{\mathbf{D}} & \dots & \underline{\mathbf{n}}^T(t-N+1) \underline{\mathbf{D}} \end{bmatrix} \right\} \quad (2.26)$$

$$\mathbf{R} = \begin{bmatrix} \underline{\mathbf{D}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} & \underline{\mathbf{D}}^T \mathbf{R}_n(1) \underline{\mathbf{D}} & \dots & \underline{\mathbf{D}}^T \mathbf{R}_n(N-1) \underline{\mathbf{D}} \\ \underline{\mathbf{D}}^T \mathbf{R}_n(1) \underline{\mathbf{D}} & \underline{\mathbf{D}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} & & \cdot \\ \cdot & & \cdot & \cdot \\ \cdot & & \cdot & \cdot \\ \underline{\mathbf{D}}^T \mathbf{R}_n(N-1) \underline{\mathbf{D}} & & \cdot & \underline{\mathbf{D}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} \end{bmatrix} \quad (2.27)$$

where

$$\mathbf{R}_n(i) = \mathbf{E}[\mathbf{n}(t) \mathbf{n}^T(t-i)] \quad (2.28)$$

$\underline{\mathbf{C}}^T \mathbf{E}[\mathbf{n}(t) \mathbf{N}^T(t)]$ is the cross-correlation between the primary and the reference microphones with respect to the noise sources. A vector $\underline{\mathbf{p}}$ representing the cross-correlation is defined

$$\underline{\mathbf{p}} = \underline{\mathbf{C}}^T \mathbf{E}[\mathbf{n}(t) \mathbf{N}^T(t)] \quad (2.29)$$

$$\underline{\mathbf{p}} = \underline{\mathbf{C}}^T \mathbf{E}\left\{\mathbf{n}(t) [\mathbf{n}^T(t) \underline{\mathbf{D}} \quad \mathbf{n}^T(t-1) \underline{\mathbf{D}} \quad \dots \quad \mathbf{n}^T(t-N+1) \underline{\mathbf{D}}]^T\right\} \quad (2.30)$$

Substituting equations (2.28) in (2.30), the cross-correlation $\underline{\mathbf{p}}$ becomes

$$\underline{\mathbf{p}} = \begin{bmatrix} \underline{\mathbf{C}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} \\ \underline{\mathbf{C}}^T \mathbf{R}_n(1) \underline{\mathbf{D}} \\ \vdots \\ \underline{\mathbf{C}}^T \mathbf{R}_n(N-1) \underline{\mathbf{D}} \end{bmatrix} \quad (2.31)$$

$\mathbf{E}[\underline{\mathbf{e}}_y(t) \underline{\mathbf{e}}_y^T(t)]$ is the autocorrelation matrix of the approximation sequence error at the reference microphone. Using $\underline{\mathbf{e}}_y(t)$'s properties, the autocorrelation becomes

$$\mathbf{R}_{\underline{\mathbf{e}}_y} = \mathbf{E}[\underline{\mathbf{e}}_y(t) \underline{\mathbf{e}}_y^T(t)] = \sigma_{\underline{\mathbf{e}}_y}^2 \mathbf{I} \quad (2.32)$$

where $\mathbf{I}$ is an $N \times N$ identity matrix.

The mse may now be expressed in a more compressed form. Substituting equations (2.24), (2.26), (2.29) and, (2.32) in (2.23), the mse is

$$\text{mse} = \underline{\mathbf{C}}^T \mathbf{R}_n(0) \underline{\mathbf{C}} + \sigma_{\text{ex}}^2 - 2 \underline{\mathbf{p}}^T \underline{\mathbf{W}} + \underline{\mathbf{W}}^T \underline{\mathbf{R}} \underline{\mathbf{W}} + \underline{\mathbf{W}}^T \mathbf{R}_{\text{cy}} \underline{\mathbf{W}} \quad (2.33)$$

Recall that the mse is strictly positive. As indicated in [13], the filter coefficients $\underline{\mathbf{W}}(t)$ has the shape of a hyperbolic function facing upward. The limits of that function is the mean square error obtained for a particular $\underline{\mathbf{W}}(t)$. The bottom of the function coincides with the minimum mean square error (mmse). Hence, this point is obtained by using the optimum filter coefficients $\underline{\mathbf{W}}_{\text{opt}}$. The mmse is obtained by taking the partial derivative of (2.33) with respect to $\underline{\mathbf{W}}(t)$ and setting it to zero.

$$\frac{\delta \text{mse}}{\delta \underline{\mathbf{W}}} = -2 \underline{\mathbf{p}} + 2 \underline{\mathbf{R}} \underline{\mathbf{W}}_{\text{opt}} + 2 \mathbf{R}_{\text{cy}} \underline{\mathbf{W}}_{\text{opt}} = 0 \quad (2.34)$$

hence

$$(\underline{\mathbf{R}} + \mathbf{R}_{\text{ey}}) \underline{\mathbf{W}}_{\text{opt}} = \underline{\mathbf{p}} \quad (2.35)$$

(2.35) is the well known Wiener-Hopf equation [14]. By inspection, $\mathbf{R}_{\text{ey}}$ introduces a bias in the estimation. Obviously, the optimum solution should not take into account the effect of $\mathbf{R}_{\text{ey}}$. However this reinforce the fact that the approximation error $\mathbf{e}_y(t)$ constitute a limiting factor. Therefore any adaptive noise canceller (ANC) using linear regression, is limited by this factor. Assuming that the approximation error at the reference is small enough so that

$$\underline{\mathbf{R}} \gg \mathbf{R}_{\text{ey}} \quad (2.36)$$

then, (2.35) may be approximated to

$$\underline{\mathbf{R}} \underline{\mathbf{W}}_{\text{opt}} \approx \underline{\mathbf{p}} \quad (2.37)$$

Substituting (2.27) and (2.31) in (2.36)

$$\begin{aligned}
 & \begin{bmatrix} \underline{D}^T \mathbf{R}_n(0) \underline{D} & \underline{D}^T \mathbf{R}_n(1) \underline{D} & \dots & \underline{D}^T \mathbf{R}_n(N-1) \underline{D} \\ \underline{D}^T \mathbf{R}_n(1) \underline{D} & \underline{D}^T \mathbf{R}_n(0) \underline{D} & & \\ \vdots & & \ddots & \\ \underline{D}^T \mathbf{R}_n(N-1) \underline{D} & & & \underline{D}^T \mathbf{R}_n(0) \underline{D} \end{bmatrix} \underline{W}_{opt} \\
 &= \begin{bmatrix} \underline{C}^T \mathbf{R}_n(0) \underline{D} \\ \underline{C}^T \mathbf{R}_n(1) \underline{D} \\ \vdots \\ \underline{C}^T \mathbf{R}_n(N-1) \underline{D} \end{bmatrix} \quad (2.38)
 \end{aligned}$$

Equation (2.37) illustrates how the noise process observed at the reference microphone can be used to estimate the noise process at the primary. It is evident that $\underline{W}_{opt}$ bridges the gap which exists between the two transfer functions $\underline{C}$ and $\underline{D}$. The whole process is done using a sequence of N samples. This is the exact same length of the FIRs defined earlier.

2.4 Model Constraints for Successful Adaptive Noise Cancellation

The mathematical model described in the previous section provides a qualitative description of the background acoustic noise system. The concept of noise cancellation is based on the correlation that exists between the captured noise at the primary and those captured at the references [2-6,8,11,13,14,18,20,21,25,26,31,33,34,38,45,46,51,53,56,57,69]. First the transfer functions linking the references to the primary are

estimated. Then using these transfer functions, the estimated noise is subtracted from the primary. Figure 1.3. illustrates the concept of adaptation.

The adaptive noise cancellation system will not work if some minimum model constraints are not met. First the observed noise at the primary must be reconstructible by a linear combination of the observed noise at the references. This is the basis of linear regression. Second, the concept of causality must be met. For an observer sitting at the reference, the noise process must occur before the one at the primary. However, the system could be non-causal to some extent. As mentioned in [1], this can be overcome by adding a delay at the primary microphone. Also, if the process is periodic over a long time frame, this will compensate for non-causality. In that case, only the phase lag matter. As a minimum, if these two constraints are not met then, the adaptive noise cancellation is not feasible. It will be shown later how this problem can be alleviated by collocating the reference microphones with respect to the noise sources.

Chapter 3 Recording set up and Testing

3.1 Introduction

This chapter covers the recording setups and the testing conditions used during the data acquisition phase. The data analysis which is carried out in a later chapter depends entirely on this critical phase.

This chapter is divided into 4 parts. The first part describes the position of each microphone with respect to its system's contribution. The second part covers the entire equipment setup used throughout the data acquisition phase. In the third part, tests which validate the equipment accurately are briefly presented and discussed. The last part talks about the various driving conditions.

3.2 Microphone Locations

The selection of each microphone location is probably the most critical operation of the entire research. If badly selected, the noise analysis and hence any course of action stemming from it could lead to inconclusive results. In order to minimize the risk of error, some basic criteria regarding the microphones placement are defined. Chapter 2 established a noise model composed of many noise sources. The model is pertinent to the normal use of a car. Logically, the aim is to capture as many different noise processes as possible using the reference microphones. This would ensure that every noise process

perceived at the primary is at least observed at the references. Also, it is desirable to get an acoustic barrier between the primary and any of the reference microphones.

Another criterion is the placing of reference microphones as close as possible to the primary. Being in a multi-noise system, the complexity of the differential transfer function linking two points grows with the distance between them. Hence, minimizing this distance contributes to reducing the transfer function complexity between the primary and the reference [1,2,20,21,25,26,69].

The two criteria mentioned above are contradictory. On one hand, it is desired to acoustically isolate the various microphones. The isolation can be achieved by increasing the distance between the microphones. On the other hand, it is desired to place the microphones as close as possible to the primary. Therefore, the selection of the microphone locations is a trade-off between these two requirements.

Throughout every tests, omni-directional microphones are used. Figure 3.1 shows the microphone configuration is as follows.

Microphone # 1 (reference # 1) is located in the engine compartment. It is placed right next to the fire wall and the hood. Also microphone # 1 is collocated with the fan motor. Its main purpose is to pick up the engine noise while being free of the other processes especially speech. Its distance with respect to the primary is about 20 cm with both microphones facing in opposite directions.

Microphone # 2 (reference # 2) is located under the steering wheel in a small glove compartment. Being in an intermediate location between the engine compartment and the primary, it should have less noise than microphone # 1 which is located inside the engine compartment. By listening tests, it was found that when the background acoustic noise is low, speech can be coupled to microphone # 2, which is facing in an opposite direction with respect to the primary. A distance of about 20 cm separates it from the

Figure 3.1 Microphone Disposition During Field Tests

primary.

Microphone # 3 is placed under the driver floor mat. It should pick up any road noise. By being inside the cabin, its differential transfer function with respect to the primary is minimized. There is about 1 meter separating microphones # 3 and the primary.

Microphone # 4 is chosen for being the primary. The microphone is located at the steering wheel facing the driver. A distance of about 20 cm separates the speaker from the microphone.

3.3 Equipment Set Up

The same equipment is used in all tests. Figure 3.2 illustrates the equipment setup. The microphones output are fed through a pre-amplifier to an 8 track tape recorder. The pre-amplifier has a flat gain over the acoustic band. Ron Belaire built the device as part of his fourth year project [70]. The RACAL 8 track tape recorder allows simultaneous recording from the four microphones. Prior to sampling the acquired data, a synchronization pulse is inserted at the beginning of each test sequence. By doing so, each channel can be sequentially sampled. A Low-Pass Butterworth filter with a cutoff frequency set at 3.7 KHz is used to remove aliasing prior to sampling. The sampling

Figure 3.2 Recording Set-Up Configuration

is performed at a rate of 10 KHz using the TECMAR A/D board. Windows of 52 K samples are saved in a file then transferred to a SUN and PC workstations where it is analyzed using the MATLAB package.

3.4 Measurement Set Up Validation

The equipment was validated through laboratory testing. Each component was individually tested. The basic tests consisted in generating various sine waves at

frequencies in the acoustic band. The MATLAB package served as a tool for validating and analyzing the data.

First the TECMAR board was tested. Then, the tape recorder was inspected. It was found that the tape recorder inputs could easily saturate due to the absence of an automatic gain controller. Therefore, close monitoring was required during recording. This could lead to a potential problem. The equipment background electronic noise is too small with respect to the observed signals. However gaging down the input power signal of a microphone in order to avoid saturation could result in burying a low power noise signal into the background electronic noise. If this happens, adaptation could be difficult to achieve using this noise signal.

The next step consisted in adding the microphones and the pre-amplifier unit. This step was repeated for each of the tape recorder track. Every microphone used was omnidirectional. The pre-amplifier unit was built by Ron Belaire as part of a project in noise cancellation. The device had a flat gain up to 20 KHz which was more than enough.

Some microphone tests were performed with and without the tape recorder. The final step consisted in reproducing the field set-up. Figure 3.2 shows the configuration used. Two components were added. A 12 Volt battery and a DC/AC converter were used as power supply. Still, the equipment was compliant.

After a preliminary analysis of the data, a test was performed on the recorded data using a spectrum analyzer. The test confirmed the data validity.

3.5 Driving Conditions

We selected the driving conditions such that a few noise processes could be observed individually. Then we varied the conditions so that the processes could be added

gradually. It wasn't always possible to isolate specific noise processes. Note that only the basic noise processes surrounding the normal car use were considered. Each tests were performed twice: with the fan off and then with the fan on. The driving conditions are indicated in table 3.1.

engine off,	fan on
engine idling, car static	fan off
engine idling, car static	fan on
car speed 60 Km/hr on a blvd	fan off
car speed 60 Km/hr on a blvd	fan on
car speed 100 Km/hr on a freeway	fan off
car speed 100 Km/hr on a freeway	fan on

Table 3.1 Driving Conditions During Field Tests

These tests allow the analysis of the engine noise alone and the fan noise alone. These two noise sources are the only one which can be analyzed independently of the others. For example, the road noise is always accompanied by the engine noise. The recording level set during the field tests are indicated in table 3.2.

test	location	fan off	fan on
car idling	under the hood	.5 Volt	1 Volt
car idling	under the steering	.2 Volt	.2 Volt
car idling	under floor mat	.1 Volt	.1 Volt
car idling	at the steering	.2 Volt	.2 Volt
60 Km/hr	under the hood	.5 Volt	.5 Volt
60 Km/hr	under the steering	.2 Volt	.2 Volt
60 Km/hr	under floor mat	.2 Volt	.2 Volt
60 Km/hr	at the steering	.2 Volt	.2 Volt
100 Km/hr	under the hood	1 Volt	1 Volt
100 Km/hr	under the steering	.2 Volt	.2 Volt
100 Km/hr	under floor mat	.2 Volt	.2 Volt
100 Km/hr	at the steering	.2 Volt	.2 Volt
engine off	under the hood	—	1 Volt
engine off	under the steering	—	.1 Volt
engine off	under floor mat	—	.1 Volt
engine off	at the steering	—	.1 Volt

Table 3.2 Recording Level During Field Tests

Chapter 4 Data Analysis

4.1 Introduction

This chapter analyzes the background acoustic noise recorded in a medium size car. It focuses only on normal driving conditions. Due to the complexity of the background acoustic noise, the analysis is performed in a qualitative manner. The results obtained in both the time and frequency domain will be used as guidelines for designing various ANC algorithms. A second aim is to evaluate in a qualitative manner the possibility of using a multiple reference microphone ANC.

First, the analysis considers the noise power spectrum density (PSD). Then, the acoustic band is split into an upper and lower band (above and below 1.5 KHz). Correlation tests are performed on both bands.

4.2 Power Spectral Density

The test conditions under which the data was acquired are described in table 3.1. The PSD is obtained by applying the Welch method [12] on a window of 4096 samples. Hence the PSD is averaged over a period of about 410 msec. The resulting curve is presented using 64 frequency bins linearly spaced from 0 to 5000 Hz. The frequency domain shows that under various driving conditions, each microphone has a particular spectral signature.

In chapter 2 a noise model was developed. It shows that each noise process goes through a transfer function prior to reaching an observation point (i.e. microphone location). For, Goubran et al. [1,2] indicated that the car cabin acts as a low pass filter. The low-pass filter cut-off frequency varies from car to car. Figure 4.1 shows the PSD of the engine noise observed from four locations. Microphone # 1 (located under the hood) is collocated with the noise source. The other microphone placed inside the cabin have a low-pass filtered PSD with respect to microphone # 1. The cabin cut-off frequency with respect to the primary (at the steering wheel) is about 450 Hz. Other spectral characteristics are observed, the most important ones are stated below.

As shown in figures 4.1 through 4.4, the reference microphone locations have some spectral signature properties. Only the observable peaks (common to the primary microphone PSD) are considered i.e. there may be some peaks buried in with uncorrelated noise but they are not considered in this chapter.

The PSD of microphone # 1 (under the hood) is composed of peaks distributed over the entire acoustic band. Two peaks are common to the primary microphone (at the steering wheel). The first peak is located below 1.5 KHz. The second peak is located at about 3 KHz when the car moves at 60 Km/hr. This peak moves to near 3.5 KHz as the car's speed is increased to 100 Km/hr. This is believed to be the air flow effect on and around the car. A simple listening test confirms this assumption.

Microphone # 2's (under the steering wheel) PSD is mainly composed of a low frequency peak located below 1.2 KHz.

Microphone # 3's (under the driver floor mat) PSD is composed of two peaks. The main peak is below 1 KHz. The second peak appears only when the car moves. It is located at 1700 Hz. As the car's speed increases, the peak remains at the same frequency but its amplitude increases.

Figure 4.1 Power Spectrum Density, Car Idling, Fan Off

From the various spectral signature observations, it seems that the upper and lower bands have different noise processes. Hence a particular reference microphone could offer its spectral signature for noise cancellation. The important point is to determine if

Figure 4.2 Power Spectrum Density, Engine Off, Fan On

a degree of correlation exists between a spectral signature observed at a reference and at the primary microphone.

Figure 4.3 Power Spectrum Density, Car Speed 60 Km/hr, Fan On

4.3 Correlation

As mentioned in an earlier chapter, the ANC effectiveness depends on the degree of correlation that exists between the reference and the primary microphones. Due to

Figure 4.4 Power Spectrum Density, Car Speed 100 Km/hr, Fan On

the complexity of background acoustic noise characteristics, the time domain analysis can only provide some guidelines for the conception of an ANC. There are two areas of concern: the signal periodicity and the degree of correlation existing between a particular

reference microphone and the primary microphone.

4.3.1 Autocorrelation

The autocorrelation is evaluated using a 2048 point FFT method. A sliding window of 2048 points was applied over 100 time steps. For each step, the correlation (and cross-correlation) is evaluated. The resulting curve is the average of the 100 time step curves.

Figures 4.5 and 4.6 show that the noise processes observed in the lower and upper bands, have a certain degree of periodicity. This indicates that the differential delays between a reference microphone and the primary microphone become, to some extent, a function of the phase. Hence, the compensating delay which must be inserted for ensuring coherence (or system causality) between the primary and the reference signal could be shortened.

4.3.2 Cross-Correlation

The cross-correlation indicates the degree of correlation between a particular reference microphone and the primary microphone. It also provides an indication of the differential delay between a noise process observed from the primary and from a reference microphone.

Figures 4.7 (for lower band) and 4.8 (for upper band) show that at 60 Km/hr, various degrees of correlation exist between each reference microphone and the primary microphone. This is true for all driving conditions. It was found that this degree of correlation depends on the driving condition, the microphone location and the frequency band.

Another important criterion is the relative differential delay. When comparing the cross-correlation of the upper and lower band, if the same noise process occupies both

Figure 4.5 Autocorrelation of the Lower Band (below 1.5 KHz), Engine Off, Fan On

bands then it should have the same differential delay in each band. As a guideline, the differential delay is normally obtained by locating the largest peak of the cross-correlation function. For example, if the cross-correlation between microphone # 1 (under the hood)

Figure 4.6 Autocorrelation of the Upper Band (above 1.5 KHz), Engine Off, Fan On

and the primary microphone is considered when the car moves at 60 Km/hr (figures 4.7.a and 4.8.a), the lower band differential delay is about 20 msec (figure 4.7.a) while it is about 0 msec for the upper band (figure 4.8.a). This reinforces the fact that the noise

Figure 4.7 Cross-Correlation Of the Lower Band (below 1.5 KHz) With Respect to the Primary Microphone (at the Steering Wheel); Car Speed 60 Km/hr, Fan Off

process observed in the upper band is different from that observed in the lower band.

Therefore, based on the frequency and the time domain analysis, it seems that various noise processes are dominant at different reference locations. Each one has a

Figure 4.8 Cross-Correlation Of the Upper Band (above 1.5 KHz) With Respect to the Primary Microphone (at the Steering Wheel); Car Speed 60 Km/hr, Fan Cff

particular spectral signature, which depends on the driving conditions. Based on the data analysis, it is clear that a multiple reference microphone ANC could be implemented. It could make use of the best location for spatial filtering and the best spectral signature

for temporal filtering. This is actually the beamformer (BF) approach which will be covered in chapter 6.

As a first step, independent adaptation should be implemented on each sub-band. This is called sub-band adaptation and it is covered in the next chapter.

Chapter 5 Two Microphone Technique for Noise Cancellation

5.1 Introduction

In the previous chapter, background acoustic noise was analyzed. It revealed the existence of noise correlation between the primary microphone and the various secondary microphones. It was also found that the degree of correlation depends on the microphone location and the driving condition of the test. Based on the results analysis, some microphone configurations are proposed for a two microphone ANC.

In this chapter, various ANC are implemented using different microphone locations. The results are discussed in terms of the ANC efficiency and performance. The first part demonstrates how the transfer function linking the reference to the primary microphone relates to the noise model. It shows that the ANC performance relies on how accurate the transfer function estimation is. It also shows what perturbation factors affect the system. The second part shows the algorithm selection process. The third part discusses the results of implementing a selected algorithm on real data. The fourth part addresses an approach for solving the upper frequency band noise enhancement observe during tests and in the literature [2,26,69]. Finally the last part discusses some results of sub-band adaptation as well as their relation to the noise model. Guidance towards a multiple-microphone ANC configuration is also presented.

5.2 Transfer Function Estimation

The ANC considered in this thesis is referred to as an identification system in the literature [4,13,14] i.e. using the noise captured by a reference microphone, the system tries to estimate and extract the common noise from the primary. This is done by estimating the transfer function linking the reference to the primary microphone. Recall that this transfer function is assumed to be approximated by a FIR. The system performance relies on the degree of correlation between noise components in the two microphones.

As shown in figure 5.1, the transfer function linking the secondary microphone to the primary can be expressed in terms of the observed signals $x(t)$ and $y(t)$. It is composed of N delays (τ_l). At the i^{th} stage, the reference signal $y(t+i)$ is transformed by a factor w_l . This however provides no insight on how the system relates to the MIMO noise source system described in chapter 2. Therefore the transfer function linking the reference microphone to the primary is more useful when expressed in terms of the noise sources.

Prior to developing an ANC, the model assumption should be recalled. It is assumed that all transfer functions are linear and that they can be approximated by a N taps finite impulse response (FIR). Also, the approximation errors $e_x(t)$ and $e_y(t)$ of figure 2.4 are independent random processes with zero mean and variance σ_x^2 and σ_y^2 . For ease of manipulation, it is assumed that no speech is active during adaptation. As pointed out in [6], if speech is present when adaptation takes place, it could result in reverberation or even speech cancellation. From figure 2.4 and equation (2.1), the observed noise process at the primary is

$$x(t) = \underline{n}^T(t) \underline{C}(t) + e_x(t) \quad (5.1)$$

Figure 5.1 Transversal Filter With Variable Coefficient

At the reference microphone it is

$$y(t) = \underline{n}^T(t) \underline{D}(t) + e_y(t) \quad (5.2)$$

It is assumed that every transfer function in the system is limited to N taps. Therefore the transfer function linking the reference to the primary makes use of the N last observations of $y(t)$. Hence a $N \times 1$ vector representing N last observation of $y(t)$ is denoted by

$$\underline{y}(t) = \underline{K}(t) + \underline{e}_y(t) \quad (5.3)$$

where

$$\underline{\mathbf{K}}(t) = \begin{bmatrix} y(t) \\ y(t-1) \\ \cdot \\ \cdot \\ \cdot \\ y(t-N+1) \end{bmatrix} \quad (5.4)$$

Substituting equation 2. in (5.4), equation (5.3) is linked to the noise processes

$$\underline{\mathbf{K}}(t) = \begin{bmatrix} \underline{\mathbf{n}}^T(t) \underline{\mathbf{D}}(t) \\ \underline{\mathbf{n}}^T(t-1) \underline{\mathbf{D}}(t-1) \\ \cdot \\ \cdot \\ \cdot \\ \underline{\mathbf{n}}^T(t-N+1) \underline{\mathbf{D}}(t-N+1) \end{bmatrix} \quad (5.5)$$

Since the system is approximated as being linear, a linear regression method as an estimation tool can be employed [4,8,13,14,58-61]. The process consists in approximating $x(t)$ using $y(t)$ and a N taps transversal filter $\underline{\mathbf{W}}(t)$. Hence the estimation is given by

$$x(t) = \underline{\mathbf{y}}^T(t) \underline{\mathbf{W}}(t) \quad (5.6)$$

Figure 5.1 shows a transversal filter. The input goes through $N-1$ delays. Each tap coefficient of $\underline{\mathbf{W}}(t)$ are adjusted in such a way that the mean square error is minimized. The error is the difference between the primary observation $x(t)$ and its estimate $\hat{x}(t)$.

$$e(t) = x(t) - \hat{x}(t) \quad (5.7)$$

By inspection of equation 5.7, the square error can only be positive. Implicitly taking the error expectation also gives a positive mean square error (mse). It can be seen as an upward cup on which surface lies the mean square error.

Figure 5.2 Mean Square Error Distribution With Respect to $\underline{W}(t)$

Figure 5.2 illustrates the process for a one tap filter. Hence, there is a minimum mse, it is at the cup bottom. This point coincides with $\underline{W}_{opt}(t)$. The mse is given by taking the expectation of the square error; from equation (5.7) it is

$$mse = E[e^2(t)] = E[x^2(t) - 2x(t)\tilde{x}(t) + \tilde{x}^2(t)] \quad (5.8)$$

Assuming that the transfer functions are constant over the observation period. The time dependence can be dropped since the expectation operator does not affect them. Substituting (5.1), (5.2), (5.3) and (5.6) in (5.8) and taking out of the expectation operator the constant terms gives

$$\begin{aligned} mse = & \underline{C}^T E[\underline{n}(t) \underline{n}^T(t)] \underline{C} + 2\underline{C}^T E[\underline{n}^T(t) \underline{e}_x(t)] \\ & + E[\underline{e}_x^2(t)] - 2\underline{C}^T E[\underline{n}^T(t) \underline{K}^T(t)] \underline{W} \\ & - 2E[\underline{e}_x(t) \underline{K}^T(t)] \underline{W} - 2\underline{C} E[\underline{n}^T(t) \underline{e}_y(t)] \underline{W} \\ & - 2E[\underline{e}_x(t) \underline{e}_y(t)] \underline{W} + \underline{W}^T E[\underline{K}(t) \underline{K}^T(t)] \underline{W} \\ & + 2\underline{W}^T E[\underline{e}_y(t) \underline{K}^T(t)] \underline{W} + \underline{W}^T E[\underline{e}_y(t) \underline{e}_y^T(t)] \underline{W} \end{aligned} \quad (5.9)$$

Using the independence properties of $\underline{e}_y(t)$ and $\underline{e}_x(t)$, (5.9) becomes

$$\begin{aligned} \text{mse} = & \underline{C}^T \mathbf{E} \left[\underline{n}(t) \underline{n}^T(t) \right] \underline{C} + \sigma_{ex}^2 - 2 \underline{C}^T \mathbf{E} \left[\underline{n}(t) \underline{K}^T(t) \right] \underline{W} \\ & + \underline{W}^T \mathbf{E} \left[\underline{K}(t) \underline{K}^T(t) \right] \underline{W} + \underline{W}^T \mathbf{E} \left[\underline{e}_y(t) \underline{e}_y^T(t) \right] \underline{W} \end{aligned} \quad (5.10)$$

$$= \underline{C}^T \mathbf{R}_n \underline{C} + \sigma_{ex}^2 - 2 \underline{C}^T \underline{p}_n \underline{W} + \underline{W}^T \mathbf{R}_K \underline{W} + \underline{W}^T \mathbf{R}_{ey} \underline{W} \quad (5.11)$$

where $\mathbf{R}_n$ is the autocorrelation of the noise source vector $\underline{n}(t)$.

$$\mathbf{R}_n = \mathbf{E} \left\{ \begin{bmatrix} [\underline{n}_1(t)] \\ [\underline{n}_2(t)] \\ \vdots \\ [\underline{n}_k(t)] \end{bmatrix} \begin{bmatrix} \underline{n}_1^T(t) & \underline{n}_2^T(t) & \dots & \underline{n}_k^T(t) \end{bmatrix} \right\} \quad (5.12)$$

It was assumed that each noise source have zero mean and are independent of each other hence

$$\mathbf{R}_n = \mathbf{E} \left[\underline{n}(t) \underline{n}^T(t) \right] = \begin{bmatrix} \mathbf{R}_{n_1} & 0 & \dots & 0 \\ 0 & \mathbf{R}_{n_2} & & \vdots \\ \vdots & & \ddots & \vdots \\ \vdots & & & 0 \\ 0 & & & 0 & \mathbf{R}_{n_k} \end{bmatrix} \quad (5.13)$$

where

$$\mathbf{R}_{n_i} = \begin{pmatrix} \mathbf{E}[\mathbf{n}_i^2(t)] & \mathbf{E}[\mathbf{n}_i(t-1) \mathbf{n}_i(t)] & \dots & \mathbf{E}[\mathbf{n}_i(t-N+1) \mathbf{n}_i(t)] \\ \mathbf{E}[\mathbf{n}_i(t) \mathbf{n}_i(t-1)] & \mathbf{E}[\mathbf{n}_i^2(t)] & & \cdot \\ \cdot & & \cdot & \cdot \\ \cdot & & \cdot & \cdot \\ \mathbf{E}[\mathbf{n}_i(t) \mathbf{n}_i(t-N+1)] & \cdot & \cdot & \mathbf{E}[\mathbf{n}_i^2(t)] \end{pmatrix} \quad (5.14)$$

$\mathbf{R}_{n_i}$ is toeplitz and symmetric with respect to the main diagonal

$\mathbf{R}_K$ is the autocorrelation of the noise sources filtered by $\underline{\mathbf{D}}$

$$\mathbf{R}_K = \mathbf{E}[\underline{\mathbf{K}}(t) \underline{\mathbf{K}}^T(t)] \quad (5.15)$$

$$= \begin{pmatrix} \begin{bmatrix} \underline{\mathbf{D}}^T \mathbf{n}(t) \\ \underline{\mathbf{D}}^T \mathbf{n}(t-1) \\ \cdot \\ \cdot \\ \underline{\mathbf{D}}^T \mathbf{n}(t-N+1) \end{bmatrix} \begin{bmatrix} \mathbf{n}^T(t) \underline{\mathbf{D}} & \mathbf{n}^T(t-1) \underline{\mathbf{D}} & \dots & \mathbf{n}^T(t-N+1) \underline{\mathbf{D}} \end{bmatrix} \end{pmatrix} \quad (5.16)$$

$$= \begin{bmatrix} \underline{\mathbf{D}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} & \underline{\mathbf{D}}^T \mathbf{R}_n(1) \underline{\mathbf{D}} & \dots & \underline{\mathbf{D}}^T \mathbf{R}_n(N-1) \underline{\mathbf{D}} \\ \underline{\mathbf{D}}^T \mathbf{R}_n(1) \underline{\mathbf{D}} & \underline{\mathbf{D}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} & \dots & \underline{\mathbf{D}}^T \mathbf{R}_n(N-2) \underline{\mathbf{D}} \\ \cdot & \cdot & \cdot & \cdot \\ \underline{\mathbf{D}}^T \mathbf{R}_n(N-1) \underline{\mathbf{D}} & \underline{\mathbf{D}}^T \mathbf{R}_n(N-2) \underline{\mathbf{D}} & \dots & \underline{\mathbf{D}}^T \mathbf{R}_n(0) \underline{\mathbf{D}} \end{bmatrix} \quad (5.17)$$

where

$$R_{ni} = E[\underline{n}(t) \underline{n}^T(t-i)] \quad (5.19)$$

the cross-correlation becomes

$$P_n = E[\underline{C}^T \underline{n}(t) \underline{K}^T(t)] \quad (5.20)$$

$$= E\left\{ \underline{C}^T \underline{n}(t) \left[\underline{n}^T(t) \underline{D} \quad \underline{n}^T(t-1) \underline{D} \quad \dots \quad \underline{n}^T(t-N+1) \underline{D} \right] \right\} \quad (5.20)$$

$$P_n = \begin{bmatrix} \underline{C}^T R_n(0) \underline{D} \\ \underline{C}^T R_n(1) \underline{D} \\ \vdots \\ \underline{C}^T R_n(N-1) \underline{D} \end{bmatrix} \quad (5.21)$$

R_{ey} is the autocorrelation of $e_y(t)$.

$$R_{ey} = E[\underline{e}_y(t) \underline{e}_y^T(t)] = \sigma_{ey}^2 \underline{I} \quad (5.22)$$

where $\underline{I}$ is an identity matrix of dimension $N \times N$ and σ_{ey}^2 is the variance of $e_y(t)$.

By inspecting figure 5.2, the minimum mse can be obtained by taking the derivative of equation (5.11) with respect to $\underline{W}$ and setting it to zero. This provides the optimum value of $\underline{W}$.

$$\frac{\partial \text{mse}}{\partial \underline{W}} = -2 P_n + 2 R_K \underline{W}_{\text{opt}} = 0 \quad (5.23)$$

$$\underline{p}_n = (\underline{R}_K + \underline{R}_{ey}) \underline{W}_{opt} \quad (5.24)$$

This is the well known Wiener-Hopf equation [14]. By inspection $\underline{R}_{ey}$ is a perturbation factor. It limits the adaptation or $\underline{W}$'s estimation by introducing a bias. This bias can be viewed as a modification of the system modes [14,67] by perturbing the main diagonal of $\underline{R}_K$. Regardless of $\underline{R}_{ey}$, it is obvious that the optimum filter coefficients depend on $\underline{R}_K$ only. This is so since the aim of the ANC is to make use of the common noise (i.e. correlated noise) to both the primary and reference microphones. Recall that the error $e_y(t)$ comes from two sources of approximation. First from the non-linear part of the system and second from the selection of a too small number of taps which in fact could be larger. Based on the system's definition, it would be fair to assume that $e_y(t)$ is negligible. Hence equation (5.19) becomes

$$\underline{p}_n \approx \underline{R}_K \underline{W}_{opt} \quad (5.25)$$

hence

$$\underline{W}_{opt} \approx \underline{R}_K^{-1} \underline{p}_n \quad (5.26)$$

Comparing $\underline{p}_n$ and $\underline{R}_K$ using equations (5.14) and (5.16), it is evident that $\underline{D}$ acts on each row of $\underline{R}_K$ for completing the gap existing between $\underline{D}$ and $\underline{C}$. Hence $\underline{W}$ makes use of the N last reference observations $y(t)$ for estimating $x(t)$ the primary output.

There are some system constraints for allowing $\underline{W}$ to exist. First, the system must be causal i.e. the delay stemming from $\underline{D}$ must be smaller than the one stemming from $\underline{C}$ [2,69]. This can be compensated by inserting a delay at the primary output prior to its processing [1,2,69]. Second, the error $e_y(t)$ must be small enough so that the bias factor does not deteriorate the ANC efficiency to a large extent. Third, $\underline{C}$ and $\underline{D}$ must be approximately FIRs of length N at the most.

5.3 Algorithm

In this section, a least square (LS) algorithm is selected for implementing an ANC. The selection is based on :

- (i) tracking capability to a time varyiant system;
- (ii) ease of implementation;
- (iii) reliability; and
- (iv) the end users operating the system.

Three algorithm are considered: the recursive least square (RLS), the block least square (BLS) and, the stochastic gradient or least mean square (LMS).

The RLS algorithm converges very fast in a non-noisy environment. However, it has been shown that in a noisy environment its convergence is about the same as that of the LMS [14]. The algorithm requires a high computational capability for inverting the matrix $\mathbf{R}_K$ of equation (5.21). Also it is a well known fact that the RLS is bound to become unstable after an unpredictable time of operation. A recovery system must therefore be implemented as a compensator. Hence, the RLS is discarded since it is unreliable and it costs too much in computation requirement.

The BLS takes a block of data and finds the optimum transfer function for it [13]. At first glance, this looks appealing since it would allow to implement an optimum coding like approach ANC. The Karhunen-Loeve Transform (KLT) could well be used with the algorithm. The aim would be to establish which dominant modes are common in the primary and reference microphones. Then a simple subtraction of it could be done from the primary signal. Preliminary tests have shown that only a few modes compose each noise signal. However, the task of comparing the modes became soon too complex. Also the computational requirement for this approach seemed too much

for a real time system. It was therefore decided to disregard the KLT but to bare in mind a sub-optimum approach using the frequency domain.

The BLS method could well have been implemented using a frequency domain technique but it was too expensive in computation time. It was decided to consider the simple BLS algorithm. A problem arises when using this algorithm. It is as demanding as the RLS since it too must carry on a matrix inversion in order to find the optimum coefficients set $\underline{W}$. Also since each block are processed independently from one to another, there sometimes is no smooth transition between them. The sudden transitions become annoying to the end user [13].

The BLS was discarded in a early stage on the ground that it is too expensive to implement and it annoys the end user.

This leaves the LMS algorithm. It is a well known algorithm in the literature and has proven to be reliable in a slowly varying environment [8,11,13,14]. This algorithm adapts to the system characteristics in an intuitive way. It uses the instantaneous gradient $[e(t) \underline{y}(t)]$ with respect to the transfer function $\underline{W}(t)$. Using equations (5.6) and (5.7) in the well known LMS algorithm [2,8,13,14] the following equations system is obtained

$$\underline{W}(t+1) = \underline{W}(t) + \beta(t) e(t) \underline{y}(t) \quad (5.27)$$

where $\underline{W}(t+1)$: is the new FIR coefficients;

$\underline{W}(t)$: is the old FIR coefficient

$\beta(t)$ is a variable step size normalized to the summation of the total instantaneous power of the observed sequence $\underline{y}(t)$. This allows the step size to adapt to the system characteristics variation. Preliminary testing have proven that a fixed step size always lead to an unstable ANC. From [5,15], it is shown that for algorithm convergence, the

step size must be bounded by

$$0 < \beta(t) < \frac{1}{\lambda_{\max}} \quad (5.28)$$

$\lambda_{\max}$ is the largest eigenvalue of $\mathbf{R}_K$, the instantaneous autocorrelation of $\mathbf{y}(t)$. It is known that the eigenvalues distribution represent the system modes distribution [14,67]. Informal testing has shown that there is only a few dominant modes i.e. eigenvalues in the system. Also from [14], $\lambda_{\max}$ is upper bounded by trace of $\mathbf{R}_K$.

$$\lambda_{\max} \leq \text{trace}(\mathbf{R}_K) \quad (5.29)$$

Further to this, in [14], it is shown that for the instantaneous autocorrelation,

$$\text{trace}(\mathbf{R}_K) = \mathbf{y}^T(t) \mathbf{y}(t) \quad (5.30)$$

hence 5.24 becomes bounded by

$$\lambda_{\max} \leq \mathbf{y}^T(t) \mathbf{y}(t) \quad (5.31)$$

In [15], $\beta(t)$ is defined in such a way that it is upper bounded by

$$\beta(t) = \frac{a_i}{[\mathbf{y}^T(t) \mathbf{y}(t) + b_i]} \quad (5.32)$$

where a_i and b_i are some limiting constants limiting $\beta(t)$ to a finite value. This prevents from having a very large $\beta(t)$ when the norm of $\mathbf{y}(t)$ is close to zero.

The LMS algorithm is implemented with a_i set to 1. This provides the fastest convergence rate hence the best tracking capability [15].

5.4 Results Of a Two Microphone ANC

The LMS algorithm described in the previous section was implemented on a SUN and PC workstations using the MATLAB package. The car data described in chapter

3 is disposed in files of 53248 samples. For each file, the mean is removed prior to any processing. The system efficiency is measured in terms of the instantaneous power of the input and output signal of the ANC. Note that this only provides a qualitative measure of the system efficiency. The efficiency is given by

$$ef = 10\log_{10} \left[\frac{\underline{e}^T(t) \underline{e}(t)}{\underline{x}^T(t) \underline{x}(t)} \right] \text{ dB} \quad (5.33)$$

Figure 5.3 Two Microphone ANC Configuration

The ANC configuration is shown in figure 5.3. A delay is added at the primary in order to compensate for the delay stemming from the adaptive filter $\underline{W}(t)$. This ensure system causality. The PSD of the ANC output signal ($e(t)$) and the input signals ($x(t)$) are plotted in a logarithmic scale. Since the estimated signal ($\tilde{x}(t)$) is subtracted from the primary signal ($x(t)$) as shown in figure 5.3, a 0 dB improvement is the superposition of the two curves. Hence, if the output signal PSD is below that of the primary signal, then there has been a SNR improvement.

Figures 5.4–5.10 show the result of a Two Microphone ANC. In every cases, good noise suppression takes place in the lower end of the acoustic band. The efficiency is about 10 dB. However, in the upper band, there is noise enhancement.

Figure 5.4 Result Of a Two MicrophoneANC, Engine Off, Fan On; Output :-+-

There are some common observations which can be made with respect to each location. These observations hold for all driving conditions. In general, location # 2 (under the steering wheel) performs better than the others for the frequency regions

Figure 5.5 Result Of a Two MicrophoneANC, Car Idling, Fan Off; Output :-+- ranging from 0–800 Hz. This can clearly be observed throughout every figures (5.4–5.10, 5.19–5.25).

Location # 3 (under the floor mat) provides the best noise cancellation for the

Mic. # 1 Under the Hood

a.

Mic. # 2 Under the Steering

b.

Mic. # 3 Under Floor Mat

C.

Figure 5.6 Result Of a Two MicrophoneANC, Car Idling, Fan On; Output :-++

frequency region ranging from 800–1500 Hz.

Location # 1 (under the hood) seems to always be the one providing the least noise suppression. However, it provides a very important information with respect to the

noise model. In the upper band, the PSD analysis revealed that a peak in the upper band is common to both location # 1 and # 2. Figures 5.7.a and 5.8.a show a partial noise suppression of a peak located at 3000 Hz. This indicates that noise suppression

Figure 5.8 Result Of a Two MicrophoneANC, Car Speed 60 Km/hr, Fan On; Output :-+-

in the upper band is possible. It also confirms the existence of correlated processes in the upper band as found in chapter 4.

In chapter 4, it was indicated that different noise processes seem to occupy the upper

**Figure 5.9 Result Of a Two MicrophoneANC,
Car Speed 100 Km/hr, Fan Off; Output :-+-**

and lower band. Also, it was shown that the two processes (from the upper and lower band respectively) did not share the same differential delay. A second approach, which

Figure 5.10 Result Of a Two MicrophoneANC,
Car Speed 100 Km/hr, Fan On; Output :-+-

minimizes the noise enhancement at high frequencies is the sub-band adaptation.

5.5 Sub-Band Adaptation

Goubran et al. [1] and Armbruster et al. [20] show how a multi-band adaptation looks like from a MIMO noise system. While, in theory, the use of many sub-bands may seem appealing. This could well lead to a tone in band problem. This is a side effect occurring at the junction of two bands. In order to avoid this potential problem, the band was only split in two: above and below 1.5 KHz. Figure 5.11 illustrates how the bands are split. A 99 taps low-pass McMillan filter is applied to a signal $x(t)$. In a second branch, the same signal is delayed by 49 taps in order to keep the two branch in phase. The low-pass signal is then coherently subtracted from the delayed original signal which provides the upper band signal.

Figure 5.11 Low-Pass and High-Pass Filtering

Figure 5.12 shows the sub-band ANC configuration for lower band adaptation. The primary signal $x(t)$ is divided in two branches. The first is low-pass filtered then a delay τ_2 is added to it for ensuring system causality with respect to the reference signal $y(t)$. The second branch is delayed by τ_1 in order to compensate for the delay stemming from low-pass filtering and to compensate for the adaptive filter. The signal estimation and optimization are obtained using the lower band. The signal estimation $\hat{x}(t)$ is also coherently subtracted from the delayed primary signal $x(t)$ [2].

Figure 5.12 Sub-Band Two Microphone ANC Configuration

5.6 Results of Sub-Band Adaptation

The results of sub-band adaptation are presented in three parts. First, some results of lower band adaptation are presented. Second, some results of the upper band adaptation are presented. Third, sub-band adaptation results of both the upper and lower band are presented. In this case upper and lower band estimation is done independently. It is found that the SNR improvement is about 11 dB. Then, the upper band estimate and the lower band estimate are subtracted from the primary output.

5.6.1 Lower Band Adaptation

Figures 5.13–5.15 show some of the lower band adaptation. Good noise suppression of the lower band is obtained without causing any effect on the upper band. Furthermore, every observations made on the lower band of figures 5.4–5.10 still hold. In that case adaptation was performed over the entire acoustic band. Hence, location # 2 provides the best noise suppression for the frequencies below 800 Hz. Location # 3 performs best for the frequency regions ranging from 800 Hz to 1500 Hz.

Figure 5.13 Result Of a Two MicrophoneSub-Band ANC
(lower band filtering), Car Idling, Fan Off; Output :-+-

5.6.2 Upper Band Adaptation

The results of the upper band adaptation confirms that in addition of uncorrelated

Figure 5.14 Result Of a Two MicrophoneSub-Band ANC
(lower band filtering), Car Idling, Fan On; Output :-+-

acoustic noise, there is some correlated noise in the upper band. This was expected after completing the noise analysis. Figure 5.16–5.18 illustrates some of the upper band

it is found that the degree of noise suppression varies with the driving conditions and with the considered location.

Figure 5.16 shows the case where the engine is off and the fan is on. Location # 1 (under the hood) proved to be the best reference for noise suppression. It was pointed out in chapter 4 that location # 1 was the most correlated with respect to the primary. Note that there is good noise cancellation at specific frequency regions. However, there is a slight noise enhancement in the frequency region ranging from 2800–3200 Hz.

Figure 5.17 shows the case where the fan is off and the car idles. In this condition, no particular peak could be observed in the upper band. As shown in figure 5.17, for every location, there is noise enhancement. This stresses the fact that only uncorrelated noise is active in the upper band.

Figure 5.18 shows the condition where the car moves at 60 Km/hr with the fan on. The power peak at 3000 Hz was found to be common to both the primary (at the steering wheel) and location # 1 (under the hood). Based on chapter 4 analysis, it was expected to obtain a resulting PSD leveled with the “background noise floor”. Instead, a major hole in the PSD results from the noise suppression. This would seem to indicate that some correlated noise are buried in the uncorrelated noise.

5.6.3 Sub-Band Adaptation Over Both Band

Figures 5.19–5.25 show the results of sub-band adaptation simultaneously performed on both bands. The general observations are that location # 2 (under the steering wheel) provides good noise suppression for the lower band. It does provide slight noise suppression in the upper band without any noise enhancement. This is only true for the cases where correlated noise can be found in the upper band.

Figure 5.16 Result Of a Two MicrophoneSub-Band ANC (upper band filtering), Engine Off, Fan On; Output :-+

Location # 1 (under the hood) performs fairly well. It provide noise suppression in the lower band as well as in the upper band high end. However, in some conditions, it

Figure 5.17 Result Of a Two MicrophoneSub-Band ANC
(upper band filtering), Car Idling, Fan Off; Output :-+-

provides some noise enhancement in certain part of the upper band spectrum.

Location # 3 (under the floor mat) performs in a similar way when compared to

Figure 5.18 Result Of a Two MicrophoneSub-Band ANC (upper band filtering), Car Speed 60 Km/hr, Fan On; Output :-+-

location # 1. However, it seems to be effective in the lower end of the upper band.

This section showed that sub-band adaptation solves the problem of noise enhance-

Mic. # 1 Under the Hood

a.

Mic. # 2 Under the Steering

b.

Mic. # 3 Under Floor Mat

C.

Figure 5.19 Result Of a Two MicrophoneSub-Band ANC (upper and lower band independently filtered), Engine Off, Fan On; Output :-+

ment of the upper band. This also confirms that different noise processes are found in the lower and upper bands.

Figure 5.20 Result Of a Two MicrophoneSub-Band ANC (upper and lower band independently filtered), Car Idling, Fan Off; Output :-+-

Figure 5.21 Result Of a Two MicrophoneSub-Band ANC (upper and lower band independently filtered), Car Idling, Fan On; Output :-+-

Figure 5.22 Result Of a Two Microphone Sub-Band ANC (upper and lower band independently filtered), Car Speed 60 Km/hr, Fan Off; Output :-+-

Mic. # 1 Under the Hood

a.

Mic. # 2 Under the Steering

b.

Mic. # 3 Under Floor Mat

C.

Figure 5.23 Result Of a Two MicrophoneSub-Band ANC (upper and lower band independently filtered), Car Speed 60 Km/hr, Fan On; Output :-+

Figure 5.24 Result Of a Two Microphone Sub-Band ANC (upper and lower band independently filtered), Car Speed 100 Km/hr, Fan Off; Output :-+-

Figure 5.25 Result Of a Two Microphone Sub-Band ANC (upper and lower band independently filtered), Car Speed 100 Km/hr, Fan On; Output: —+—

2 of/de 2

MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS
STANDARD REFERENCE MATERIAL 1010a
(ANSI and ISO TEST CHART No. 2)

Chapter 6 Parallel Adaptation

6.1 Introduction

It was shown in chapter 5 that some microphones (or locations) perform better than others depending on the driving conditions. This is also true for particular frequency regions as demonstrated in sub-band adaptation. These phenomena were somewhat expected based on the noise analysis in chapter 4. In light of these phenomena, it would be desirable to develop a multiple reference ANC system which would always make use of the best location and the best frequency contribution. The system could use a parallel architecture similar to that of a beamformer (BF) [14,19]. The literature refers to the best location selection as spatial filtering. Further to it, the system should be able to extract from each location the pertinent feature or signal component for achieving a high degree of noise cancellation. For instance, it was shown that some location allows good noise suppression at a particular frequency region. Hence its contribution should be limited to that frequency region. This frequency region selection is referred to as temporal filtering. In this chapter, two basic configurations based on a BF like approach are presented as well as their results on real car data.

6.2 General Beamformer Approach

The introduction of a parallel structure as a back bone for a multiple reference ANC requires a three dimensional analysis i.e. the system output depends on temporal

and spatial filtering. Temporal for the noise located at a particular frequency region and spatial filtering for selecting the best location for background acoustic noise suppression. Temporal and spatial filtering must be performed simultaneously which renders the system very complex. Figure 6.1 illustrates the concept of a multiple reference ANC.

Figure 6.1 Multiple Reference ANC Configuration

A transfer function matrix must be evaluated in order to perform noise cancellation. Using the beamformer approach, the analysis is broken down into two 2-dimensional systems. Each system is analyzed independently. Hence, the structure analysis is broken down into a temporal and spatial part. For ease of analysis, it is assumed that adaptation takes place during speechless period.

6.2.1 Temporal Filtering

An algorithm for temporal filtering can be developed in exactly the same way as a

2 Microphone ANC. Only one reference microphone is considered with respect to all noise sources. This algorithm development was carried through in chapter 5 using the LMS algorithm. Applying, equation 5.27 to the i^{th} reference location gives

$$\underline{W}_i(t+1) = \underline{W}_i(t) + \beta(t) e(t) \underline{y}_i(t) \quad (6.1)$$

where $\underline{w}_i(t+1)$: is the new set of coefficients;

$\underline{w}_i(t)$: is the old set of coefficients;

$\beta(t)$ is the step size normalized to the instantaneous power contained in the sequence $\underline{y}_i(t)$.

$$\beta(t) = \frac{a_i}{b_i + \underline{y}_i^T(t) \underline{y}_i(t)} \quad (6.2)$$

where a_i and b_i are some limiting constants ensuring system stability when $\underline{y}_i(t)$ is close to zero.

$e(t)$: is the difference between the actual primary output $x(t)$ and its estimate $\hat{x}(t)$. In the subsequent section a complete explanation on the error provenance will be defined in terms of the entire system.

$\underline{y}_i(t)$: is a $N \times 1$ vector composed of the last N observations of the i^{th} reference location.

This ends the temporal filtering portion of the analysis. Figure 6.2 illustrated how temporal filtering fits in the entire system.

6.2.2 Spatial Filtering

For spatial filtering the system can be represented by figure 6.3. Here the temporal dimension is omitted. This simplifies the spatial filtering analysis.

Figure 6.2 Temporal Filtering in the Multiple Reference ANC

Spatial filtering consists in estimating the primary output $x(t)$ by a linear combination of the filtered reference output (temporally filtered) $\underline{z}(t)$. The linear combination is then

Figure 6.3 Spatial Filtering Configuration

minimized in a mean square sense.

$$\underline{z}(t) = \begin{bmatrix} z_1(t) \\ z_2(t) \\ \cdot \\ \cdot \\ \cdot \\ z_m(t) \end{bmatrix} \quad (6.3)$$

where

$$z_i(t) = \underline{y}_i^T(t) \underline{W}_i(t) \quad (6.4)$$

the estimation error is given by the difference between the actual primary output $x(t)$ and its estimate $\hat{x}(t)$

$$e(t) = x(t) - \hat{x}(t) \quad (6.5)$$

where

$$\hat{x}(t) = \underline{z}^T(t) \underline{h}(t) \quad (6.6)$$

As previously obtained in chapter 5, the mse is

$$\text{mse} = E[e^2(t)] = E[x^2(t) - 2x(t)\tilde{x}(t) + \tilde{x}^2(t)] \quad (6.7)$$

substituting equation (6.6) in (6.7) and assuming that the system statistics are constant over the period of observation, the mse becomes

$$\text{mse} = E[x^2(t)] - 2\mathbf{h}^T E[\mathbf{z}(t) \mathbf{x}(t)] + \mathbf{h}^T(t) E[\mathbf{z}(t) \mathbf{z}^T(t)] \mathbf{h}(t) \quad (6.8)$$

$$= \sigma_x^2 - 2\mathbf{h}^T(t) \mathbf{p} + \mathbf{h}^T \mathbf{R}_z \mathbf{h} \quad (6.9)$$

where $\mathbf{p}$ is the cross-correlation between the primary output $\mathbf{x}(t)$ and the filtered references output $\mathbf{z}(t)$

$$\mathbf{p} = E[\mathbf{x}(t) \mathbf{z}(t)] \quad (6.10)$$

$\mathbf{R}_z$ is the autocorrelation of the sequence $\mathbf{z}(t)$

$$\mathbf{R}_z = E[\mathbf{z}(t) \mathbf{z}^T(t)] \quad (6.11)$$

For ease of manipulation, it is assumed that each reference output are independent of one another with zero mean. The i^{th} filtered output reference has a variance $\sigma_{z_i}^2$. Substituting equation (6.3) in (6.11), the autocorrelation becomes

$$\mathbf{R}_z = E \left\{ \begin{bmatrix} \mathbf{z}_1(t) \\ \mathbf{z}_2(t) \\ \vdots \\ \mathbf{z}_m(t) \end{bmatrix} \begin{bmatrix} \mathbf{z}_1(t) & \mathbf{z}_2(t) & \dots & \mathbf{z}_m(t) \end{bmatrix} \right\} \quad (6.12)$$

$$= \begin{bmatrix} \sigma_{z_1}^2 & 0 & & 0 \\ 0 & \sigma_{z_2}^2 & & . \\ & & . & . \\ & & & . \\ & & & 0 \\ 0 & . & . & . & 0 & \sigma_{z_w}^2 \end{bmatrix} \quad (6.13)$$

By inspection of equation (6.7), the mse is strictly positive. It has the shape of a cup facing upward when plotted against the filter coefficient $\underline{h}(t)$. The bottom of the cup coincides with the minimum mse. It is obtained by a set of optimum coefficient $\underline{h}_{opt}$. The optimum set of coefficient is obtained by taking the partial derivative of equation (6.9) with respect to $\underline{h}$ and to setting to zero.

$$\frac{\partial \text{mse}}{\partial \underline{h}} = -2 \underline{p} + 2 \underline{R}_z \underline{h}_{opt} = 0 \quad (6.14)$$

the optimum set of coefficient is then given by

$$\underline{h}_{opt} = \underline{R}_z^{-1} \underline{p} \quad (6.15)$$

Again, this is the well known Wiener-Hopf equation. This concludes the spatial filtering analysis. Now, the next step is to integrate both temporal and spatial filtering in an algorithm using multiple references. Prior to doing so, some constraints may be defined and forced onto the system in order to optimize its use.

6.3 Use Of Constraint For Algorithm Optimization

A multiple reference ANC is a very complex system. As shown in the previous section, two levels of adaptation must be performed: temporal and spatial. In order to

alleviate the system task and to ensure system stability, some constraints may be defined and forced onto it.

The first constraint results from the work done in chapter 5. It was shown that adaptation over the entire acoustic band provides good noise suppression in the lower band while yielding noise enhancement in the upper band. Therefore sub-band adaptation is selected as the first constraint.

The second constraint deals with system stability. Through preliminary testing, a two level adaptation multiple reference ANC was implemented. It will be thoroughly described in a subsequent section. The first adaptation level deals with temporal filtering while the second deals with spatial filtering [2,69]. It was found that the set of coefficients $\underline{h}(t)$ while minimizing the squared error, would grow without bound. Due to the computer's finite arithmetic limitation, the system would always become unstable. The solution lied in the BF approach. The spatial filtered output must be bounded to the primary output level $x(t)$. This is achieved by normalizing the spatial filter. Using the Lagrange multipliers [14,19], normalization with respect to the primary output is obtained by simply forcing $\underline{h}(t)$ to have a unity norm. Hence

$$|\underline{h}(t)| = 1 \quad (6.16)$$

6.4 4 Microphone Adaptive Noise Cancellation and Results

In this section, two 4-microphone ANC structures are presented as well as some experimental results. The first structure is a 2 level adaptation system. Temporal and spatial filtering each form a level. The second structure simultaneously tackles both temporal and spatial filtering using a sequential form.

6.4.1 2 Level Adaptation System and Results

As mentioned earlier, the 2 level adaptation system structure performs two tasks. First, temporal filtering is done, spatial filtering follows. This is done in a quasi independent way. The LMS algorithm is implemented for both levels. Figure 6.4 shows the system configuration.

Figure 6.4 Parallel Structure, 2 Level ANC Configuration

At the first level, temporal filtering is performed for each reference microphone. This structure gears or controls each reference microphone contribution with respect to its power level output. I.E. the step size for the i^{th} reference microphone $\beta_i(t)$ is given by

$$\beta_i(t) = \frac{a_i}{b_i + \underline{y}_i^T(t) \underline{y}_i(t)} \quad (6.17)$$

where a_i and b_i are some limiting constants bounding the value of $\beta_i(t)$. $\underline{y}_i(t)$ is a $N \times 1$ vector composed of the last N observations from the i^{th} reference location. It is known that the power level varies for each location. Evaluating $\beta_i(t)$ this way offers a great flexibility since it tends to normalize the primary estimate with respect to the

power level of each reference. This renders each reference power level transparent to the spatial filter. The system is maximized using a global (or common) error $e(t)$. This error is used for each of the three temporal filters and for the spatial filter. From these definition, equation (5.27) is adapted to the system. Hence each temporal filter set of coefficient are updated using

$$\underline{W}_i(t+1) = \underline{W}_i(t) + \beta_i(t) e(t) \underline{y}_i(t) \quad (6.18)$$

where $\underline{W}_i(t+1)$ and $\underline{W}_i(t)$ are respectively the new and old coefficients.

The second level of adaptation performs spatial filtering. The evaluation of the coefficient $\underline{h}(t)$ is critical in this phase. It was found through simulation and experimentation that $\underline{h}(t)$ must be normalized to unity in order to ensure system stability. Again, using equation (5.27), spatial filtering is ruled by

$$\underline{h}(t+1) = \underline{h}(t) + \alpha(t) e(t) \underline{z}(t) \quad (6.19)$$

subject to

$$|\underline{h}(t)| = 1 \quad (6.20)$$

this is achieved using

$$\underline{h}(t) = \frac{\underline{h}(t)}{\sum_{i=1}^3 h_i(t)} \quad (6.21)$$

Obviously, $\underline{h}(t+1)$ and $\underline{h}(t)$ are respectively the new and the old coefficients. $\alpha(t)$ is the adaptation step size. This is the most critical factor of the entire system.

$$\alpha(t) = \frac{a}{b + \underline{z}^T(t) \underline{z}(t)} \quad (6.22)$$

a and b are some limiting constant bounding $\alpha(t)$. The variable $z(t)$ is the temporal filter output vector

$$\underline{z}(t) = \begin{bmatrix} z_1(t) \\ z_2(t) \\ z_3(t) \end{bmatrix} \quad (6.23)$$

the error $e(t)$ is the global system error: it is the difference between the primary output and its estimate.

It must be pointed out why evaluating $\alpha(t)$ is so critical. The step size must be such that it tracks the system statistics variation without reacting to the temporal estimation errors. Through experimental fine tuning, it is found that the constant a must be set 0.5 as a maximum otherwise the system is unstable. Despite this, the structure reveals itself to sometimes lose its tracking capability. An in depth investigation should be carried out on the step size selection effect on the system tracking capability.

The 2 level adaptation structure is very effective in suppressing the lower band acoustic noise. This is shown in figures 6.5 and 6.6.

Figure 6.5 shows a noise suppression of up to 20 dBs in the frequencies below 500 Hz.

Figure 6.6. shows the major problem with the 2 level adaptation structure. For various driving conditions, excellent noise suppression takes place in the lower band while a slight noise enhancement takes place in the upper band. This phenomena occurs even though sub-band adaptation of the lower band is performed. This is believed to be caused by a bad step size ($\alpha(t)$) selection.

A tremendous amount of research needs to be done on the 2 level adaptation structure. If the step size selection problem could be resolved, this would be the best structure ever developed using the simple LMS algorithm. Meanwhile, the sequential structure has proven to being the best solution since it is always stable.

Parallel Adaptation, Parallel Structure

Figure 6.5 Result Of a 4 Microphone Sub-Band ANC
(lower band filtering), Car Idling, Fan Off; Output :-+-

6.4.2 Sequential Approach

Figure 6.7. illustrates the concept of the sequential approach.

Each of the three reference outputs are fed in the three part of a global filter $\underline{W}(t)$. The system equations become the same as for a 2 microphone ANC. The primary output estimation is given by

$$\tilde{\mathbf{x}}(t) = \underline{\mathbf{y}}^T(t) \underline{\mathbf{W}}(t) \quad (6.24)$$

Parallel Adaptation, Parallel Structure

Figure 6.6 Result Of a 4 Microphone Sub-Band ANC (lower band filtering), Car Speed 100 Km/hr, Fan Off; Output :-+

where

$$\underline{y}(t) = \begin{bmatrix} \underline{y}_1(t) \\ \underline{y}_2(t) \\ \underline{y}_3(t) \end{bmatrix} \quad (6.25)$$

and

$$\underline{W}(t) = \begin{bmatrix} \underline{W}_1(t) \\ \underline{W}_2(t) \\ \underline{W}_3(t) \end{bmatrix} \quad (6.26)$$

Figure 6.7 Parallel Adaptation, Sequential Structure

$y_i(t)$ is a $N \times 1$ vector composed of the last N observations of the i^{th} reference output.

$W_i(t)$ is the $N \times 1$ FIR filter associated to the i^{th} reference output.

Using equation (5.27), the coefficient are updated as such

$$\underline{W}(t+1) = \underline{W}(t) + \alpha(t) e(t) \underline{y}(t) \quad (6.27)$$

where $\underline{W}(t+1)$ and $\underline{W}(t)$ are respectively the new and the old coefficients.

$\alpha(t)$ is the step size. It is evaluated by

$$\alpha(t) = \frac{a}{b + \sum_{i=1}^3 \underline{y}_i^T(t) \underline{y}_i(t)} \quad (6.28)$$

Evaluating $\alpha(t)$ with respect to the summation of all power level of each reference brings in a limiting factor. This is so since each reference power level is different from one another. The system task is very complex. It must perform temporal and spatial

filtering simultaneously while gaging the adaptation to various power level. Obviously this does not seem optimum. Therefore, an in depth research should be done on the step size selection. Ideally it should be selected adaptively.

The error $e(t)$ is simply the difference between the primary output $x(t)$ and its estimate $\hat{x}(t)$. The variable $y(t)$ was defined earlier.

This structure is very stable and provides in general, better noise suppression than the 2 microphone noise canceller. The main difference is that it makes use of the best noise cancellation feature of each location.

This structure is implemented using sub-band adaptation of the lower band. Figures 6.8 and 6.9 show that it provides good noise suppression in the lower band without affecting the upper band.

Comparing figures 6.5, 6.6 (parallel structure) with figures 6.8 and 6.9 (sequential structure), it is clear that the parallel structure performs better. However, due to its step size selection, it sometimes lose its tracking capability. The sequential structure performs better than the 2 microphone ANC and never loses its tracking capability.

The two structures presented in this chapter prove that it is possible to perform excellent noise cancellation using a multiple reference microphone ANC. The system efficiency was about 12 dB for the sequential structure versus 15 dB for the parallel structure. The sequential approach prove itself to always be effective while the parallel structure sometimes loses its tracking capability. Further research must be carried through in order to fully define and understand the constraints surrounding the proposed structures. Also research toward an adaptive step size for the parallel structure should be investigated.

Parallel Adaptation; Sequential Structure

**Figure 6.8 Result Of a 4 Microphone Sub-Band ANC
(lower band filtering), Car Idling, Fan Off; Output :-+-**

Parallel Adaptation; Sequential Structure

Figure 6.9 Result Of a 4 Microphone Sub-Band ANC (lower band filtering), Car Speed 100 Km/hr, Fan Off; Output :-+-

Chapter 7 Conclusion

7.1 Discussion on the Results

The thesis aim was to investigate the use of 2 or more microphones for cancelling the correlated background acoustic noise in medium size cars. An overview of existing background acoustic noise suppression techniques was presented.

The EM method based on the LMS algorithm was selected for testing the various ANC structures introduced throughout the thesis.

A qualitative noise model defining the interaction that exists between the multiple noise sources surrounding the normal use of a car with the various points of observation was developed. This constituted a first step toward completing the data analysis on real car data. It also helped in optimizing the various structure conceptions.

Using the noise model as system's insight, the data analysis was carried on real car data recorded on an 8 track tape recorder.

It was found that various noise processes associated to specific driving conditions had a particular spectral signature. The latter also depended on the point of observation in the car. Further more, it was found that the PSD could be divided in at least two sub-bands: the upper and the lower acoustic band. Because of the background acoustic noise complexity, the noise characteristics were fairly complex when analyzed in time domain. Hence the correlation could only be used in a qualitative manner. The time domain analysis performed on both sub-bands seemed to indicate that the upper band

noise process differs from that observed in the lower band. This lead to developing a sub-band ANC.

A sub-band adaptation structure was successfully developed and tested on the car data. Background acoustic noise was achieved to a good level without enhancing the noise in any part of the acoustic band.

It was observed that under particular driving condition, some microphone locations provided a better reference source for noise suppression at specific frequencies. No microphone could prove itself as being the best one. It depended on both the driving condition and the microphone location.

Hence, there was a need for developing an algorithm which would control each microphone contribution with respect to the frequency band of interest. The problem was solved by introducing a two stage adaptation system. The first stage performed temporal filtering (frequency selection). The second performed spatial filtering (mic selection). Two primitive structures were presented, both of which offered concluding results.

Despite the fact that excellent results were obtained, there are still many unanswered question. For example, the mathematical model derived was based on a linear noise system. Recent researches seem to indicate that the background acoustic noise characteristics are non-linear. Nevertheless, the system does react as the model predicted. This could well be due to the intuitive nature of the LMS algorithm. This is the object of further researches.

7.2 Areas of Further Research

As previously mentioned, it is a known fact that the background acoustic noise characteristics are rapidly changing. Throughout the thesis these were assumed constant

for the period of interest. However, it is a factor worth researching. Further to it, the adaptive filter length could have been too long for allowing proper tracking of the system characteristics. I.E. the noise characteristics could vary too much for the adaptive filter response. Also, it is known that the LMS acts intuitively. Adding these factors seem to explain why the conventional ANC provides good noise suppression in a sub-band while yielding noise enhancement in the other band when noise suppression is performed over the entire acoustic band. These factors would also seem to indicate that there just enough time for adapting to the high power peak of the noise signal. Extensive research needs to be done on the matter in order to define an optimum adaptive filter length.

Also, the parallel ANC structures introduced provided good results. However, the better the results, less stable was the algorithm. Hence, research on algorithm stability should be carried on a large parallel structure variety.

Throughout the thesis, the adaptation step size were always set with respect to the noise power level. Various algorithms selecting the adaptation step size should be optimized.

Another area of research is the sub-band selection. I.E. in mobile telephony, the frequency band of interest ranges from about 150 Hz to 3500 Hz. Adaptation should only be confined to this band. Also, the band could be split in more than two sub-band. This could however lead to a tone in band problem which can only be perceived by a listener.

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