Adaptive Cancellation of Adjacent Channel Interference

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by

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Abstract

A new method to combat adjacent channel interference encountered with multi-channel receivers is presented. In the case of a two-channel receiver, there exits two crosstalk paths which allow the desired signal to become present in the reference of the interference, thus traditional adaptive noise cancellation is ineffective.

The two-channel receiver is similar to two-microphone systems used for speech enhancement. Models describing the baseband and passband crosstalk are developed. The Crosstalk Resistant Adaptive Noise Canceller (CTRANC), designed to work in the two-microphone case, fails when confronted with the two-channel receiver.

A new system is proposed which uses *a priori* knowledge of the crosstalk gained by the injection of a known signal into the input of the receiver. This injection systems is then compared with the CTRANC for both baseband and passband systems by extensive computer simulation.

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Contents

Figures

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Dedication

to my wife, Carole

Notation

List of Abbreviations

ANC — adaptive noise canceller
BPF — band-pass filter
CR — crosstalk ratio
CTRANC — crosstalk resistant adaptive noise canceller
DSBSC — double side band suppressed carrier
FIR — finite impulse response
HPF — high-pass filter
IR — interference ratio
LMS — least mean-square
LPF — low-pass filter
MSE — mean-square error
MMSE — minimum mean-square error
RF — radio frequency
SNR — signal-to-noise ratio

List of Principal Symbols

$x(n)$ = adaptive filter reference input
$d(n)$ = adaptive filter primary or desired input
$e(n), \varepsilon(n)$ = error
M = number of samples in signal vectors
$\mathbf{x}(n)$ = reference input vector
$\mathbf{w}(n)$ = adaptive filter coefficient vector
$y(n)$ = filter output
$H(z)$ = z-domain transfer function
s = generic signal
n_0, n_1 = generic noise

β = adaptation step size
$\nabla_x(\cdot)$ = gradient operator with respect to x
$E[\cdot]$ = expectation operator
s_0 = injected signal
s_1 = signal on channel 1 (interfering signal)
s_2 = signal on channel 2 (desired signal)
s_{12} = leakage from channel 2 to channel 1 (interference)
s_{21} = leakage from channel 1 to channel 2 (crosstalk)
H_1 = channel 1 BPF
H_2 = channel 2 BPF
H_{11} = channel 1 direct path
H_{12} = cross-channel path from channel 2 to channel 1
H_{21} = cross-channel path from channel 1 to channel 2
H_{22} = channel 2 direct path
f_1 = channel 1 carrier frequency
f_2 = channel 2 carrier frequency
B = bandwidth
$\hat{s}_1$ = estimate of s_1
$\hat{s}_2$ = estimate of s_2
$\hat{H}_{12}$ = estimate of H_{12}
$\hat{H}_{21}$ = estimate of H_{21}
I_1 = improvement on channel 1
I_2 = improvement on channel 2
$\sigma_{s_0}^2$ = variance of s_0
$\sigma_{s_2}^2$ = variance of s_2

Chapter 1
Introduction

Adaptive noise cancellation has been studied extensively since the 1960's [1]. It has been applied to almost every aspect of signal processing. Generally the problem is that there exists some signal which is corrupted by noise. The task of the adaptive noise canceller is to remove the noise while leaving the signal in tact. The nature of the signal and noise as well as their interrelation depend on the environment under study. In this paper noise cancellation, as it applies to adjacent channel interference exhibited in radio communications, is examined.

In most commercial radio systems, signals are separated into specific frequency bands or channels (Frequency Division Multiplexing). Often times two different channels may have little frequency separation which may result in frequency overlap. This allows one channel to corrupt its neighbor (see Fig. 1.1). The result is adjacent channel interference.

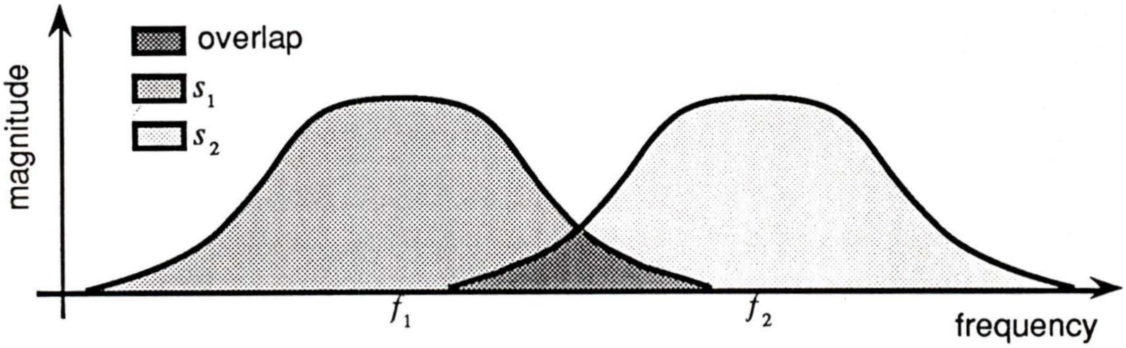

Figure 1.1 — Adjacent channel interference.

The problems associated with this interference are determined by the relative strengths of the signals. If the desired signal is strong with respect to the interfering signal, the presence of adjacent channel interference may go unnoticed and little or no noise reduction is required. If, on the other hand, the two signals have equal strength or if the interfering signal is greater than the desired signal, some measure of noise cancellation is needed.

Classical adaptive noise cancellation requires a reference to the interference as well as the noisy signal. In the adjacent channel problem, not only is the desired signal corrupted by the interfering signal, but components of the desired signal may be present in the noise reference. This complicates the task of noise cancellation.

There have been a few methods proposed for combating adjacent channel interference of analog signals but none employ the adaptive approach [2—4]. The advantage of adaptive noise cancellation is that generally little information is required regarding the nature of the signals;

the noise cancelling system adapts to its environment. Therefore this paper concentrates on adaptive noise cancellation.

There has been some investigation into the effects of signal components present in the noise reference [1] and some methods proposed to deal with it [5, 6]. These systems were developed primarily for the speech enhancement in noisy environments employing multiple microphones. When filtering of the primary paths as well as the crosstalk paths is considered, a more realistic model, the problem becomes more complicated [7]. This situation is quite similar to the adjacent channel problem. Therefore the adaptive adjacent channel interference canceller presented in this paper has fundamental similarities to and will be compared with the crosstalk resistant noise cancellers found in the literature.

All signals are assumed to be discrete representations of their analog counterparts where the index n refers to the current sample or time index. For convenience the index is often omitted where $x = x(n)$.

An an introduction to adaptive filter theory is provided in chapter 2 for the reader who may be unfamiliar with the subject. The treatment is not rigorous but will give the understanding necessary to follow this work. The least-mean square adaptive algorithm is used in this work. Although other adaptive filtering algorithms may be used (e.g. Least Squares, Fast Kalman), the goal of this research is not to find an improved adaptation algorithm, but to use a known adaptive process in a new interference cancelling methodology, applying it to a problem which has yet no satisfactory solution. Thus for simplicity we have chosen the stochastic gradient algorithm for the adaptation.

Models describing the behavior of adjacent channel interference and the multiple microphone scenario are developed in chapter 3. The existing methods of dealing with crosstalk will be introduced in chapter 4 and from these the new system is developed.

The study is carried out by extensive computer simulation, the results of which are considered in chapter 5. The scenarios are developed and tested with real systems in mind. Little analytical development is presented since established adaptive algorithms are used. The different systems are evaluated by computer simulation and their performance characteristics compared.

Chapter 2
A Brief Review of Adaptive Filter Theory

2.1 Introduction

There exists much literature dealing with adaptive filtering, most of which provides derivations of adaptive filter theory based on optimal (Wiener) filter theory [1, 8—10]. Since the foundation of this project relies on adaptive filtering, a elementary introduction will be provided.

One of the common uses of adaptive filters is the removal of noise which has corrupted a signal. In many cases noise may be removed by passing the corrupted signal through a filter that suppresses the noise while leaving the signal relatively unchanged. The design of such filters is in the realm of optimal filtering. Much of the original work was carried out by Wiener [1], therefore optimal filters often are referred to as Wiener filters. Although a Wiener filter provides the best noise reduction in the mean-square sense, the ensemble statistics of the signal are required. Since *a priori* knowledge of signal statistics is generally unavailable, Wiener filters are not realizable.

Adaptive filters may be constructed such that they iteratively estimate the Wiener solution given no knowledge of signal statistics and little knowledge of the system with which they interact. These filters are not necessarily complex and often are easy to realize.

One of the most common forms is the joint process estimator which may be used as an adaptive noise canceller (ANC). Adaptive filters employ two structures: lattice and transversal, the latter of which will be examined. Of the many adaptive algorithms, the least-mean-square (LMS) or stochastic gradient (SG) will be considered here.

2.2 Classification

The adaptive filter may be classified into three groups based on its connections to the outside world (see Fig. 1.1) [9]. In the first case the filter responds to one input and has no explicit output. As the filter adjusts its internal parameters, it is estimating some aspect of the input signal. Therefore the internal parameters, the coefficients of the filter, provide some information about the system.

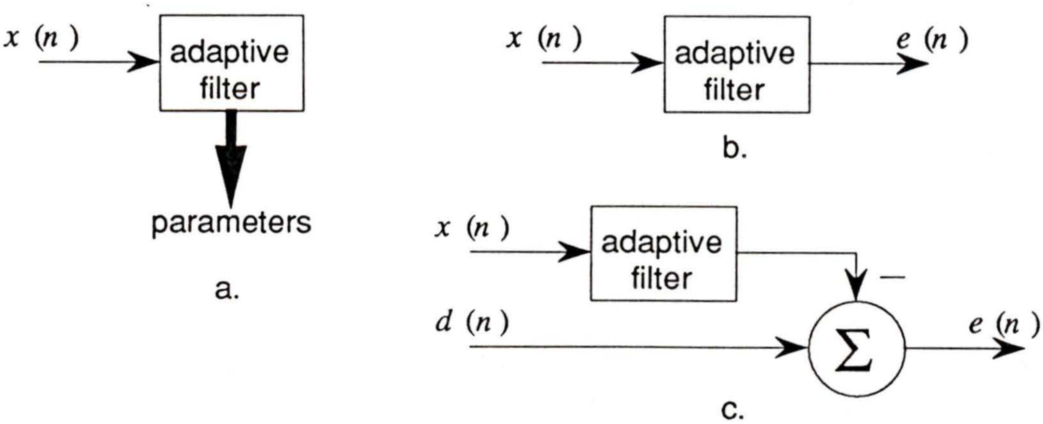

Figure 2.1 — Classes of adaptive filters: a) estimator, b) predictor, c) joint process estimator (9).

The second class is the predictor which is an estimator with the addition of an explicit output, generally an error signal which is minimized in some sense within the constraints of the filter. The predictor is often used to estimate the next sample, which also provides information about the system, and the resulting prediction error is used to further adapt the filter.

The third class, and perhaps the most common, is the joint process estimator. In this case there are two inputs: the reference input, $x(n)$, which is acted upon by the adaptive filter and then subtracted from the primary input, $d(n)$. The difference between the two signals, again generally some form of an error, $e(n)$, is minimized in some sense; thus $d(n)$ is being estimated given $x(n)$. In this manner the correlation between $d(n)$ and $x(n)$ is estimated. It is this class of adaptive filters that will be used in this paper.

2.3 Structure

Of the two basic structures common to adaptive filters, the transversal finite impulse response (FIR) will be used. It is the most common form and its implementation is straightforward. The FIR filter simply multiplies the present and $M-1$ past samples of a signal by a coefficient vector of length M (see Fig. 2.2).

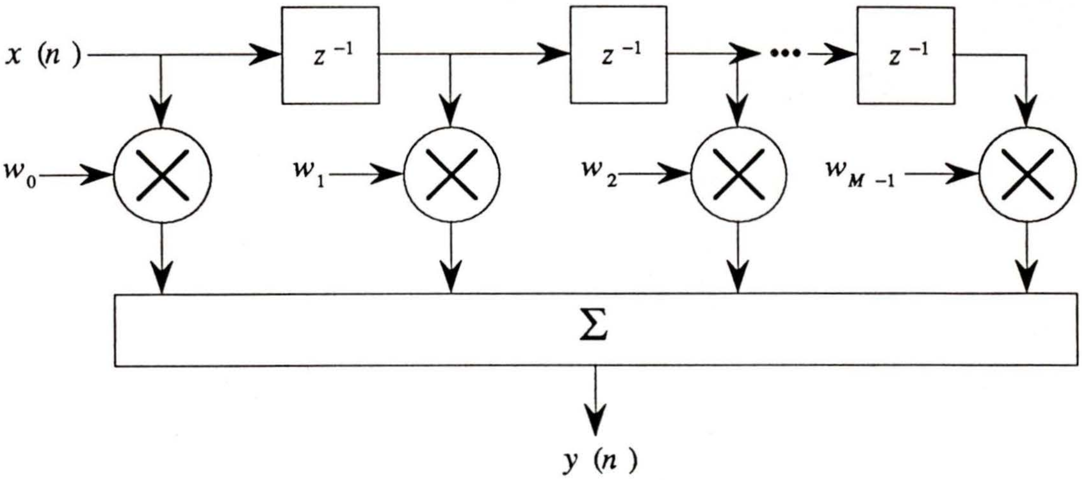

Figure 2.2. — Transversal filter.

Vector notation is very useful when dealing with time windows of signal samples. Thus when dealing with signals in vector form, the following conventions will be used. The input vector, $\mathbf{x}(n)$, to an FIR filter of length M, is

$$\mathbf{x}^T(n) = [\,x(n) \quad x(n-1) \quad \dots \quad x(n-M+1)] \tag{2.1}$$

The coefficient vector $\mathbf{w}(n)$ at time n is

$$\mathbf{w}^T(n) = [w_0(n) \quad w_1(n) \quad \dots \quad w_{M-1}(n)] \tag{2.2}$$

The output of the FIR filter is

$$y(n) = \sum_{i=0}^{M-1} w_i(n)x(n-i) \tag{2.3}$$

which may be expressed in vector form as

$$\mathbf{y}(n) = \mathbf{w}^T(n)\mathbf{x}(n) \tag{2.4}$$

The transfer function of the FIR filter in the z-domain is

$$H(z) = \sum_{i=0}^{M-1} w_i z^{-i} \tag{2.5}$$

Thus the transfer function is linearly related to the coefficient vector [9]. Since the transfer function is all-zero, nonrecursive filters are always stable [11]. The transfer function may be altered simply by changing the filter length, M.

2.4 Adaptive Algorithm

There are a variety of adaptive algorithms, each having its own particular applications and merits. None have been more studied or more used as the least-mean-square (LMS), also commonly called the stochastic gradient (SG), algorithm. The LMS algorithm is very simple and has very little computational overhead. It provides the best approximation to the Wiener solution in the LMS sense.

The LMS algorithm will be introduced for the joint process estimator (see Fig. 2.3) with very little mathematical development in order to give the reader some insight into the LMS structure without laboring through the details of Wiener filtering. A rigorous treatment of the LMS algorithm may be found in the literature [1, 8—10].

The joint process estimator, often acting as an adaptive noise canceller, is developed for the case where two signals are available: 1) signal corrupted by noise ($s + n_1$) present at the primary input, $d(n)$, and 2) a reference to the noise (n_0) present at the reference input, $x(n)$ (see Fig. 2.3). It is assumed that s is uncorrelated with either n_0 or n_1 and that n_0 and n_1 have some unknown linear relationship. All signals are unbiased and stationary. Given n_0, the adaptive noise canceller estimates the correlation, $\hat{H}(z)$, between the signal plus noise and the noise reference. s and n_0 are uncorrelated so will not contribute to the estimation of the correlation between n_0 and $s + n_1$. Thus the adaptive filter estimates the transfer function, $\hat{H}(z)$, of the path by which the noise corrupts the signal.

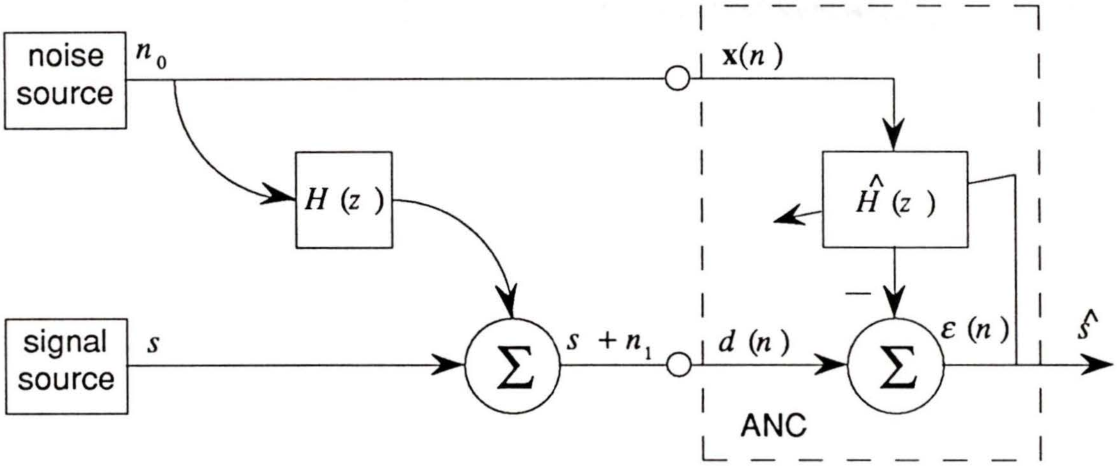

Figure 2.3 — Adaptive noise canceller.

The LMS algorithm is derived from the minimum mean-square error (MMSE) solution employing the method of steepest decent. The filter coefficient update equation from the MMSE solution is [9]

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \tfrac{\beta}{2}\nabla_{\mathbf{w}(n)}\{E[\varepsilon^2(n)]\} \tag{2.6}$$

where $\mathbf{w}(n)$ is the current coefficient vector, β is the small adaptation step size, and $\nabla_{\mathbf{w}(n)}\{E[\varepsilon^2(n)]\}$ is the error gradient. Since the gradient of the error is in the direction of greatest increase in error, moving in the opposite direction reduces the error, hence the error gradient is subtracted from the coefficient vector.

The MMSE gradient algorithm will converge on the optimum solution, however the exact gradient is required for each iteration. This requires knowledge of the ensemble statistics which generally is not available. Also computation of the gradient requires matrix inversion. From the orthogonality principle it may be shown that the error gradient is the negative of the cross-correlation between the error, $\varepsilon(n)$, and each member of the reference input vector, $\mathbf{x}(n)$ [9]

$$\nabla_{\mathbf{w}(n)}\{E[\varepsilon^2(n)]\} = -2E[\varepsilon(n)\mathbf{x}(n)] \tag{2.7}$$

The computation of the gradient has been simplified but the troublesome expectation operator remains. The LMS algorithm makes instantaneous estimates of the gradient by substituting the time average for the ensemble average. Thus (2.7) becomes [10]

$$\nabla_{\mathbf{w}(n)}\{E[\varepsilon^2(n)]\} \approx \hat{\nabla}(n) = -2\varepsilon(n)\mathbf{x}(n) \tag{2.8}$$

resulting in a "noisy" or stochastic gradient. The entire LMS algorithm is simply

$$\begin{gathered} \varepsilon(n) = d(n) - \mathbf{w}(n)^T\mathbf{x}(n) \\ \mathbf{w}(n+1) = \mathbf{w}(n) + \beta(n)\varepsilon(n)\mathbf{x}(n) \end{gathered} \tag{2.9}$$

The adaptation step size determines the magnitude of the change made on the coefficient vector from one sample to the next. The size of β governs two aspects of the adaptive filter: the rate of convergence and the mean-square error. The stability is also dependent on β. To assure that the LMS algorithm converges for the transversal filter [8],

$$0 < \beta < \frac{1}{(M+1)(\text{power of reference signal})} \tag{2.10}$$

where again M is the length of the filter.

There is a trade-off involved in the choice of β. For large β, subject of the above constraints, the filter will converge rapidly. However, the final MSE or misadjustment $\mathcal{M}$ increases as β increases [8],

$$\begin{aligned} \mathcal{M} &= \frac{\text{excess MSE}}{\text{MMSE}} \\ &\approx \frac{M+1}{4\tau_{mse}} \end{aligned} \tag{2.11}$$

where τ_{mse} is the average time constant, a measure of the rate of convergence, which is inversely proportional to β.

One method which allows for both a rapid convergence and small misadjustment is to reduce β as the filter converges. The method used in this research as well as [5, 12] provides an exponentially weighted time average of the input signal power, σ

$$\beta(n) = \frac{a}{\sigma^2(n) + b} \tag{2.12}$$

where $\sigma^2(n+1) = (1-\alpha)\sigma^2(n) + x(n)^2$. a, b, and α are constants determined heuristically.

2.5 Summary

Adaptive filters may be used in situations where a priori knowledge of the system is not available. They may be used to estimate system parameters, predict subsequent samples, and cancel noise.

The LMS algorithm is simple to implement and is computationally very efficient. Although it is not the optimal solution, the LMS algorithm provides the best approximation of the MMSE solution in the least mean-square sense. These properties have allowed the LMS algorithm to become one of the most widely used adaptive algorithms for signal processing.

Chapter 3
Crosstalk Models

3.1 Introduction

Since crosstalk is the theme of this paper, it will be defined in the context of this research. Crosstalk generally refers to the undesirable presence of one signal in another[1]. In the communications domain, this is often seen in the form of adjacent channel interference. Although the terms *crosstalk* and *adjacent channel interference* describe the same phenomenon, for this research they have slightly different connotations which will be defined.

Crosstalk may be modeled differently for different systems. In the case of two signals, crosstalk may be present in one or two directions, depending on the system. The nature of the crosstalk channel or path depends on the application. When the crosstalk is present in only one direction, it may be adequately cancelled by the adaptive noise canceller as presented in the previous chapter.

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[1] "...crosstalk is the reception of portions of a signal from one channel in another channel," from G. Hennedy, *Electronic Communication Systems*, pp. 506 McGraw-Hill Book Co., New York, 1985.

When crosstalk is present in two directions, the task of cancellation is complicated. Some characteristics of bi-directional crosstalk will be examined.

3.2 Crosstalk classification

Consider two signal paths or channels which may have some cross-channel interaction (see Fig. 3.1). *Interference* will refer to the leakage of the undesired signal into the desired channel. *Crosstalk* will refer to the leakage of the desired signal into the interfering channel. This convention will be adhered to for subsequent discussions.

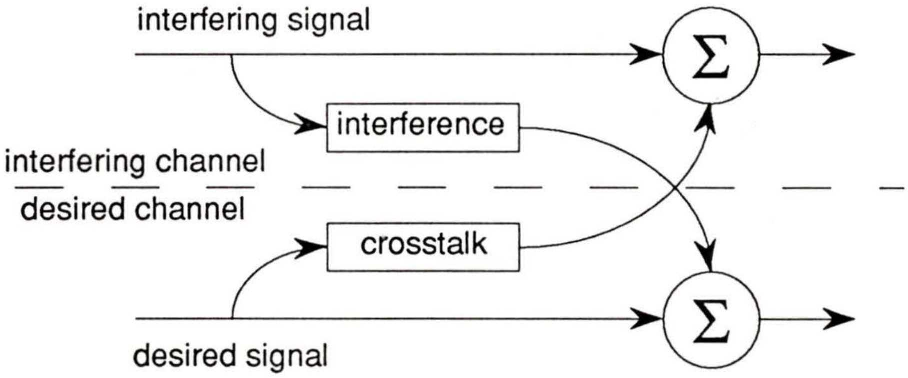

Figure 3.1 — Conventions adopted for *interference* and *crosstalk.*

Bi-directional crosstalk, model 1

The adaptive noise canceller is effective when an accurate reference of the interference (or noise) is available. Such is not always the case. Often the reference of the interference is tainted with components of the desired signal. As the level of crosstalk increases, the effectiveness of the adaptive noise canceller is diminished.

Fig. 3.1 will be expanded such that the channel carrying the interfering signal, s_1, is taken to be channel 1 and the channel carrying the desired signal, s_2, is taken to be channel 2 (see Fig. 3.2). In this case s_1 is the interfering signal via cross-channel path H_{21}; similarly s_2 is the crosstalk signal via H_{12}. s_{21} represents the interference which may be cancelled by the ANC as shown in Section 2.4. However, some component, s_{12}, of the desired but unknown signal is present in the interference reference. Therefore an accurate reference to the interference is not available. Widrow *et al.* [1] discussed the performance degradation of the ANC due to signal components present in the noise reference input. From unconstrained Wiener filter theory it was found that the output signal-to-noise density ratio after convergence is

$$\rho_{out}(z) = \frac{1}{\rho_{ref}(z)} \tag{3.1}$$

where

$$\rho(z) = \frac{\text{Signal Power Spectral Density}}{\text{Noise Power Spectral Density}} \tag{3.2}$$

Thus the output signal-to-noise density ratio decreases as the level of crosstalk increases.

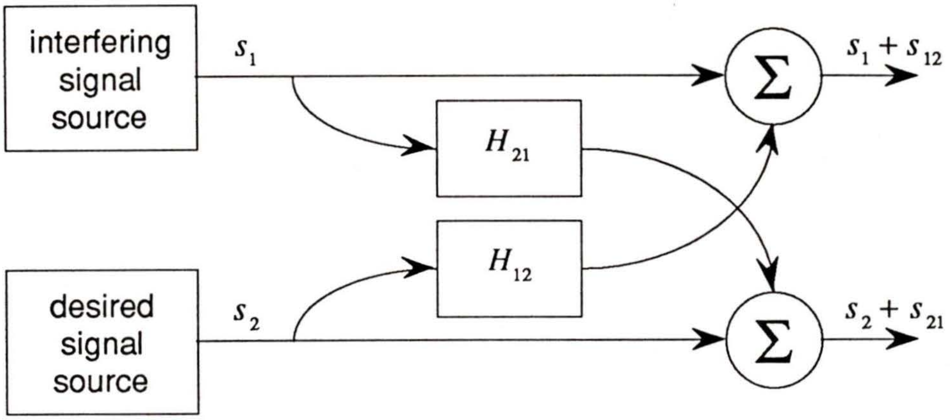

Figure 3.2 — Crosstalk model 1.

This crosstalk problem has been observed when processing speech in noisy environments. Generally two microphones are employed: one for the speech (with additive noise) and the other for the reference to the noise. In order to obtain a noise reference which is highly correlated with the interfering noise, the two microphones must be placed in proximity with each other. This also allows some of the desired signal to leak into the noise reference [13].

The crosstalk resistant adaptive noise canceller (CTRANC), to be covered later, was designed to solve this problem [5]. Although the crosstalk model stems from spatially separated baseband signals, it will be shown later that CTRANC may also be applied to spectrally separated passband signals.

Bi-directional crosstalk, model 2

Another situation that may arise is the case when the primary signal and interference paths are nominally frequency diverse (see Fig. 3.3). Depending on the relationships between the signals and the filters (i.e. the relationship between s_1, s_{11}, and s_{21}), the correlation between the interference and the reference to the interference may be very low, similarly for the correlation between the crosstalk and its reference. This can severely inhibit cancellation.

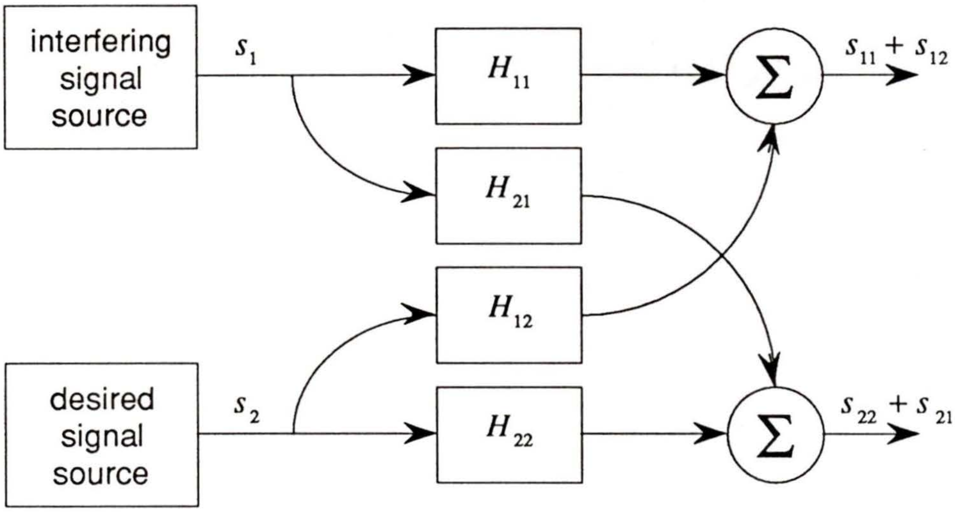

Figure 3.3 — Crosstalk model 2.

This general bi-directional crosstalk model may be applied to various applications. Using two-port matrix notation, the crosstalk model is described by

$$\begin{bmatrix} s_{11} + s_{12} \\ s_{21} + s_{22} \end{bmatrix} = \begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \end{bmatrix} \tag{3.3}$$

where the H_{ij} terms represent a distributed leakage between signal channels. The nature of the signal channels, be they wires or RF, are described by the H_{ii} terms. By letting H_{11} and H_{22} equal unity, model 2 reduces to two-microphone situation, model 1.

This model may also be applied to the problem of adjacent channel interference present in a multi-channel receiver. Consider two transmitters sending two different messages, s_1 and s_2, over two proximate but different carriers, f_1 and f_2, which are then received by a two-channel radio receiver. The front-end RF passband filters, H_1 and H_2, are centered on their respective carriers (see Fig. 3.4). If the center frequencies are relatively close, there will be some overlap in the spectra of the two passband signals as well as in the skirts of the filters. Some of channel 1 will leak into channel 2 and visa versa.

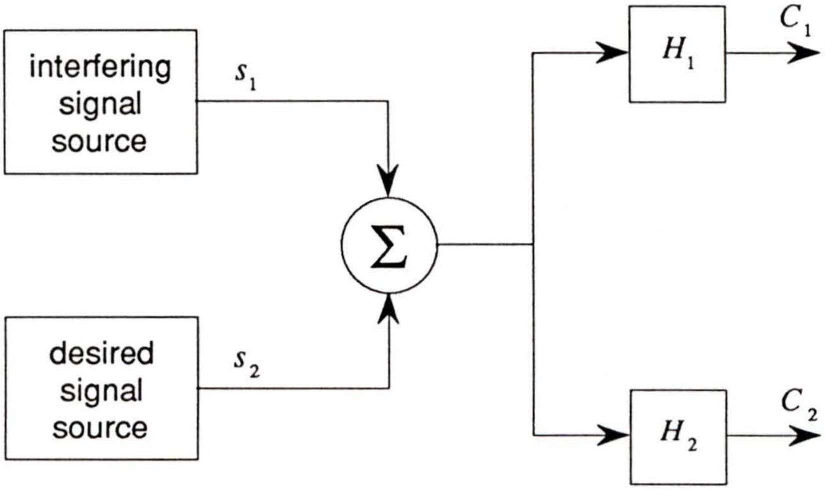

Figure 3.4. — Two-channel receiver model.

This situation holds in Fig. 3.3 if the characteristics of the signals and filters are examined. H_1 and H_2 are bandpass filters of bandwidth B centered on f_1 and f_2 respectively, thus separating channel 1 and channel 2 (see Fig. 3.5). Therefore the direct path filters, H_{11} and H_{22}, represent the bandpass filters H_1 and H_2. Since the portion of s_2 received on channel 1 must pass through H_1, the cross-channel filter H_{12} represent the upper skirt of H_1. Similarly H_{21} corresponds the lower skirt of H_2.

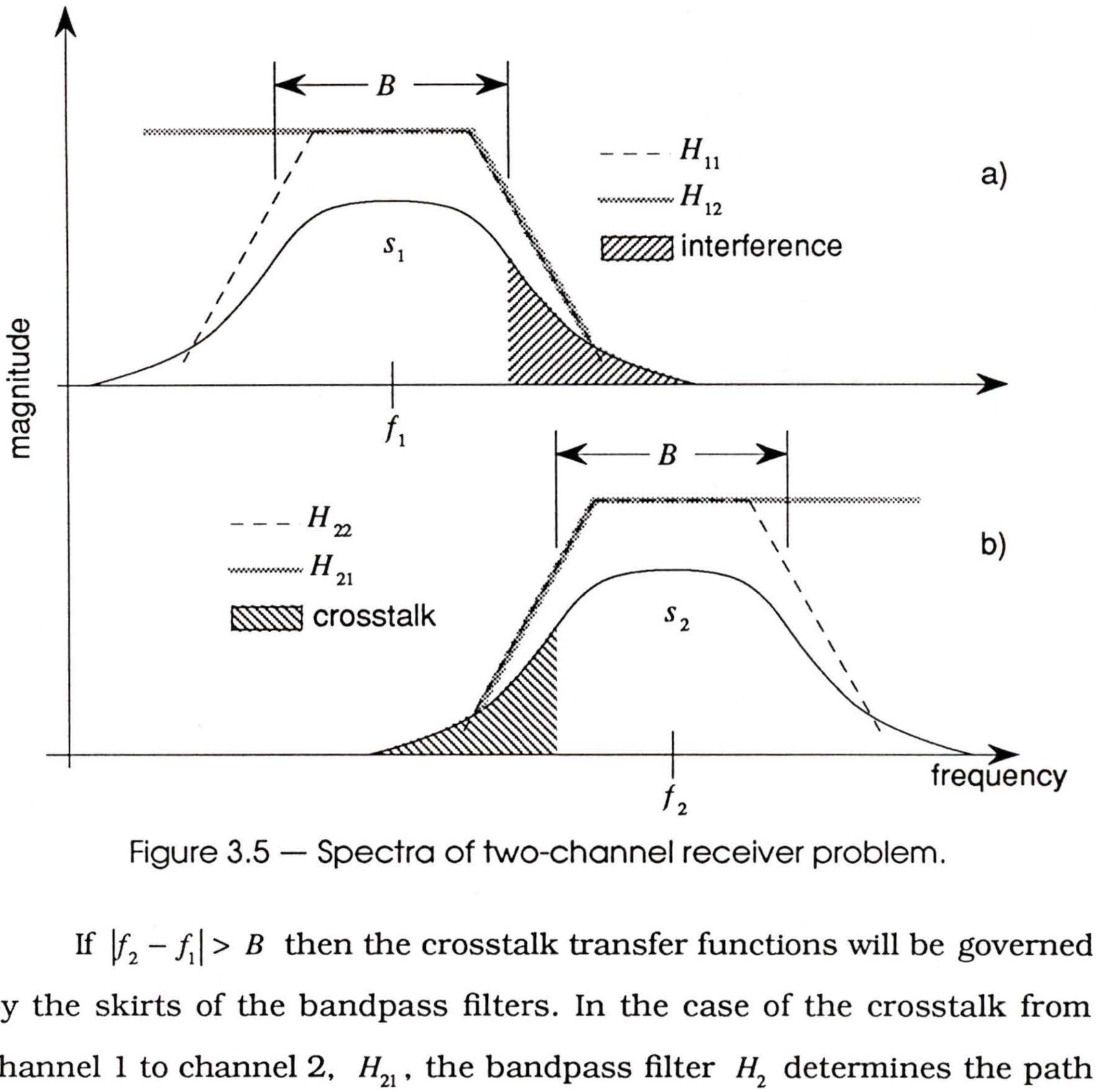

Figure 3.5 — Spectra of two-channel receiver problem.

If $|f_2 - f_1| > B$ then the crosstalk transfer functions will be governed by the skirts of the bandpass filters. In the case of the crosstalk from channel 1 to channel 2, H_{21}, the bandpass filter H_2 determines the path by which s_1 leaks into channel 2, conversely for H_{21}. Outside the area of frequency overlap, $f < f_1, f > f_2$, the cross-channel transfer functions do not influence the interference and crosstalk because of the bandpass nature of s_1 and s_2. The direct RF channels are described by H_{11} and H_{22}. Thus the signal on channel 1 is

$$C_1 = H_1[s_1 + s_2] = H_{11}s_1 + H_{12}s_2 = s_{11} + s_{12} \qquad (3.4)$$

and the signal on channel 2 is

$$C_2 = H_2[s_1 + s_2] = H_{21}s_1 + H_{22}s_2 = s_{21} + s_{22} \qquad (3.5)$$

It is in this manner in which adjacent channel interference for a two-channel receiver will be modeled.

3.3 Summary

Interference, crosstalk, and applicable models have been defined for their use in this research. Starting from additive noise and the adaptive noise canceller, the model was developed for the crosstalk present at the input to the multichannel radio receiver.

Chapter 4
Adaptive Noise Cancellation in the Presence of Crosstalk

4.1 Introduction

One method developed to combat the bi-directional crosstalk problem introduced in the previous chapter is the Crosstalk Resistant Adaptive Noise Canceller (CTRANC) [5]. It was designed primarily for use with speech in noisy environments, which may be modeled with bi-directional crosstalk model 1.

CTRANC and Sakai's [6] systems were designed to operate in the environment of crosstalk model 1. In this situation they perform well. However, when confronted with crosstalk model 2, they provide little improvement. Therefore a new system is proposed that is to perform well in the case of the multi-channel receiver.

4.2 Previous Systems

CTRANC

The CTRANC topology is composed of two joint-process estimators in a complimentary fashion (see Fig. 4.1). One joint process estimator cancels the crosstalk which allows the other to effectively work as an adaptive noise canceller.

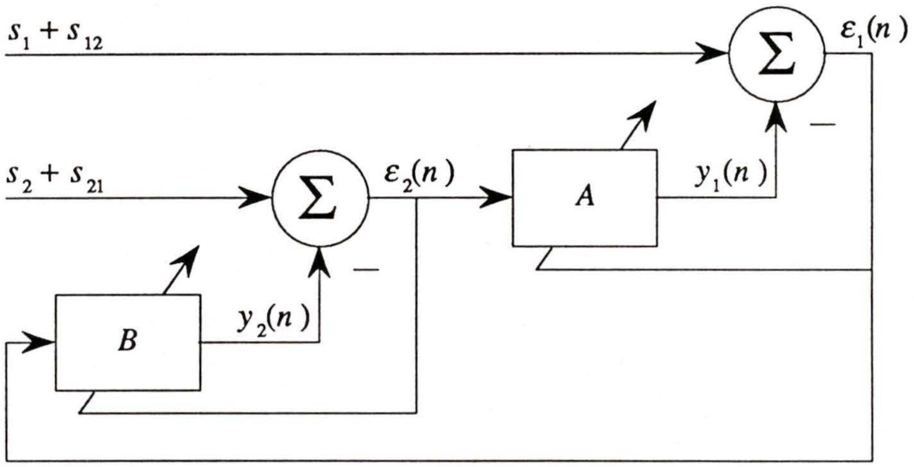

Figure 4.1 — Crosstalk Resistant Adaptive Noise Canceller (5).

Two formulations are presented: one based on the transversal filter and the second based on the lattice filter. Only the transversal case will be examined here. The full development may be found in [5].

The stochastic gradient approximation to the MMSE gradient algorithm was used in the development of the CTRANC system. However, the update algorithm differs from the LMS algorithm present in Section 2.4 in that the gradient is approximated recursively. The MMSE gradient algorithm, repeated here for convenience, is

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \tfrac{\beta}{2}\nabla_{\mathbf{w}(n)}\{E[\varepsilon^2(n)]\} \tag{4.1}$$

In the CTRANC SG algorithm, time averages replace ensemble averages, but the orthogonality principle is not used to replace the error gradient with the cross-correlation between the error and the reference input as in the case of the LMS algorithm in Section. 2.4. Thus the gradient becomes

$$\nabla_{\mathbf{w}(n)}\{E[\varepsilon^2(n)]\} \approx \nabla_{\mathbf{w}(n)}\{\varepsilon^2(n)\} = \varepsilon(n)\nabla_{\mathbf{w}(n)}\varepsilon(n) \tag{4.2}$$

which results in coefficient vector update equations, for filters A and B, of the form

$$\begin{aligned} \mathbf{w}^A(n+1) &= \mathbf{w}^A(n) - \beta_1(n)\varepsilon_1(n)\nabla_A\varepsilon_1(n) \\ \mathbf{w}^B(n+1) &= \mathbf{w}^B(n) - \beta_2(n)\varepsilon_2(n)\nabla_B\varepsilon_2(n) \end{aligned} \tag{4.3}$$

where the error gradients $\nabla_A\varepsilon_1(n)$ and $\nabla_B\varepsilon_2(n)$ are calculated recursively.

In our simulations, the CTRANC topology is implemented with the LMS algorithm as described in Section 2.4.

The CTRANC system was developed to combat the crosstalk present in the two-microphone speech in a noisy environment situation, crosstalk model 1 (see Fig. 4.2). When the CTRANC is connected to the model, it may be seen that the A filter cancels the crosstalk, H_{21}, and the B filter cancels the interference, H_{12}. Thus the error signals, ε_1 and ε_2, are the estimates of the interference, s_1, and the desired signal, s_2.

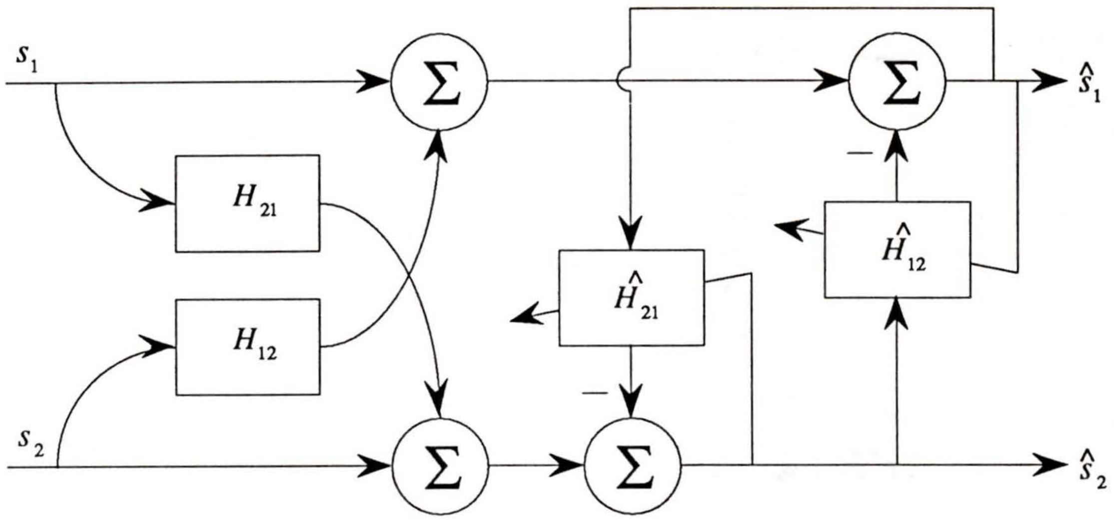

Figure 4.2 — CTRANC connected to crosstalk model 1.

The CTRANC system has been implemented in hardware which allows for comparisons between CTRANC and other noise cancelling schemes [12]. CTRANC was compared to the ANC for the case of two microphones receiving recorded speech and noise; CTRANC generally performed better than the ANC for high levels of crosstalk.

A New CTRANC

Another system, proposed by Sakai, *et al.* [6] which is similar to the CTRANC system. This one was designed to use the standard LMS algorithm and has no explicit feedback loop as in the case of CTRANC. In this case one of the joint process estimators is split into two parts (see Fig. 4.3). The first filter, connected to the interfering channel is simply a copy of the final joint process estimator, which cancels the interference. The middle joint process estimator cancels the crosstalk which gives the final adaptive filter an accurate interference reference.

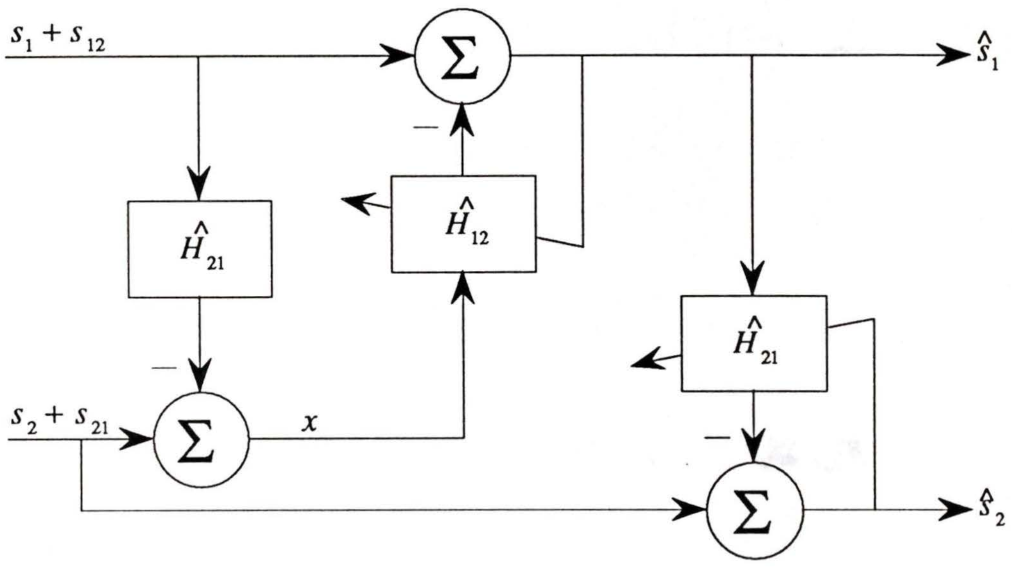

Figure 4.3. — Sakai's new CTRANC.

4.3 Proposed System

Injection Method

The initial design of the injection method is similar to both CTRANC and Sakai's in that two joint process estimators are used; one estimates the crosstalk and the other estimates the interference. Also as in the case of Sakai's, the coefficients of one of the joint process estimators are used in a standard FIR filter (see Fig. 4.4). To allow the first joint process estimator to more accurately approximate the crosstalk, a signal with known statistics is injected at the input of the receiver. The same signal is then used as the reference input to the first joint process estimator. Therefore the cross-channel transfer function is estimated given partial knowledge of the crosstalk. This results in a more accurate cross-channel approximation.

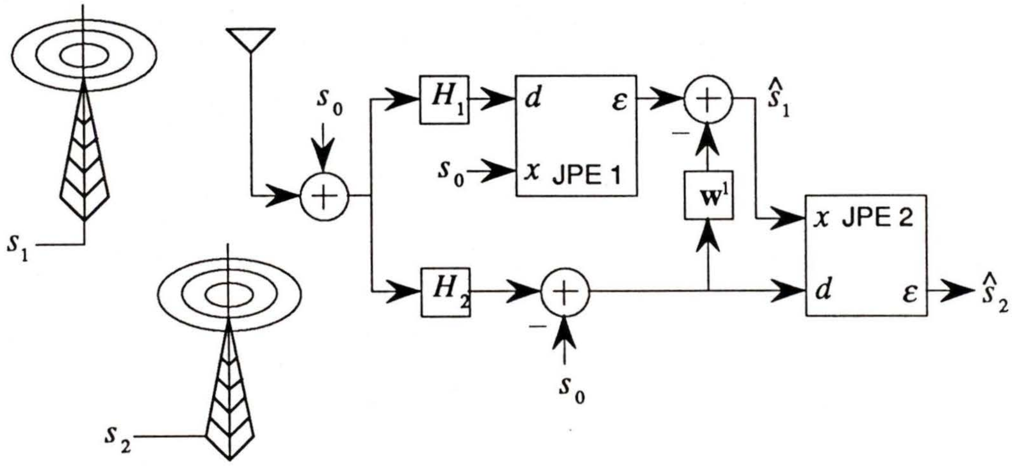

Figure 4.4 — Multi-channel receiver with injection type adjacent channel interference canceller.

In the first version of the injection system, the injected signal, s_0, is added to the desired channel, thus estimating the crosstalk path using the partial *a priori* signal statistics. Given this estimate of the cross-channel transfer function, the crosstalk may be cancelled by filtering the desired channel through this estimate and subtracting the result from the interfering channel. This results in removing the components of the desired signal that are present in the interfering signal. The resulting signal, $\hat{s_1}$ is then used as the reference input of the second joint process estimator to cancel the interference yielding $\hat{s_2}$.

Since the previous two systems are designed around the first crosstalk model, the injection system will also be analyzed for this case (see Fig. 4.5). s_1 and s_2 are on two different carriers. s_0 is injected into channel 2 with the same carrier frequency as s_2. Thus the path by which s_2 crosses into channel 1 will be the same for s_0. The input to the first adaptive filter is

$$d_1 = s_1 + H_{12}(s_0 + s_2) \tag{4.4}$$

The reference input to the first joint process estimator, x_1, is s_0, which results in an output of

$$\begin{aligned} \varepsilon_1 &= d_1 - \hat{H}_{12}x_1 \\ &= s_1 + H_{12}(s_0 + s_2) - \hat{H}_{12}s_0 \\ &= s_1 + H_{12}s_2 + s_0\left(H_{12} - \hat{H}_{12}\right) \end{aligned} \tag{4.5}$$

Assuming that s_0 and s_2 are uncorrelated, ε_1 will be minimized when $\hat{H}_{12} = H_{12}$. Thus the transfer function from channel 2 to channel 1 is estimated. Once the filter has converged, the output error becomes

$$\varepsilon_1 = s_1 + H_{12}s_2 \tag{4.6}$$

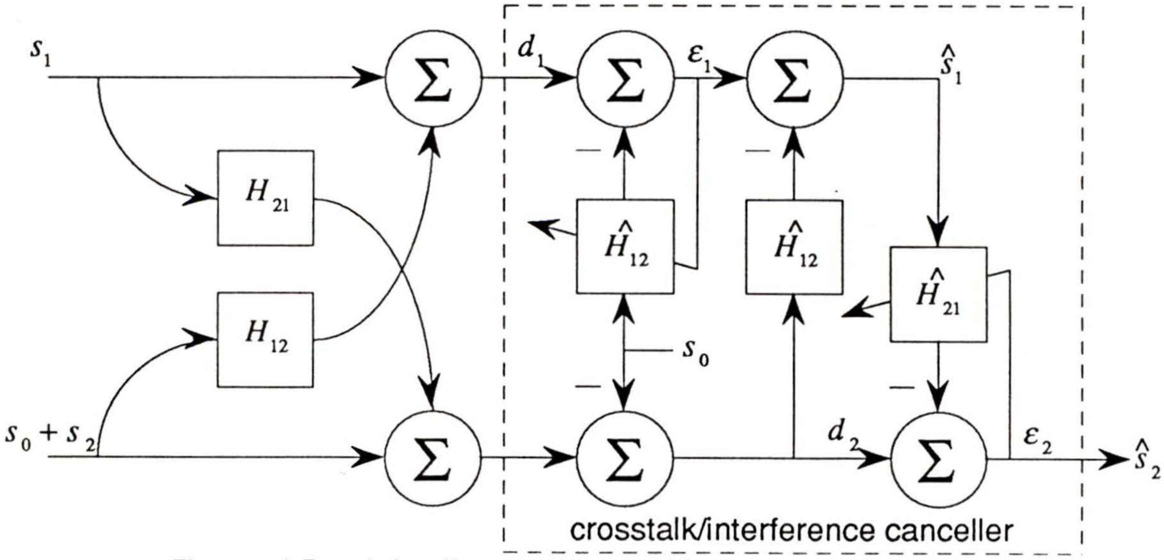

Figure 4.5 — Injection method with crosstalk model 1.

This results in an estimate of H_{12} but there still remains components of s_2 in channel 1. This is where the standard FIR filter, $\hat{H}_{12}$, comes into play. The coefficient vector of the first joint process estimator, $\mathbf{w}^1$, is used as the weight vector of the FIR filter. In this way the transfer function from channel 2 to channel 1 has been duplicated. Once s_0 is removed from channel 2 resulting in

$$d_2 = s_2 + H_{21}s_1, \tag{4.7}$$

the signal is passed through the FIR filter and subtracted from channel 1. The estimate of s_1 becomes

$$\begin{aligned}\hat{s}_1 &= \varepsilon_1 - \hat{H}_{12}d_2 \\ &= s_1 + H_{12}s_2 - \hat{H}_{12}(s_2 + H_{21}s_1) \\ &= s_1\left(1 - \hat{H}_{12}H_{21}\right) + s_2\left(H_{12} - \hat{H}_{12}\right)\end{aligned} \tag{4.8}$$

If $\hat{H}_{12} = H_{12}$ then the second term is zero leaving only components of s_1. The crosstalk has been estimated, duplicated, and removed. The $1 - \hat{H}_{12}H_{21}$ term will be examined in the next chapter.

The second joint process estimator may now function as an adaptive noise canceller since an accurate reference to the interference exists. The output of the ANC is

$$\begin{aligned}\varepsilon_2 &= d_2 - \hat{H}_{21}x_2 \\ &= s_2 + H_{21}s_1 - \hat{H}_{21}\hat{s}_2\end{aligned} \tag{4.9}$$

If the estimate of s_1 is accurate, then the cross-channel transfer function H_{21} may also be accurately estimated and its effects cancelled which results in $\varepsilon_2 = \hat{s}_2$.

The problem of the $s_1(1-\hat{H}_{12}H_{21})$ term in (4.8) may be reduced by subtracting $\hat{s}_2$ from channel 1 instead of i_2; essentially feeding back the estimate of s_2 for the estimation of s_1 (see Fig. 4.6). Therefore as s_2 improves, so does s_1. This feedback is also present in the CTRANC.

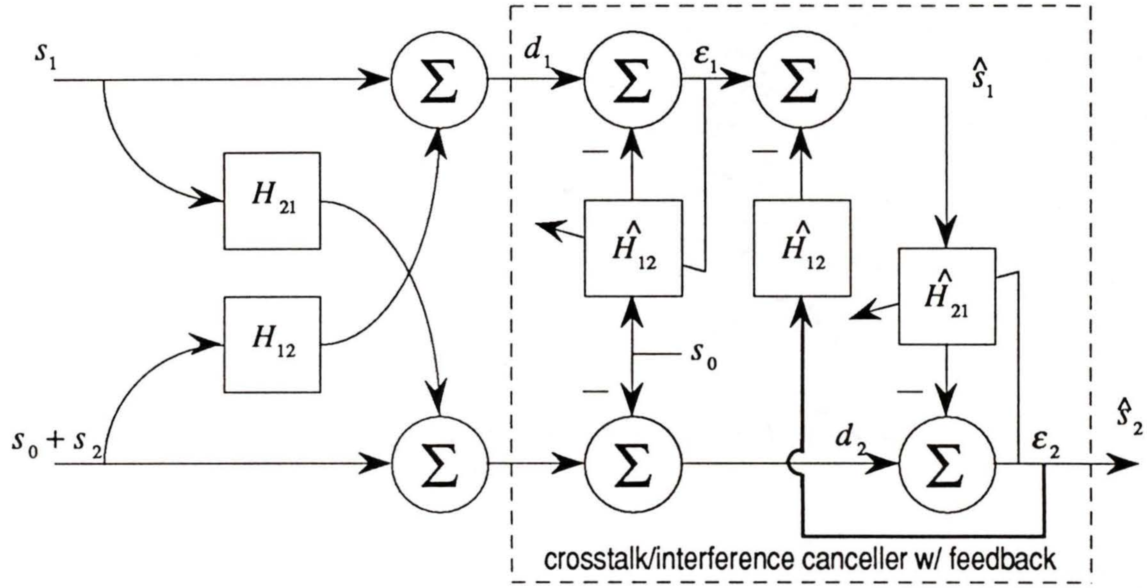

Figure 4.6 — Injection method with feedback and crosstalk model 1.

When crosstalk model 1 is replaced by model 2, cancellation is complicated. The model is implemented as described in Chapter 3 resulting in the system shown in Fig. 4.7. The interference canceller is the same as above with the exception of the delays which will be discussed later. In this case, the primary input to the first adaptive filter is

$$d_1 = H_1(s_0 + s_1 + s_2) \qquad (4.10)$$

following the conventions of crosstalk model 2 this becomes

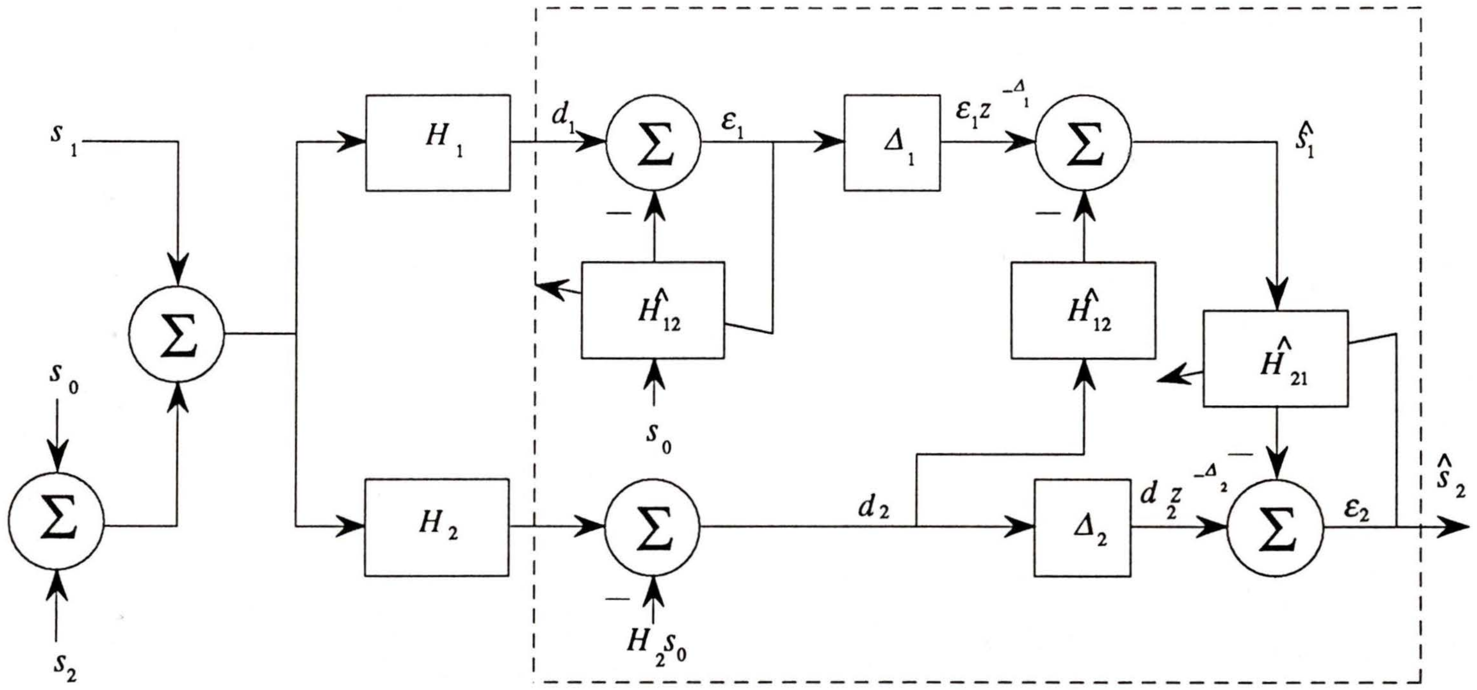

Figure 4.7 — Two-channel receiver with injection type adaptive adjacent channel interference canceller.

$$d_1 = H_{11}s_1 + H_{12}(s_0 + s_2) \tag{4.11}$$

Given d_1 and s_0, the output of the first joint process estimator is

$$\begin{aligned} \varepsilon_1 &= d_1 - \hat{H}_{12}x_1 \\ &= H_{11}s_1 + H_{12}(s_0 + s_2) - \hat{H}_{12}s_0 \\ &= H_{11}s_1 + H_{12}s_2 + s_0\left(H_{12} - \hat{H}_{12}\right) \end{aligned} \tag{4.12}$$

which will be minimized when $\hat{H}_{12} = H_{12}$. In this case $H_2 s_0$ is removed from channel 2, the result, d_2, is filtered by $\hat{H}_{12}$ and subtracted from channel 1 resulting in

$$\begin{aligned} \hat{s}_1 &= \varepsilon_1 - \hat{H}_{12}d_2 \\ &= H_{11}s_1 + H_{12}s_2 - \hat{H}_{12}(H_{22}s_2 + H_{21}s_1) \\ &= s_1\left(H_{11} - \hat{H}_{12}H_{21}\right) + s_2\left(H_{12} - \hat{H}_{12}H_{22}\right) \end{aligned} \tag{4.13}$$

At this point it is not clear if any cancellation of s_2 has been accomplished. This will be investigated further in the next chapter since it depends on the nature of H_{ij}. If (4.13) is compared to (4.8), it may be seen that model 1 is a special case of model 2 where $H_{11} = H_{22} = 1$.

Channel 1 must be time delayed before the subtraction is carried out in order to keep the components of s_2 present in channel 1, s_{12}, synchronized in time with s_2 present in channel 2, s_{22}. The time discrepancy is due to the fact that s_{12} has gone through one filter, H_1, which causes a delay whereas s_{22} that is being subtracted has been filtered by H_2 and $\hat{H}_{12}$, each of which delays the signal. Therefore the delay on channel 1 is required so that s_{22} may "catch up" with its corresponding components in s_{12}.

Assuming that the crosstalk has been cancelled at the reference input x_2, the output of the adaptive noise canceller is

$$\begin{aligned}\varepsilon_2 &= d_2 - \hat{H}_{21} x_2 \\ &= H_{22} s_2 + H_{21} s_1 - \hat{H}_{21} \hat{s}_1 \qquad (4.14)\end{aligned}$$

which should be simply $H_{22} s_2$ if $\hat{s}_1 = s_1$.

Again the delay is required because of the different paths the signals may take. The delay on channel 2 compensates for the delay placed in channel 1 plus the delay imparted by the adaptive filter. Widrow *et al.* [1] showed that the solution arrived at by the causal adaptive filter best approximates the unconstrained Wiener solution when the primary input has been delayed by about half of the time delay of the adaptive filter. Due to the presence of these delays, the feedback approach of the injection method is not applicable. It is not possible to time synchronize $\hat{s}_2$ with s_{12}.

4.4 Summary

Both the CTRANC system and the one presented by Sakai will later be evaluated when dealing with both crosstalk models. Both systems use the same LMS algorithm presented in Chapter 2.

A new method of cancelling adjacent channel interference has been proposed. It has been analyzed for both crosstalk models, although its primary use is for crosstalk model 2. There are some results which have not been fully interpreted; they will be examined in the next chapter.

Chapter 5
Evaluation

5.1 Introduction

In the previous chapter the different crosstalk noise cancelling schemes were briefly examined analytically. Although this provides insight into their capabilities, their performance may be better judged in actual operation. This is accomplished by computer simulation.

The three signals s_0, s_1, and s_2 are zero-mean stationary random signals generated by filtering Gaussian random numbers through a third-order Butterworth filter with a cut-off frequency of $3\,\mathrm{kHz}$. These baseband signals are then DSBSC modulated by carrier frequencies $f_1 = 96\,\mathrm{kHz}$ for s_1 and $f_2 = 104\,\mathrm{kHz}$ for s_0 and s_2. The bandwidth of these passband signals is much less than the frequencies of the carriers so sub-Nyquist sampling is used where $f_s = 80\,\mathrm{kHz}$. The low-pass, high-pass, and band-pass filters are all implemented with linear-phase FIR filters. All signal processing is done with passband signals.

The worst case convergence of the adaptive filters is approximately 50 000 samples; therefore each system is allowed to process 100 000 samples and the performance measurements (SNR, MSE) are based on the last 50 000 samples. The weight vectors of the adaptive filters are always initialized to zero.

The different systems are analyzed for both crosstalk models. The performance is judged by the accuracy of the transfer function estimates as well as the overall signal quality improvement.

5.2 Crosstalk model 1

From Fig. 3.5 it may be seen that in the case of two spectrally separated passband signals the cross-channel transfer functions H_{12} and H_{21} may be modeled by low-pass and high-pass filters respectively. For the signals described above, H_{12} and H_{21} are realized as shown in Fig. 5.1.

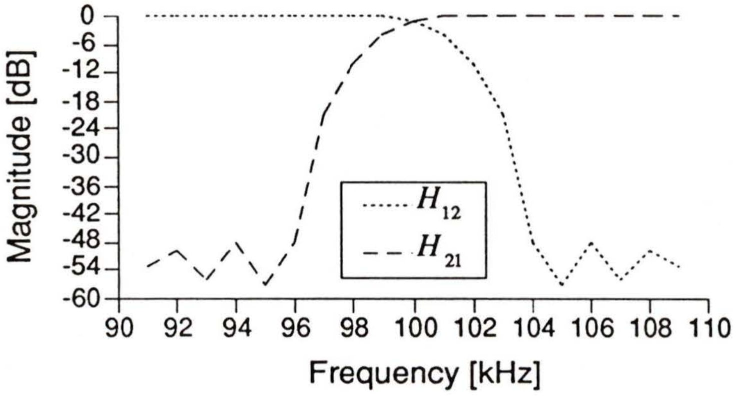

Figure 5.1 — Implementation of crosstalk model 1.

To explore the upper limit of the improvement gained by the injection method the first simulations are carried out such that full a priori knowledge of the crosstalk is available. This is accomplished by setting s_2 equal to zero so the crosstalk is solely composed of s_0.

The first comparison made between the systems is the examination of the accuracy of the cross-channel transfer function estimates. Once the adaptive filters have converged, their transfer functions are plotted for the frequencies of interest (see Fig. 5.2). Although the plots shown are based on the instantaneous transfer functions of the adaptive filters, it was found that once the filters have converged the transfer functions remain nearly constant.

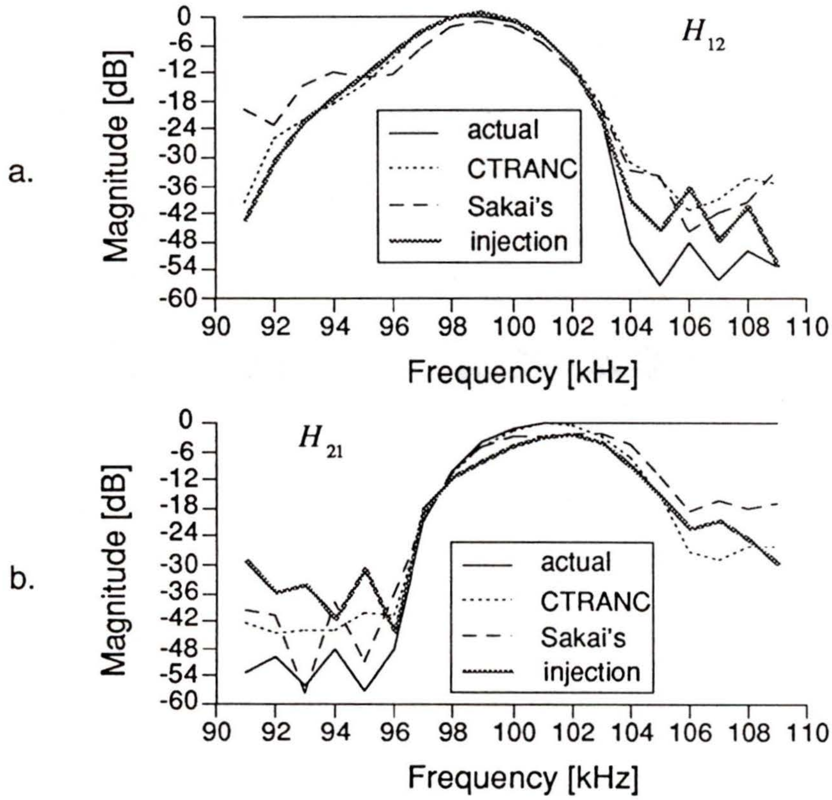

Figure 5.2 — Comparison of transfer function estimates.

All three systems approximate both cross-channel transfer functions reasonably well for the frequency range of signal overlap, 96 kHz to 104 kHz. For the frequencies outside this range the approximations are less accurate because there is very little signal energy present. Since the signals are not present in these areas, knowledge of the cross-channel transfer functions is only required for the overlap band.

In the case of the estimate of H_{12}, the transfer function approximations are all nearly identical although the injection system appears slightly more accurate than the other systems. This is of no surprise given full knowledge of the crosstalk. On the other hand, the injection method's approximation of H_{21} is not as accurate as the CTRANC method. This is due to the $1-\hat{H}_{12}H_{21}$ factor present in (4.8). For the given H_{21} and $\hat{H}_{12}$, this results in the frequency domain transfer function in Fig. 5.3.

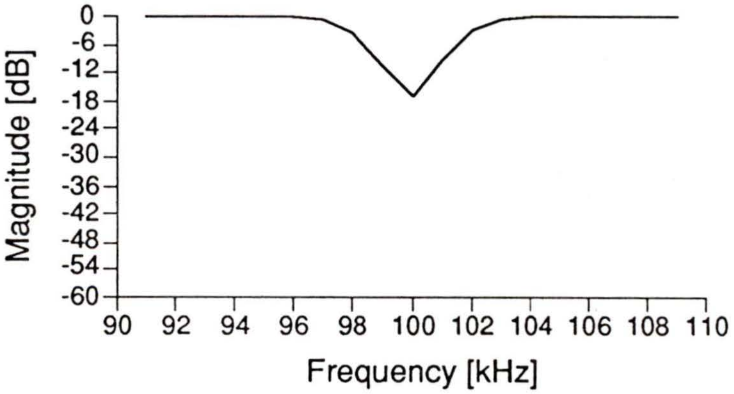

Figure 5.3 — $1-\hat{H}_{12}H_{21}$ for the realization of crosstalk model 1.

For frequencies near 100 kHz, the $1-\hat{H}_{12}H_{21}$ term results in the attenuation of s_1. Thus the estimate of H_{12} is less accurate for this frequency range. This problem may be countered by feeding back $\hat{s}_2$ to improve $\hat{s}_1$. When the injection feedback system is used, the estimate of H_{21} is improved by as much as 4 dB (see Fig. 5.4).

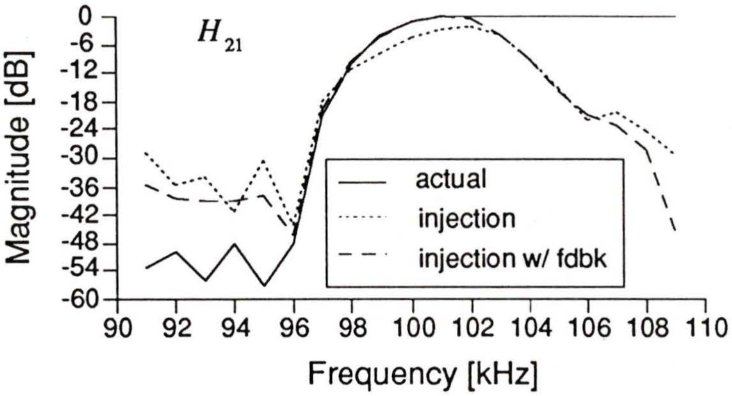

Figure 5.4 — Improvement in the estimation of H_{21} due to feedback in the injection system.

The second method of evaluation is the comparison of the overall signal improvement as a function of input signal-to-noise ratio. The various systems are actually improving two signals, s_1 and s_2, therefore input and output SNRs must be defined for each channel. In the case of channel 1, the input SNR is defined as a crosstalk ratio where

$$\begin{aligned} CR &= \text{relative level of crosstalk} \\ &= \frac{\text{power of crosstalk}}{\text{power of } s_1} \\ &\approx \frac{\sum_{n=0}^{N} \left| H_{12}[s_0(n) + s_2(n)] \right|^2}{\sum_{n=0}^{N} \left| s_1(n) \right|^2} \end{aligned} \tag{5.1}$$

The inclusion of s_0 in the calculation of the power in the crosstalk may not be totally justified since it is a known signal and may be removed much more effectively than an unknown signal. This may have the effect of artificially inflating the improvement on channel 1. This discrepancy is only present in the injection system since it is the only one which uses s_0. However, in the first comparison where s_2 is not present, the crosstalk ratio would have little meaning if s_0 were not included. The effect of including s_0 in these calculations will be investigated later.

In the case of channel 2, the input SNR is defined as an interference ratio where

$$\begin{aligned} IR &= \text{relative level of interference} \\ &= \frac{\text{power of interference}}{\text{power of } s_2} \\ &\approx \frac{\sum_{n=0}^{N} \left| H_{21} s_1(n) \right|^2}{\sum_{n=0}^{N} \left| s_2(n) \right|^2} \end{aligned} \tag{5.2}$$

In all cases N is the number of samples processed.

The output SNR or signal improvement for channel 1 is

$$\begin{aligned} I_1 &= \frac{\text{power of crosstalk}}{\text{MSE of estimate}} \\ &\approx \frac{\sum_{n=0}^{N} \left| H_{12}[s_0(n) + s_2(n)] \right|^2}{\sum_{n=0}^{N} \left| s_1(n) - \hat{s}_1(n) \right|^2} \end{aligned} \tag{5.3}$$

and for channel 2 is

$$
\begin{aligned}
I_2 &= \frac{\text{power of interference}}{\text{MSE of estimate}} \\
&\approx \frac{\sum_{n=0}^{N} \left| H_{21} s_1(n) \right|^2}{\sum_{n=0}^{N} \left| s_2(n) - \hat{s}_2(n) \right|^2}
\end{aligned}
\tag{5.4}
$$

In estimating the MSE, it was found that the error is zero mean and the mean square is therefore approximated by the variance.

The improvements may be interpreted such that any improvement greater than 0 dB results in the reduction of noise; i.e. signal enhancement. If the improvement is negative, the noise cancelling scheme is actually degrading the signal. If the improvement is 0 dB, the output signal quality is identical to the input signal.

As a matter of completeness, the ANC is also tested in this evaluation to see how its performance is effected as the level of crosstalk varies. The ANC is used only to cancel the interference (see Fig. 5.5). Since there is no processing done on channel 1, no performance characteristics will appear for the ANC when applied to channel 1.

The performance curves reflect the improvement on each channel as a function of input crosstalk ratio or input interference ratio. The crosstalk and interference ratios are related in a complementary fashion since they are defined relative to one another; as the level of (relative) crosstalk increases, the corresponding level of interference decreases (see Fig. 5.6).

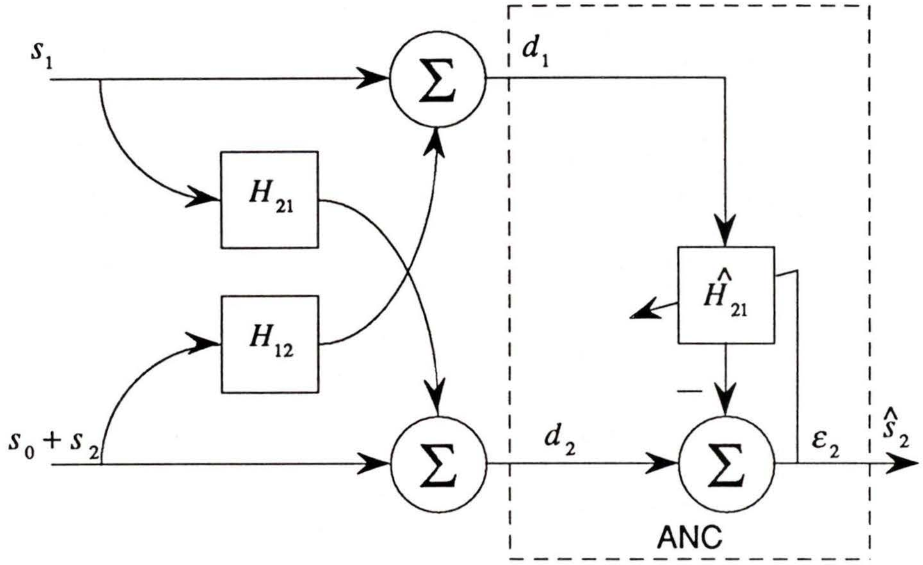

Figure 5.5 — ANC with crosstalk model 1.

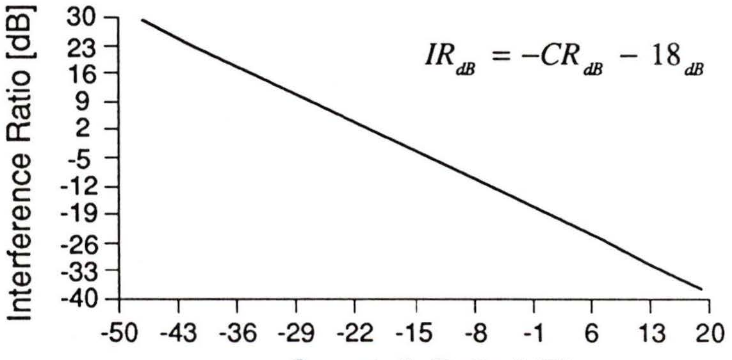

Figure 5.6 — Relationship between crosstalk and interference ratios.

First the effectiveness of removing the crosstalk from channel 1 is examined for each system (see Fig. 5.7). For $CR > 0$ dB, the crosstalk level greater than the interference level, CTRANC, Sakai's, and the injection method all give improvements which seem to approach about 15—18 dB as the crosstalk begins to dominate. The improvement is maximum when crosstalk is high because it effectively "drowns out" the interference present in the reference of the crosstalk. Thus the reference input to the H_{12} adaptive filter is highly correlated to the crosstalk present in channel 1 and may more effectively be removed. It is also apparent that the addition of feedback in the injection system results in an improvement of up to 20 dB over the injection system without feedback.

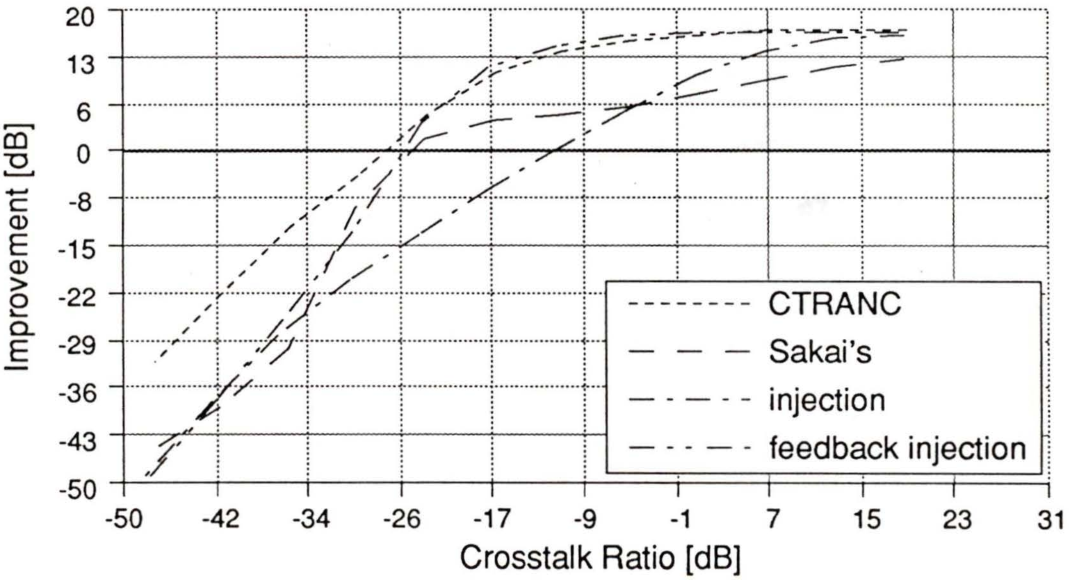

Figure 5.7 — Comparison of the improvement on channel 1 using model 1. $s_2 = 0$ for the injection system.

As the crosstalk level decreases such that $CR < 0$ dB, the interference, s_1, begins to dominate. As the level of interference increases relative to the level of crosstalk, the crosstalk, s_1, becomes "buried" in the interference and thus is estimated less accurately causing the improvement on channel 1 to become more difficult to achieve (there is little improvement). Once the level of crosstalk becomes small enough, it becomes too buried in the interference to be improved at all. The injection system seems particularly sensitive to this especially when no feedback is used. Once $CR < -10$ dB there is no longer any improvement in $\hat{s}_1$. CTRANC and Sakai's systems are more robust in this regard failing for $IR < -25$ dB. In essence the H_{12} adaptive filter is not given an accurate enough reference to the crosstalk, s_1, to accurately estimate H_{12}.

Many of the same observations apply in the case of channel 2 (see Fig. 5.8). Here also the degradation of the ANC due to crosstalk may be observed. As long as the crosstalk level is low, $IR > 10$ dB, the ANC provides the best interference cancellation. For these levels of interference and crosstalk, the other systems degrade $\hat{s}_1$ thus their estimate of $\hat{s}_2$ is also degraded. As the crosstalk begins to increase, the cancellation provided by the ANC begins to fall off and completely fail for $IR < -16$ dB. This is the problem that the CTRANC system is designed to solve. For low levels of crosstalk, the CTRANC provides less improvement than the ANC. However for $IR < 10$ dB, the CTRANC continues giving a high degree of cancellation until the crosstalk dominates the interference, $IR < -30$ dB.

The injection system with feedback gives the best improvement for $IR < 7$ dB but falls off rapidly as the level of interference increases. The injection system without feedback provides a relatively flat 5 dB improvement. This is again due to the $1 - \hat{H}_{12}H_{21}$ factor in (4.8). These curves justify our approach, at least for smaller interference ratios where the ANC is less effective. Through total knowledge of the crosstalk, we add as much as 16 dB improvement in this situation. As s_2 is added to channel 2 we have less knowledge of the crosstalk.

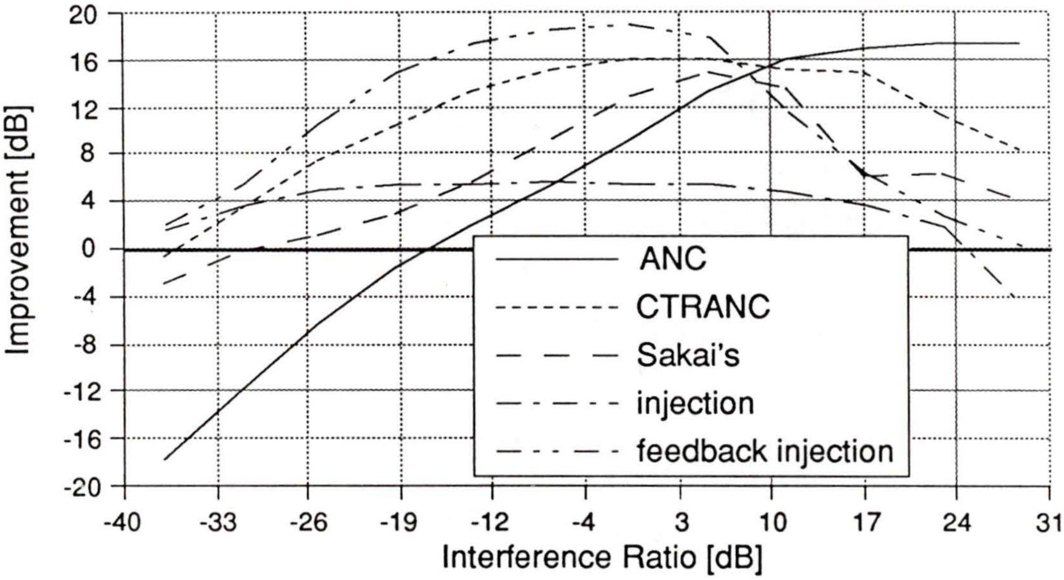

Figure 5.8 — Comparison of the improvement on channel 2 using model 1. $s_2 = 0$ for the injection system.

In the next simulation s_2 is restored in channel 2 for the injection system where s_0 and s_2 have the same power. The estimate of H_{12} is effected very little by the presence of s_2 since it contributes very little to the correlation of the test signal in the H_{12} adaptive filter. However the estimate of H_{21} is greatly effected in the case of the injection system with feedback (see Fig. 5.9). This is due to the presence of s_1 and s_2 at both the reference and primary inputs of the H_{21} adaptive filter.

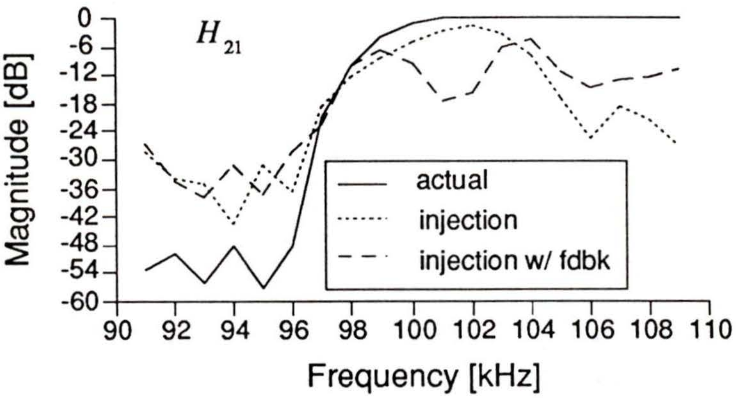

Figure 5.9 — Degradation of $\hat{H}_{21}$ due to the presence of s_2.

In the case when $s_2 = 0$, the only signal present at the reference input is s_1 and at the primary input is $H_{21}s_1$. Thus the adaptive filter is able to accurately estimate H_{21}. When s_2 is present, it is also present at each input of the H_{21} adaptive filter. Thus it is more difficult to estimate the correlation between the primary and reference inputs. Since the filter starts with no information about H_{21}, the initial error in the estimate of s_2 is high. This error is then fed back and subtracted from channel 1 resulting in the degradation of $\hat{s}_1$ (see Fig. 5.10). Since this increased error is always fed back, $\hat{s}_1$ and $\hat{H}_{21}$ will always suffer. Given this poor estimate of s_1, the improvement of channel 2 will also be reduced (see Fig. 5.11).

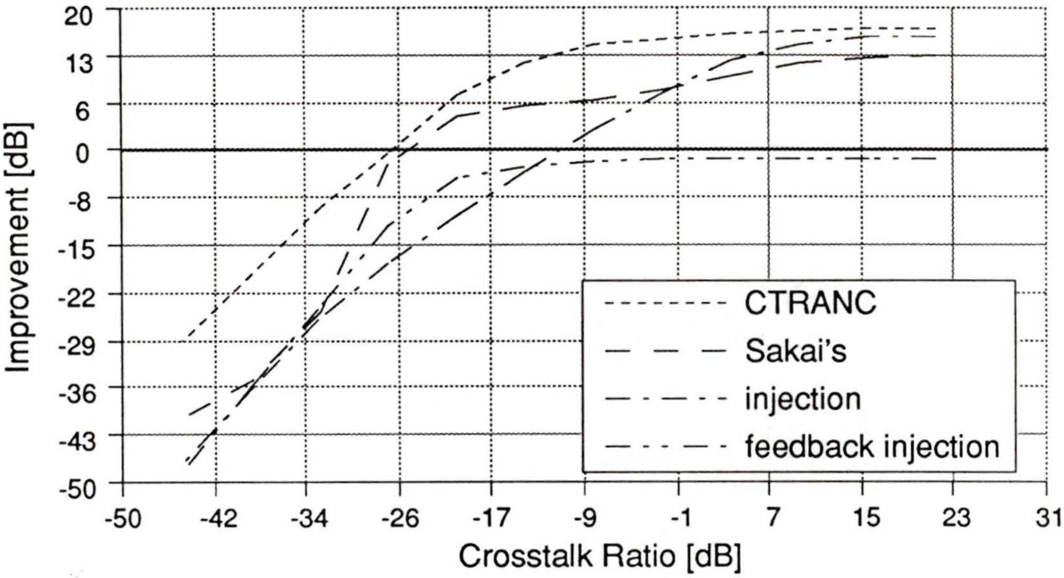

Figure 5.10 — Comparison of the improvement on channel 1 using model 1. s_2 is present in the injection system.

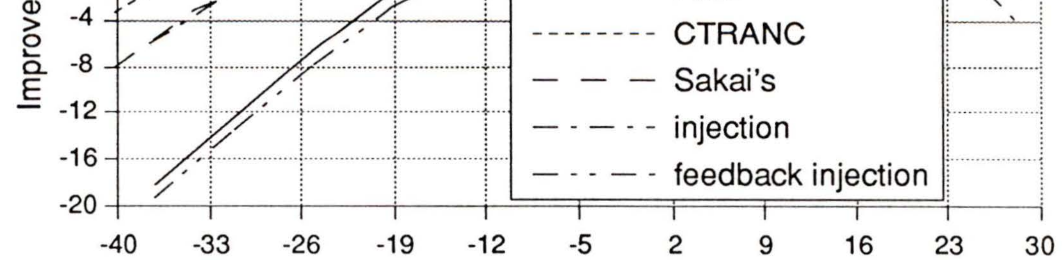

Figure 5.11 — Comparison of the improvement on channel 2 using model 1. s_2 is present in the injection system.

As stated previously the inclusion of s_0 in the computation of the crosstalk may lead to artificially inflated improvements. Therefore Fig. 5.10 is repeated with the exception of not including s_0 in the computation of the level of crosstalk in the injection system (see Fig. 5.12). In the case of the injection system without feedback, for $CR > 0$ dB the improvement is reduced by about 3 dB. In the feedback case, the improvement is also reduced by about 3 dB for $CR > -25$ dB. This is to be expected since s_2 and s_0 have the same power, the inclusion of s_0, which is then effectively removed by the H_{12} adaptive filter, doubles the level of crosstalk.

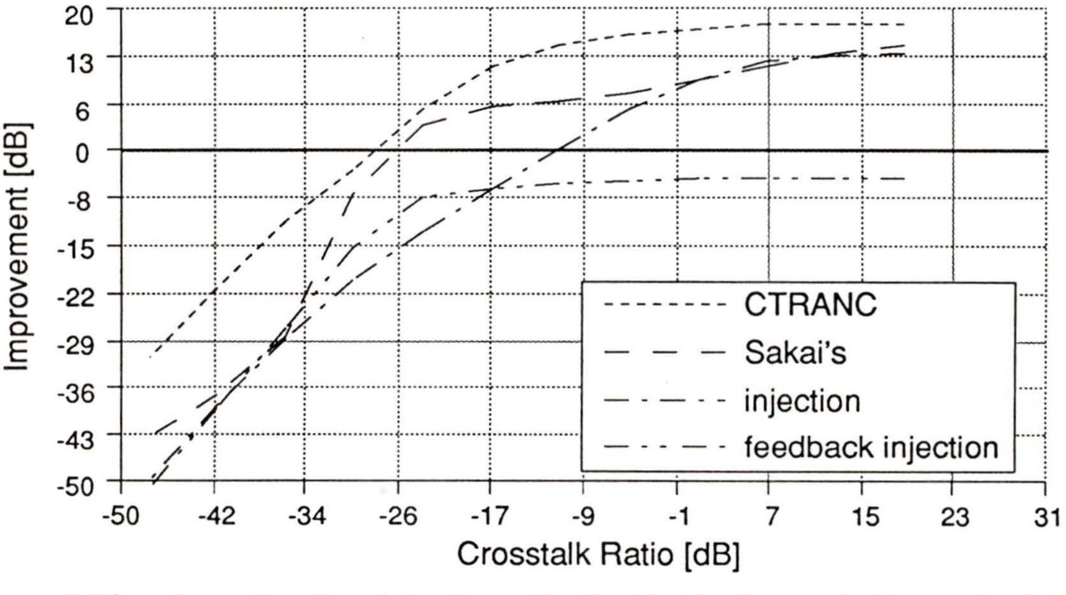

Figure 5.12 — Investigation into the effect of including s_0 in the calculation of the improvement on channel 1 with model 1.

5.3 Crosstalk model 2

The second crosstalk model is implemented as shown in Fig. 3.4. H_1 and H_2 are band-pass filters whose center frequencies are f_1 and f_2 respectively (see Fig. 5.13). The bandwidth of each filter is 6 kHz.

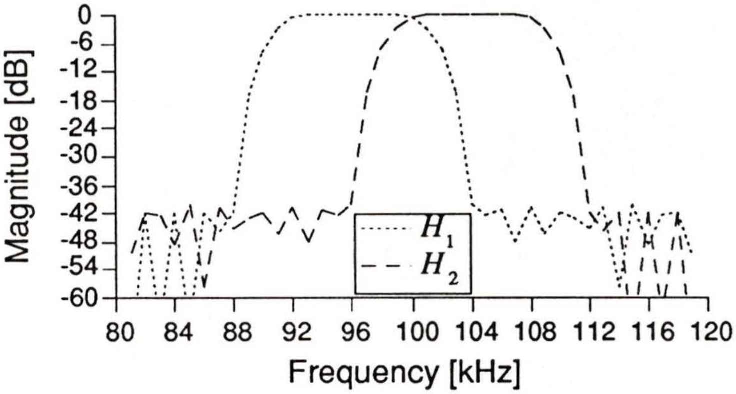

Figure 5.13 — Implementation of crosstalk model 2.

With this realization H_{12} and H_{21} will be the same as in model 1, however H_{11} and H_{22} are no longer unity but are equal to H_1 and H_2 respectively. This simulates the receiver of Fig. 3.4.

As in the case of the first simulation of model 1, s_2 is set to zero. With model 2 no feedback for the injection system is possible because of the delay; $\hat{s}_2$ is always delayed in time with respect to s_2 present at the point where $\hat{s}_2$ would be subtracted from channel 1. A completely parallel system with appropriate delay would be needed to realize feedback of $\hat{s}_2$. The adaptive filter transfer function estimates show that the CTRANC method is not able to approximate either of the cross-channel transfer functions (see Fig. 5.14). Sakai's method does somewhat better but is not as accurate as the injection method in the case of H_{12}. However the injection system does not estimate H_{21} as accurately as Sakai's. Looking at (4.13) which is repeated here for convenience

$$\hat{s}_1 = s_1\left(H_{11} - \hat{H}_{12}H_{21}\right) + s_2\left(H_{12} - \hat{H}_{12}H_{22}\right) \tag{5.5}$$

and considering Fig 3.5, it becomes apparent that

$$H_{11} - \hat{H}_{12}H_{21} = H_{12} - \hat{H}_{12}H_{22} \tag{5.6}$$

because $H_{11} = H_{12}$ and $H_{21} = H_{22}$. Therefore s_1 and s_2 are essentially filtered by the same transfer function at the reference input of the H_{21} estimator (see Fig 5.15).

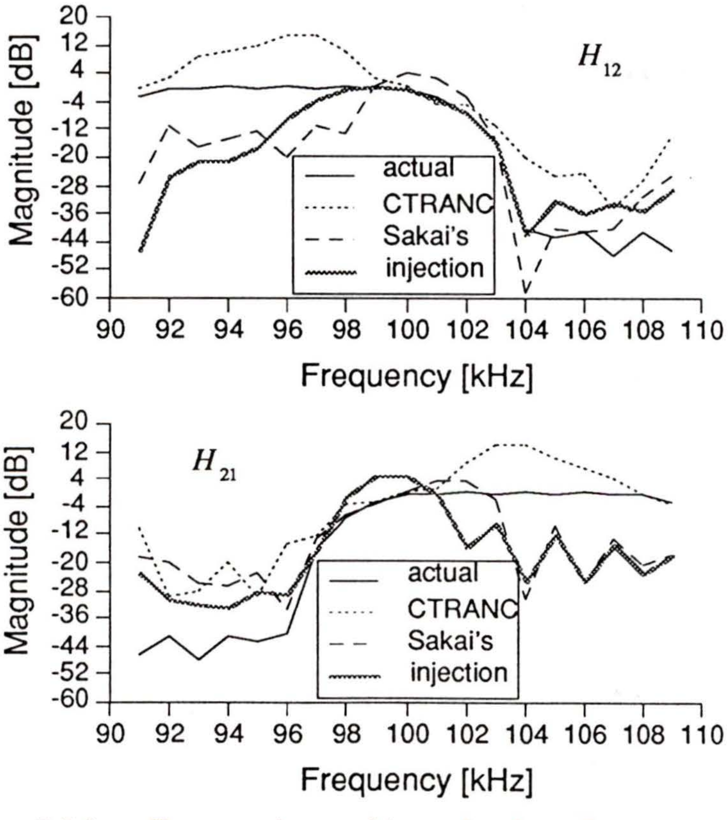

Figure 5.14 — Comparison of transfer function estimates.

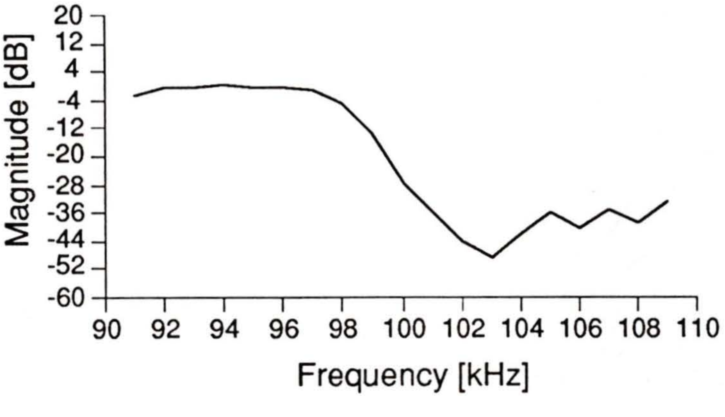

Figure 5.15 — Filtering of $\hat{s}_1$ as compared to s_1.

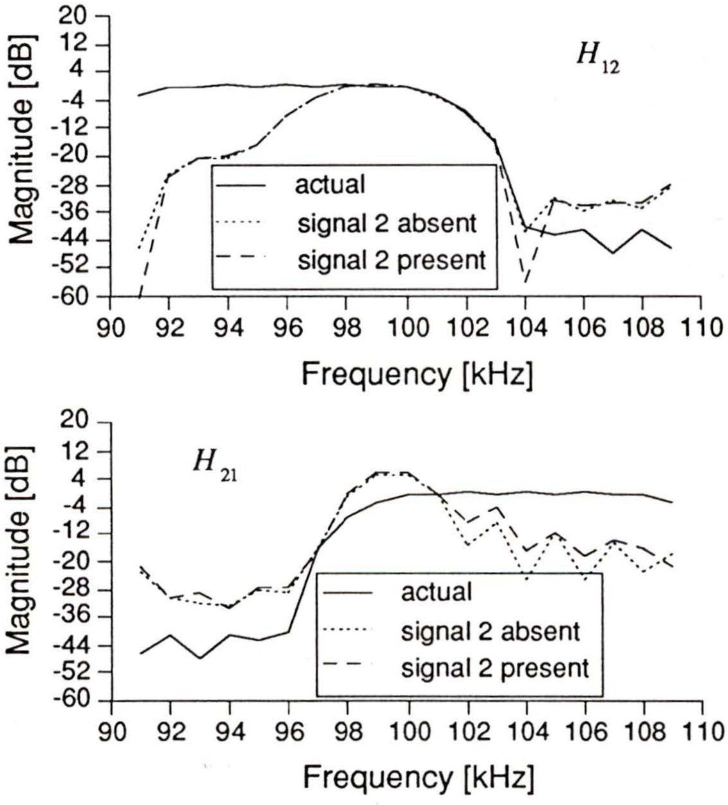

Figure 5.16 — Effect on the transfer function estimates due to the presence of s_2.

Although s_2 has been removed from channel 1 by this process, the components of s_1 above 99 kHz have also been removed. This results in a very poor reference to the interference, hence H_{21} is poorly approximated. The inclusion of s_2 for the injection system has little effect (see Fig. 5.16).

For the performance curves the crosstalk and interference ratios will be altered slightly to take into account H_{11} and H_{22}. Thus the crosstalk ratio becomes

$$CR \approx \frac{\sum_{n=0}^{N} \left| H_{12}[s_0(n) + s_2(n)] \right|^2}{\sum_{n=0}^{N} \left| H_{11} s_1(n) \right|^2} \tag{5.7}$$

and the interference ratio becomes

$$IR \approx \frac{\sum_{n=0}^{N} \left| H_{21} s_1(n) \right|^2}{\sum_{n=0}^{N} \left| H_{22} s_2(n) \right|^2} \tag{5.8}$$

The expressions for improvement on each channel also change such that

$$I_1 \approx \frac{\sum_{n=0}^{N} \left| H_{12}[s_0(n) + s_2(n)] \right|^2}{\sum_{n=0}^{N} \left| H_{11} s_1(n) - \hat{s}_1(n) \right|^2} \tag{5.9}$$

for channel 1 and

$$I_2 \approx \frac{\sum_{n=0}^{N} \left| H_{21} s_1(n) \right|^2}{\sum_{n=0}^{N} \left| H_{22} s_2(n) - \hat{s}_2(n) \right|^2} \tag{5.10}$$

for channel 2.

The performance curves for channel 1 show that CTRANC and Sakai's method show no real improvement (see Fig. 5.17). The injection method improves $\hat{s}_1$, when $CR > -10$ dB. This is the case whether full or partial knowledge of the crosstalk is available. Although some reduction in the improvement results with the inclusion of s_2. This is a pleasing result, again justifying our approach, although it is really channel 2 that we are trying to enhance.

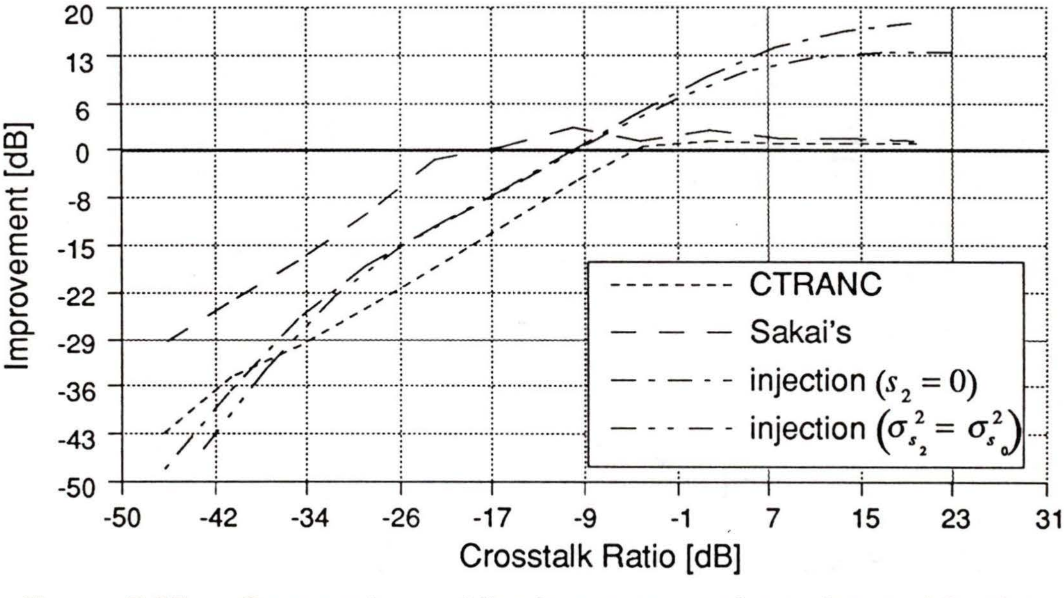

Figure 5.17 — Comparison of the improvement on channel 1 using model 2.

The performance for channel 2 yields similar results for CTRANC and Sakai (see Fig. 5.18). Again for low levels of crosstalk (high interference ratio) the ANC does the best job. However, the injection system provides a nearly constant 4 dB improvement for $IR > -10$ dB regardless of the level of s_2. When s_2 is absent, representing total knowledge of s_0 and s_2, the injection method never degrades the signal. Thus a switch over to injection for lower interference ratios (lower error detections in a data channel) may be justified.

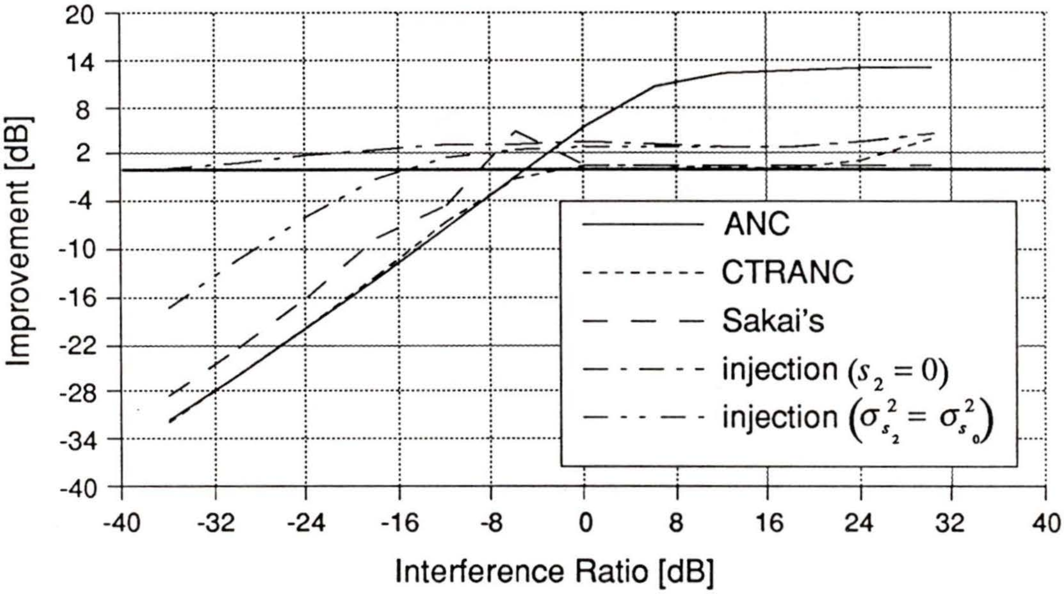

Figure 5.18 — Comparison of the improvement on channel 2 using model 2.

5.4 Conclusion

The analysis for model 1 reveals that the CTRANC system does the best job of cancellation on channel 1 for crosstalk levels from –20 dB to +20 dB. This is of no surprise since the CTRANC system is designed for this model. The injection system does not perform as well but also does not fail when confronted with this model. When $s_2 = 0$ the addition for feedback does improve the performance of the injection system, and it is the best choice for lower interference levels, $IR < 7$ dB as shown in Fig. 5.8. This indicates that the injection feedback system could be used if the system were given a training period where s_2 was not present. This would allow the filters to converge accurately. Once the filters have converged, they could be frozen, the test signal removed, and s_2 restored.

The analysis of model 2 shows that the CTRANC and Sakai's systems are not suited for this environment. When the level of crosstalk is low, the ANC provides the best cancellation. However, the interference ratio may be unknown or vary with time in which case the ANC may degrade the signal. This is were the injection system is superior. Given a training period, $s_2 = 0$, the injection system will provide approximately 3 dB improvement regardless of the interference ratio. For crosstalk ratios below -10 dB, the injection system maintains the 3 dB improvement even when s_2 is present. For low interference ratios, high crosstalk, the curves for the injection system with and without s_2 (Figs. 5.17 and 5.18) reveal that upper and lower bounds of the improvement that may be gained.

When $s_2 = 0$, this implies that the ratio of the power in the test signal to the power in the message signal, $\sigma_{s_0}/\sigma_{s_2}$, is infinite. Thus no better improvement may be expected. As the power in the the message signal is increased, $\sigma_{s_0}/\sigma_{s_2}$ decreases and the improvement for $IR < -10$ dB begins to decline. For $\sigma_{s_0}/\sigma_{s_2} = 1$, the test and message signals have the same power which reduces the improvement is reduced by 15 dB for $IR < -32$ dB. Thus the best system would allow the filters to converge given only the test and interfering signal, then replace the test signal with the message signal.

Chapter 6
Conclusion

Adaptive noise cancellation in the presence of crosstalk has been examined. Models representing various types of crosstalk have been developed and implemented in software. Due to the bidirectional crosstalk, the interference and crosstalk ratios were defined. Different cancellation schemes have been examined and compared for varying levels of crosstalk. A new system for adjacent channel interference has been presented.

It has been shown that the baseband two microphone system is closely related to adjacent channel interference. A model which may be used in both cases has been developed and simulated.

The crosstalk resistant adaptive noise cancellers from literature have been compared to the new injection system in both the case of the two microphone system, model 1, and the two channel receiver, model 2. It has been found that the CTRANC system yields the best improvement in the case of model 1. However, when confronted with the multichannel receiver model, the CTRANC system and its derivatives fail and the injection system becomes superior.

In the case of model 2, when the level of interference is greater than the level of crosstalk, the ANC provides the best cancellation. However, as the crosstalk becomes prominent, $IR < 5\text{ dB}$, the performance of the ANC falls off rapidly. It is in this range of crosstalk where the injection system becomes superior. As for the CTRANC and Sakai's method, they never provide any improvement regardless of the level of crosstalk.

Especially at high levels of crosstalk, the injection system is better able to estimate the cross-channel transfer functions given full knowledge of the crosstalk (i.e. $s_2 = 0$). This implies that the injection system would best function if given a training period in which to estimate the crosstalk. Once the cross-channel transfer functions are estimated, the injected signal can be removed and the data signal, s_2 restored.

In the case of model 1 the injection system with feedback performed well in certain situations. This may be an area of further study. The problem of applying the feedback method to model 2 is the delays present in the canceller. Using a parallel receiver with appropriate delays may allow the last feedback stage to be exploited.

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Appendix A
Computer Simulation Details

The programs are written in C and executed on a Sun Microsystems® 3/280 computer. The Bode plots are generated using Ctrl-C[2]. The generation of the random numbers is accomplished by the IMSL[3] routine *GGNQF*. The routine is reported to (and seemed to) generate a reasonably flat spectrum. Independent signals are created by starting *GGNQF* with a different seed for each signal. The estimates of the cross-correlation indicate that the different signals are, relative to their variances, independent. The different levels of crosstalk and interference are obtained by increasing or decreasing the variances of the signals.

The passband signals are double side band, suppressed carrier. This is accomplished by multiplying the baseband signals by $A_c \cos(2\pi f_c t)$ where f_c is the carrier frequency. This method of modulation is used because it is convenient with which to work.

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[2] Ctrl-C® is a computer-aided engineering package from Systems Control Technology, Inc., Palo Alto, CA.

[3] IMSL® is a library of FORTRAN functions and subroutines from IMSL Inc., Houston, TX.

Since the signals are narrow band compared to the frequency of their carriers, sub-Nyquist sampling is used which has the advantage of not requiring as many samples to simulate the same amount of "real time". The sampling frequency is chosen to be 80 kHz which results in the spectrum shown in Fig. A.1.

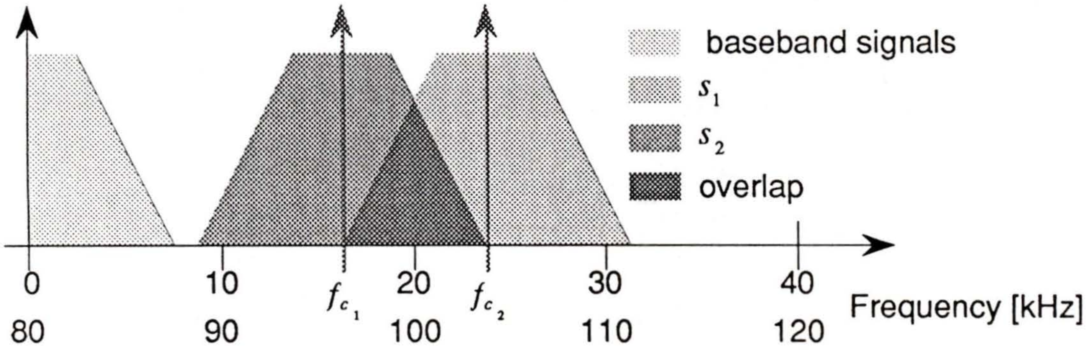

Figure A.1 — Spectrum of simulated signals.

All of the filters used are finite impulse response with linear phase. This maintains a constant delay for all frequencies which allowed the signals to easily be time synchronized which is required for comparison. The errors are estimated by subtracting the actual signal sample from its sample estimate and summing the squares of their difference. The mean of the error is about to be two orders of magnitude less than the variance so the mean square error is estimated by the variance of the mean.

The adaptive filters are initialized to zero and have the same length as the filters which they are estimating, thus the delay caused by the adaptive filters are nearly equal to (but not exact since the adaptive filters will not necessarily be linear phase) the FIR filters. This also facilitated time synchronization.

Generally the adaptive filters converge during the first few thousand samples. However the systems are allowed to process 100 000 samples and the interference and crosstalk ratios as well the improvement are estimated from the last 50 000 samples. Thus the adaptive filters are given ample time to converge in all cases before any comparisons are made.

The crosstalk and interference ratios were generated by varying the variance of s_1 while leaving $\sigma_{s_0}^2$ and $\sigma_{s_2}^2$ constant.

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