of the signals, the logarithmic frequency response of the model is not separable into signal and channel components.

Another way of interpreting the problem with LPC features is to consider each frame of the corrupted speech signals. The spectrum at each frame will be different for the two signals, and the model will fit each one regardless of the possible relation between them. If normalization is applied prior to modeling, the two spectra will be very similar and, consequently, the difference between models will be reduced.

In this experiment, the normalization was applied before and after doing LPC modeling and the error was computed over the LPC power spectrum. In order to apply channel normalization before LPC modeling, we processed the STFT power spectrum of the corrupted signals and computed their inverse Fourier transforms to obtain the modified autocorrelation functions. From the modified autocorrelation functions, we obtained the new LPC models and used their spectra in the error computation. A tenth-order LPC model was used in this particular case.

The results of this experiment are shown in Table III. Observe that these are similar to those obtained for the auditory-like features, also indicating the advantage of applying normalization before spectral smoothing.

<table>
<thead>
<tr>
<th></th>
<th>NONE</th>
<th>MS</th>
<th>RASTA</th>
</tr>
</thead>
<tbody>
<tr>
<td>log[LPC spectrum]</td>
<td>0.1769</td>
<td>0.0343</td>
<td>0.0282</td>
</tr>
<tr>
<td>log[L(n,f)]</td>
<td>0.1769</td>
<td>0.0009</td>
<td>0.0020</td>
</tr>
</tbody>
</table>

V. CONCLUSION

We have shown that when the frequency response of the distorting channel is not constant within the passband of the analysis bands, the effect of the channel is not additive in the logarithmic domain and the commonly used channel compensation techniques such as mean subtraction can be less effective. We demonstrate that the situation can be improved by an order of magnitude if the normalization is performed on the high-resolution short-term spectrum of speech rather than on the critical-band integrated spectrum.

The results should be interpreted in terms of the relative effectiveness of the two compared techniques. We do not discuss their relevance in any particular ASR system where many other engineering compromises may dominate the final result. Thus, it is left to the reader to decide whether the particular ASR application justifies the implementation of an improved channel normalization scheme at the cost of increased arithmetic complexity as proposed in this paper.

REFERENCES


A Secondary Path Modeling Technique for Active Noise Control Systems

Sen M. Kuo and Dipa Vijayan

Abstract—A secondary path modeling technique for active noise control systems is developed for both on-line and off-line modeling with faster convergence and higher modeling accuracy. The optimum delay for the adaptive prediction error filter to reduce the interference in system modeling is equal to the length of the impulse response of the secondary path being modeled.

I. INTRODUCTION

Active noise control (ANC) [1], [2] has developed rapidly in recent years because it permits improvements in noise attenuation along with potential benefits in size, weight, volume, and cost of the overall system. In order to enable the adaptive filter to converge properly to a desired solution, it is necessary to compensate for the transfer function of the secondary path, \( S(z) \), from the secondary source to the error sensor. This results in the filtered-X least mean squares (LMS) algorithm that was developed by Morgan [3]. This algorithm was also independently derived by Widrow [4] in the context of adaptive control and by Burgess [5] for ANC applications. \( S(z) \) may be obtained by using an off-line modeling technique when the primary noise is absent. However, for some applications the primary noise exists even during off-line modeling, and this adversely affects the convergence of the modeling filter. Furthermore, since the secondary path can be time varying, \( S(z) \) has to be estimated on line in some applications to ensure stability and convergence of the ANC system.

Fig. 1 without the prediction error filter \([i.e., \, g(n) = \epsilon(n)]\) represents the on-line modeling technique using additional random noise as originally proposed by Eriksson [6]. Zero-mean white noise \( u(n) \) is internally generated and mixed with the antinoise \( g(n) \) to excite the secondary path while the ANC filter \( W(z) \) is in operation. The adaptive filter \( \hat{S}(z) \), excited only by the white noise, is used to model \( S(z) \). The interference to the secondary path modeling can be expressed as

\[
f(n) = d(n) + g(n) * s(n)
\]  

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where * denotes linear convolution, $d(n)$ is the primary noise, and $s(n)$ is the impulse response of $S(z)$. Assuming that the primary noise $d(n)$ consists of several narrowband components, signal $f(n)$ will consist of the same narrowband components. Unfortunately, this interference $f(n)$ is large (as would be expected in most ANC applications), so the adaptive model $\hat{S}(z)$ may fail to converge. As shown by Bao [7], it would take 75 times as long for $\hat{S}(z)$ to converge with interference (signal-to-noise ratio $=-31$ dB) as it would to converge without interference. In order to allow faster convergence, a much larger amplitude of the training signal $u(n)$ is required, which thereby increases the residual noise and degrades the performance of the overall system.

In this correspondence, a secondary path modeling algorithm using an adaptive prediction error filter [8] is developed to eliminate the effect of the interference $f(n)$. The optimum value of delay that decorrelates the training signal component measured by the error microphone is derived. Computer simulations are conducted to verify the effectiveness of the algorithm.

**II. Optimized Adaptive Prediction Error Filter for Interference Reduction**

The basic concept of the proposed algorithm is to eliminate the interference $f(n)$ that affects the convergence of the modeling filter $\hat{S}(z)$. Since the interference is time varying, an adaptive predictor is used to track the changes and mitigate its effect. The complete ANC system with an optimized adaptive predictor for on-line modeling (or $y(n) = 0$ for off-line modeling) is illustrated in Fig. 1. The method of using a prediction error filter or adaptive line enhancer for enhancing secondary path modeling has been presented in earlier paper [7]. The delay $\Delta$ is used to ensure that the broadband noise components used for modeling are decorrelated while the narrowband components remain correlated in the interference $f(n)$. The optimum delay is derived and discussed in this work.

Assuming that the $\hat{S}(z)$ can be modeled by a finite impulse response filter of order $M$, from Fig. 1, the error signal measured
Fig. 3. Amplitude responses of $S(z)$ (solid line) and $\hat{S}(z)$ (dashed line) with adaptive predictor $\Delta = 64$ and step size 0.01.

Fig. 4. Modeling error of system using adaptive predictor versus different delay $\Delta$.

by the error microphone can be expressed as

$$
e(n) = d(n) + [g(n) + u(n)] * s(n)
= f(n) + u(n) * s(n)
= f(n) + \sum_{j=0}^{M-1} s_j(n)u(n - j)$$

(2)

where $s(n)$ is the impulse response and $s_j(n)$ is the $j$th impulse response of the secondary path $S(z)$ at time $n$.

Assuming that the training signal $u(n)$ is a zero-mean, uniformly distributed white noise [2], which is uncorrelated with the interference $f(n)$, we can show that

$$E[e(n)e(n - \Delta)]]
= E[f(n)f(n - \Delta)] + \sum_{j=0}^{M-1} s_j(n) \sum_{i=0}^{M-1} s_i(n)
\cdot [E[u(n - j)u(n - i - \Delta)]]$$

(3)

where the first term is due to the interference $f(n)$ and the second term comes from the training signal $u(n)$. Since $u(n)$ is a zero-mean white noise, we can show that

$$E[u(n - j)u(n - i - \Delta)] = 0 \quad \text{for } 0 \leq i, j \leq M$$

(4)

if

$$\Delta \geq M.$$ 

(5)

Therefore, the training signal component in $e(n)$ and $e(n - \Delta)$ will be uncorrelated for $\Delta \geq M$. As a consequence, the prediction filter $D(z)$ will not be able to predict the training signal components in $e(n)$. The components of the interference $f(n)$ that remain correlated after the delay $\Delta$ will be predicted and canceled by the predictor $D(z)$. Therefore, the prediction error filter output can be approximated as

$$g(n) \approx u(n) * s(n)$$

(6)

which is equivalent to a system in which the interference $d(n)$ and $y(n)$ are absent, thus preventing the modeling filter $\hat{S}(z)$ from being corrupted by the presence of the narrowband components. From Fig. 1, it is clear that the adaptive filter $\hat{S}(z)$ can model $S(z)$ correctly. If the delay $\Delta < M$, the second term in (3) will be nonzero, resulting in the cancellation of the training signal components by
$D(z)$, thus affecting the convergence of the modeling filter $\hat{S}(z)$. The modeling error will decrease as the delay $\Delta$ increases for $\Delta < M$, which will be verified by computer simulations given in the next section.

The optimal delay is also dependent upon the time scale of variations present in the narrowband components of $x(n)$. Obviously, if the delay is too long relative to these variations, the system performance will be degraded. In most applications, it would seem that this constraint would not be a serious problem. It is also important to note that this technique not only allows on-line modeling (both $d(n)$ and $y(n)$ are present) of the secondary path but also improves the performance of off-line modeling ($g(n)$ is absent) when the primary noise $d(n)$ is present. Therefore, off-line modeling can also be performed efficiently when the machine is in operation.

III. SIMULATION RESULTS

The secondary path used in simulation was measured from an actual test set-up in which the path was modeled as a finite impulse response (FIR) filter of order 64. The effect of the primary noise $d(n)$ on the modeling of the secondary path without the adaptive prediction error filter was simulated. The modeling accuracy and the rate of convergence are better when a white noise $u(n)$ of larger variance is used; however, the drawback is that the residual noise $e(n)$ in the system will increase correspondingly. In order to maintain low residual noise in steady state, zero-mean white noise of variance 0.05 was used to model the secondary path. The primary noise was a sinusoidal signal of normalized frequency 0.4 with an amplitude of two. The primary noise was sufficiently large as compared to the training signal in order to simulate practical conditions in ANC applications. The order of the filter $\hat{S}(z)$ was chosen to be 64 because $\hat{S}(z)$ is assumed to be of order 64. The step size for the adaptive filter $\hat{S}(z)$ was 0.005. The amplitude responses of the adaptive estimate filter $\hat{S}(z)$ and the secondary path $S(z)$ are shown in Fig. 2. As shown in the figure, $\hat{S}(z)$ identifies the secondary path poorly at the frequency of the interfering primary noise $d(n)$. A reduction of the step size improved system identification to some extent, but at the cost of slow convergence. It still showed a deterioration at the frequency of the primary noise. The simulations clearly demonstrate the adverse effect of secondary path modeling without compensating for the presence of the primary noise, $d(n)$.

The simulations were repeated using the developed modeling scheme with an adaptive prediction error filter being used to eliminate the interference during modeling. When a narrowband signal was the primary noise, a low-order $\hat{S}(z)$ was sufficient to predict and then cancel the narrowband components. $D(z)$ was chosen of order 25 with step size 0.0002, and the step size for modeling filter $\hat{S}(z)$ of order 64 was 0.01. When the value of the delay used was one, modeling was not very effective. The delays of the adaptive predictor were then increased and the modeling accuracy improved significantly. A delay corresponding to the order of the filter $\hat{S}(z)$ or greater gave the best modeling, as predicted by (5). Fig. 3 shows the modeling of the secondary path with an adaptive predictor of delay 64, which results in faster convergence and better model. It is important to note that if the delay $\hat{S}(z)$ forms deep notches in response to the behavior of the prediction filter, the ability of the overall system to remove tonal components will be degraded. As shown in Fig. 3, the notch at normalized frequency 0.4 is insignificant since the order of the filter $\hat{S}(z)$ is low.

In order to ascertain the optimum delay to be used for the adaptive predictor filter, the delay was varied from 1 to 75. The primary input was a sinusoidal signal at normalized frequency 0.4 with an amplitude of two. The modeling error is estimated by

$$\sigma^2 = \frac{1}{M-1} \sum_{i=0}^{M-1} |s_i - \hat{s}_i|^2$$

where $s_i$ is the $i$th coefficient of $\hat{S}(z)$ after the convergence of $\hat{S}(z)$. The estimated modeling error was plotted for different values of delay in Fig. 4. As seen in the figure, the modeling error is high when the delay is low, and it decreases when the delay increases. When the delay is greater than the length of the impulse response of $S(z)$, the modeling error is very low, i.e., the modeling of the secondary path is very accurate. This confirms the conclusion drawn in the previous section that the modeling error can be reduced by increasing the delay for $\Delta < M$, where $M$ is the order of the filter $S(z)$.

IV. CONCLUSIONS

The simulations conducted for a secondary path modeling technique using an optimized adaptive prediction error filter demonstrate that the secondary path can be effectively estimated despite the presence of narrowband interference. The proposed technique can be adapted to an on-line modeling scheme or can be used to improve the off-line modeling when the primary noise is present. The optimum delay for the adaptive predictor is determined to be equal to the length of the impulse response of the secondary path being modeled.

REFERENCES