REducing the negative effects of ear-canal occlusion

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Abstract

The negative effects of ear-canal occlusion are discussed as are methods that have been tried to reduce those effects. An adaptive filtering algorithm that could reduce the negative effects of ear-canal occlusion is proposed. Experiments and subjective listening tests are performed to test its effectiveness. It is concluded that the algorithm can effectively reduce the body-conducted signals trapped in the occluded ear canal that escape when the canal is unoccluded. Before it is implemented in hardware, a real-time simulation of the algorithm should be done and several people should judge its effectiveness.

Symbols

\( \delta(n) \)  
Delta function

\( e(n) \)  
Error signal used in adaptive filter update equation

\( \mu \)  
Step size in adaptive filter update equation

\( \omega \)  
Frequency in radians per second

\( \Sigma \)  
Used to represent a summation of signals

\( e^{j\omega} \)  
Complex representation of the phase of a signal

\( e(n) \)  
Error signal controlling adaption of adaptive scalar

\( f_0 \)  
Center frequency of bandpass filter

\( H(z), h(n) \)  
Representation of path of sound from a hearing aid speaker to microphone

\( \hat{H}(z)^{-1} \)  
Approximate inverse of \( H(z) \)

\( m \)  
Adaptive filter coefficient index

\( n \)  
Sample-time index

\( \text{noise} \)  
Variable representing a series of random numbers added to all but the first coefficient of a delta function to create a new impulse response

\( o(n) \)  
Signal representing the effects of occlusion at a point near an in-the-canal microphone of an occlusion-canceling hearing aid

\( \hat{o}(n) \)  
Primary estimate of \( o(n) \)

\( \hat{o}_2(n) \)  
Secondary estimate of \( o(n) \)

\( s(n) \)  
Input to hearing aid

\( s_{sec}(n) \)  
Signal in the ear canal near the speaker of an occlusion-canceling hearing aid

\( s_h(n) \)  
Output of a normal (non-occlusion-canceling) hearing aid

\( sp(n) \)  
Speaker output

\( \text{switch 1} \)  
Switch controlling whether or not the hearing aid output is adjusted to reduce the occlusion effect

\( \text{switch 2} \)  
Switch controlling when adaptive filter trains

\( \text{switch 3} \)  
Switch controlling when adaptive scalar trains

\( W(z) \)  
Adaptive filter

\( W_2(z), w_2(n) \)  
Adaptive scalar

\( w_m(n) \)  
The \( m^{th} \) coefficient of the adaptive filter

\( x(n) \)  
Input to adaptive filter

\( y(n) \)  
Output of adaptive filter

\( z \)  
Complex variable of the "z-domain". Used whenever a z-transform has been done on a discrete-time signal or impulse response
Introduction

The ear canal is occluded, or plugged, whenever a person puts something, such as a hearing aid or earplug, in his or her ear. Objects worn in the ear are generally put there to help a person hear or to block out unwanted sounds, but plugging the ear also has undesirable effects. Those undesirable effects are known to audiologists as the occlusion effect. The occlusion effect and a method of reducing it will be described in this paper.

The research presented in this article was done with the intent of improving hearing aids and will thus focus on how a hearing aid might be designed to reduce the occlusion effect. The research could be applied, however, to any electronic device that is worn in the ear. An electronic earplug or receiver that fits in the ear canal could be designed to reduce the occlusion effect using the same principles described in this article.

Occlusion Effect

The occlusion effect is caused by sounds that are conducted through a person's neck and head to the ear canal when a person speaks, chews, or otherwise generates noises with his or her own body. When the ear is open, most of the sound energy that enters the ear canal from these sources is able to escape, but when the ear canal is occluded, low-frequency energy is trapped in the ear canal. The energy trapped in the ear is usually greatest around 125 to 500 Hz. This makes a person's own voice sound louder and different as he speaks which may be very annoying to that person. Thus hearing aid wearers often complain about the sound of their own voices when they wear their hearing aids.\(^1\)

In order to reduce the occlusion effect caused by hearing aids, vents are often added to hearing aids, or earmolds are made to extend deeper into the ear canal.\(^1\) Active cancellation of the extra sound energy in the occluded ear canal has also been attempted using the output of the hearing aid.\(^2,3\) The existing methods help reduce the occlusion effect in many cases, but none of the methods appear to reduce the occlusion effect enough to satisfy all hearing aid wearers.\(^1\)

Algorithm

For these reasons, a new active cancellation algorithm is proposed in this paper. A block diagram of the algorithm is shown in Figure 1.

The occlusion-canceling hearing aid would begin by processing its input \(s(n)\) as would a normal hearing aid. This processing would generally include breaking the signal into frequency bands and scaling the amplitude of the signal in those frequency bands to compensate for a person's hearing loss. The signal \(s_h(n)\) would thus be equivalent to the output of a normal hearing aid that does not reduce the occlusion effect.

In deriving the algorithm, the author of this paper assumed that the path of sound from the hearing aid speaker to an in-the-canal microphone could be represented by a transfer function \(H(z)\). An adaptive filter \(W(z)\) is used in the algorithm to model that path.

The algorithm begins with a training period in which no occlusion is present. During that period, switch 1 is open, switch 2 is closed, and switch 3 is open. While switch 2 is closed the adaptive filter adapts using the LMS algorithm. This means that each of the filter coefficients would be updated according to the equation

\[
w_m(n + 1) = w_m(n) + \mu \epsilon(n)x(n - m),
\]

where \(n\) is the time-sample index, \(w_m\) refers to the \(m^{th}\) coefficient of \(W(z)\), \(\mu\) is a small constant determining step size, and \(\epsilon(n)\) is an error term fed back to control adaptation.\(^4\)

The difference \(micin(n) - y(n)\) is called \(\delta(n)\) and is fed back to the adaptive filter to guide its adaptation. It is used as \(\epsilon(n)\) in equation 1. At the end of the training period, the output of the adaptive filter \(y(n)\) approximates \(micin(n)\) the input to the in-the-canal microphone of the hearing aid. Since switch 1 and switch 3 are open, the adaptive scalar \(W_2(z)\) is held constant and the speaker output \(sp(n)\) is equivalent to \(s_h(n)\).

After the training period, switch 1 and switch 3 are closed and switch 2 is open. Thus the adaptive filter ceases adaptation and \(\delta(n)\) serves as a preliminary estimate of \(o(n)\), which is a signal representing the extra sound energy in the ear canal due to the occlusion effect. This preliminary estimate of \(o(n)\) is then multiplied by an adaptive scalar \(W_2(n)\) which adapts to compensate for the gain of the transfer function whenever the adaptive filter is not training. The scalar adapts using the LMS algorithm also. The error signal \(\epsilon(n) = micin(n) - s_h(n)\) is used as \(\epsilon(n)\) in equation 1 because when the signal in the ear canal is approximately equal to the signal that would be output from a normal hearing aid, the occlusion effect will have been reduced significantly. The occlusion estimate \(\hat{o}(n)\) is then subtracted from \(s_h(n)\) to form the speaker output \(sp(n)\). That speaker output can reduce the occlusion effect because of the estimate that is subtracted from the speaker output. Subtracting the occlusion estimate from the output is mathematically equivalent to adding a second speaker that outputs a signal nearly equal and opposite \(o(n)\) (180° out of phase with \(o(n)\)).

The signal \(s_{ae}(n)\) represents a signal at a point in the ear canal near the hearing-aid speaker. This is used as the output of the algorithm because it does not include the effects of the transfer function \(H(z)\) and someone
listening to it would be able to tell if the occlusion signal were reduced. The transfer function $\hat{H}(z)^{-1}$ is an approximate inverse of $H(z)$. When included in the algorithm, it modifies $o(n)$ to compensate for the gain of $H(z)$.

**Experiments**

Three experiments were performed to test the algorithm. For the experiments, a signal representing the occlusion signal $o(n)$ was either created artificially or recorded, and the algorithm was tested on a computer to see if $o(n)$ could be canceled. In all three of the experiments, the hearing aid processing was set for unity gain or omitted so a normal-hearing person could tell how well the occlusion signal was reduced.

**Reducing Artificial Occlusion**

For the first experiment, the transfer function $H(z)$ was chosen to have an impulse response similar to that of a delta function or a decaying exponential function. The algorithm was then tested on a computer. During the training period, $s(n)$ was a white noise signal and $o(n)$ was silence. After the training period, a speech file was used as $s(n)$. Because the occlusion effect is a low-frequency phenomenon, the signal $o(n)$ was generated from the speech file by bandpass filtering the speech file with a filter that had a center frequency of 250 or 500 Hz, and then lowering the pitch. Gain was added so the artificial occlusion was exaggerated and could be heard well when mixed with $s(n)$.

The experiment was repeated using various transfer functions, speech files, and artificial occlusion files. A listening test was then created to determine how well the algorithm canceled the artificial occlusion. For the test, 7 listeners sat in a double-walled sound suite at Brigham Young University and listened through earphones to three types of signals. They were asked to rank the naturalness of the signals on a scale of 1 to 10, 10 being the most natural. The three types of signals were unoccluded, occluded and processed, and occluded and unprocessed. The unoccluded files consisted of speech alone. The occluded and unprocessed signals each contained a speech signal mixed with an artificial occlusion signal which was generated by bandpass filtering and lowering the pitch of that speech signal. The occluded and processed signals contained the output $s_{ec}(n)$ of the algorithm when a speech file represented $s(n)$ and an artificial occlusion signal represented $o(n)$.

The results of the listening test are summarized in Table 1. In most cases, the gain error introduced by $H(z)$ was ignored and $\hat{H}(z)^{-1}$ was set equal to one. When this was the case, the files processed with transfer functions that had magnitudes approximately equal to one were judged to sound more natural than the transfer functions with magnitudes unequal to one. The author attributed this to the lack of compensation for the gain of the transfer function.

Since the adaptive scalar adapts to cancel $o(n)$ after the output of the hearing aid has been modified by the transfer function $H(z)$, the estimate of $o(n)$ being output from the speaker was not large enough to cancel
Table 1
Average rankings of naturalness of word lists that were (a) unoccluded and unprocessed, (b) occluded with artificial occlusion and processed with the algorithm proposed in this paper, and (c) occluded with artificial occlusion but not processed with the algorithm proposed in this paper. Seven people participated in the listening test that produced these results. The variable noise refers to random numbers added to the 2nd to 24th coefficients of $h(n)$. When the transfer function was “compensated” the occlusion signal was multiplied by a gain-compensation factor.

(a) Unoccluded and Unprocessed Word List

<table>
<thead>
<tr>
<th>Word List Read By Female</th>
<th>Word List Read By Male</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>9</td>
</tr>
</tbody>
</table>

(b) Word List Occluded With Artificial Occlusion and Processed With Algorithm

<table>
<thead>
<tr>
<th>Transfer Function Used In Algorithm Represented By $h(n)$=</th>
<th>Occlusion Signal Created Using 250 Hz Bandpass Filter</th>
<th>Occlusion Signal Created Using 500 Hz Bandpass Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta(n)$</td>
<td>9</td>
<td>6</td>
</tr>
<tr>
<td>$\delta(n) + noise/100$</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>$2^{-n}(\text{compensated})$</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>$2^{-2n}$</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>$\delta(n) + noise$</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>$2^{-n}$</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

(c) Word List Occluded With Artificial Occlusion But Not Processed

<table>
<thead>
<tr>
<th>Occlusion Signal Created Using 250 Hz Bandpass Filter</th>
<th>Occlusion Signal Created Using 500 Hz Bandpass Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word List Read By Female</td>
<td>Word List Read By Male</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>
\( o(n) \) at the speaker. This theory was tested by including a sound file in the listening test that included a more realistic estimate of \( \hat{H}(z)^{-1} \). Since the artificial occlusion was narrow banded, \( \hat{H}(z)^{-1} \) was defined as

\[
\frac{1}{|H(z)|_{\omega=2\pi f_0}}
\]

which represents the inverse of the magnitude of the transfer function \( H(z) \) at the center frequency \( f_0 \) of the bandpass filter used to create the artificial occlusion signal. In this equation, \( z \) is assumed to have a magnitude of 1 and is thus equal to \( e^{j\omega} \) in polar form.

Those participating in the listening test ranked the occluded and processed signals as sounding more natural than the occluded and unprocessed signals even when no gain compensation was made for the transfer function. When gain compensation was made or the magnitude of the transfer function was approximately equal to one, the processed signals sounded almost as natural as the unoccluded signals. These results suggest that the algorithm was successful in reducing the artificial occlusion.

Reducing Recorded Occlusion

To generate signals for the second experiment, a subject sat in a double-walled sound suite at Brigham Young University and a probe microphone was placed in one of his ears. His ear was then plugged and another microphone was hung about 5 cm from the same ear. The signal recorded using the hanging microphone was called \( s(n) \), and the signal recorded using the probe microphone was called \( o(n) \).

For this experiment, \( H(z) \) was chosen to represent a delta function. Once \( H(z) \) was chosen and the recordings were made, the algorithm was tested on a computer as in the previous experiment.

A subjective listening test was performed by six people. For the test, each subject sat in a double-walled sound suite and was asked to compare two files played one right after another through headphones. They were asked if one file sounded better than the other and, if so, which file sounded better. The two files played to them, in random order, were the occluded and unprocessed file and the occluded and processed file created using recordings of sound inside and outside of the ear canal.

Four out of six people judged the occluded and processed file to be more natural than the occluded and unprocessed file. The other two people did not believe either of the files to sound better than the other. This result also supports the theory that the algorithm would be effective at reducing the unwanted signals in the occluded ear canal.

Reducing Recorded Bone-Conducted Signals

In order to record bone-conducted signals for this experiment, a person sat in a double-walled sound suite and a bone vibrator was placed on his forehead as shown in Figure 2. The tube from a probe microphone was placed in the person’s ear canal and his ear was plugged with a perforated earplug that had a tube through it. A tube from a small loudspeaker was connected to the tube of the earplug permitting air-conducted signals to pass through the earplug from the loudspeaker.

![Figure 2. Setup for recording bone-conducted signals](image-url)

Six recordings were made using the setup of Figure 2 which was just described. For all six recordings, a word list was played from a CD through the small loudspeaker into the ear canal. During one recording, the bone vibrator was off. During each of the other five, it was calibrated to generate speech noise at 10, 20, 30, 40, and 50 dB HL, respectively. Thus, the probe microphone recorded an air-conducted signal alone once and an air-conducted and a bone-conducted signal together five times.

The algorithm was again tested on a computer using those recordings. The recording of the air-conducted signal alone was used as \( s(n) \) of the algorithm and the recordings of the air-conducted and bone-conducted signals together were used to represent \( s(n) + o(n) \). In other words, the transfer function \( H(z) \) was assumed to equal one.

The weights of the adaptive filter were forced to have the impulse response of a delta function so that \( W(z) = 1 \) when testing the algorithm using these recordings. Thus no training period was necessary. Also, since \( o(n) \) was not isolated in this experiment as it was previously, \( micin(n) \) was generated by subtracting \( \hat{o}_2(n) \) from the signal representing \( s(n) + o(n) \). This is comparable to the other experiments where \( micin(n) \) was created by filtering \( s(n) - \hat{o}_2(n) \) with \( H(z) \) and then
adding the result to $o(n)$. When $H(z) = 1$, $micin(n) = s(n) - o2(n) + o(n)$ in both cases. For this experiment $sec(n)$, the output of the algorithm, is equal to $micin(n)$ since $H(z) = 1$.

The sound file containing 50 dB HL of bone-conducted speech noise and the sound file containing no bone-conducted signal were used to create a sound file that was listened to by seven subjects in a subjective listening test. The processed file and the file containing 50 dB HL of bone-conducted speech noise were played one right after another in random order to the seven subjects. They were asked if the second file was easier or harder to understand than the first one and how many times easier or harder. They were not given an upper or lower limit on that judgment. The subjects said that the processed file was from four to one hundred times easier to understand. On average they ranked the processed file to be 33 times easier to understand than the unprocessed file.

In this experiment, the algorithm was successful at reducing the bone-conducted component of a signal. The occlusion effect is caused by body-conducted signals, so these results also support the theory that the algorithm could be successful at reducing the negative effects of the occluded ear canal.

Summary of Results

In all three experiments, the "occlusion signal" that was either artificially created or recorded was reduced by the algorithm. When compared to unprocessed files that contained occlusion and another signal, the processed files were judged to sound more natural or be easier to understand than the unprocessed. When compared to a sound file with no occlusion present in the first experiment, the processed files were sometimes ranked almost as natural as the unoccluded files. This was true when the transfer function $H(z)$ had a magnitude very near one at low frequencies or when gain compensation was included in the algorithm. The author believes that gain compensation will not be a problem in a real ear canal because the compensation is an attempt to model what would naturally take place if the experiment were performed real time in a real ear canal.

Conclusion

The experiments suggest that the algorithm could significantly reduce the negative effects of ear-canal occlusion if implemented in a hearing aid or other device that occludes the ear canal. Since the algorithm uses adaptive filtering to model the path of sound in the ear canal it could reduce the occlusion effect in all types of ears. Before implementing it in a hearing aid, further research should be done to see if the algorithm can work in real time. In other words, the algorithm needs to be tested using signals that are not prerecorded but are recorded at the time of processing with the algorithm.

Future Research

Future research should include at least a real-time simulation in the ear canal. Several people should then judge whether or not the occlusion-effect cancellation is satisfactory. In addition it could include the following:

- Determine the stability of the algorithm.
- Find methods of improving the stability.
- Determine how much training provides a "good reduction" of the negative effects of occlusion.
- Add a signal detector to the algorithm or find another way to have it start and stop training without user interaction.

If these things were done, the algorithm could be improved and it could likely be implemented in a device that occludes the ear canal.

REFERENCES