Chapter 2

Adaptive filtering for Sensorineural Impairment

2.1 Introduction

Digital signal processing techniques are applied for reducing the effect of background noise in digital hearing aid. Adaptive system with directional microphones is the best way to improve the signal to noise ratio, for hearing impairment [46, 49 & 54]. Hence, in this chapter different structures of adaptive filters are implemented to reduce the effect of noise in digital hearing aid for SNHL persons.

Adaptive filters can adapt their filter coefficients to the environment according to preset rules. These filters are capable of learning from the statistics of current conditions, and change their coefficients in order to achieve a certain goal. Adaptive filters are used in situations where it is impossible to use a pre-designed filter. This chapter starts with the basic concepts and theoretical background of FIR adaptive filters. It includes the implementations of adaptive noise canceller using two sources and single source with normalized LMS adaptive filter for SNHL persons. Finally, results of the algorithms are evaluated.

2.2. FIR Adaptive filters

FIR filters are commonly used in adaptive noise cancellation algorithms. There are several reasons for the popularity of FIR adaptive filters. First, stability can be easily controlled by ensuring that the filter coefficients are bounded. Second, there are simple and efficient algorithms for adjusting the coefficients. Third, the performance of these
algorithms is well understood in terms of their convergence and stability. Finally, FIR adaptive filters very often perform well enough to satisfy the design criteria.

An FIR adaptive filter for estimating a desired signal $d(n)$ from the input signal $x(n)$ is as illustrated in Fig 2.1. The estimation of $d(n)$ is given by

$$\hat{d}(n) = \sum_{k=0}^{p} w_n^*(k)x(n-k) = w_n^*x(n)$$  \hspace{1cm} 2.1

Here, both the signals $x(n)$ and $d(n)$ are non-stationary speech signals and the goal is to find the coefficient vector $w_n$ at time $n$ that minimizes the mean-square error, $\xi(n) = E[|e(n)|^2]$. Where

$$e(n) = d(n) - \hat{d}(n) = d(n) - w_n^*x(n)$$  \hspace{1cm} 2.2

The solution to this minimization problem may be found by setting the derivative of $\xi(n)$ with respect to $w_n^*(k)$ equal to zero for $k = 0,1,\ldots,p$ and $*$ represents the complex conjugate. The result is

$$E\{e(n)x^*(n-k)\} = 0 \hspace{1cm} k = 0,1,\ldots,p$$  \hspace{1cm} 2.3

Substituting equation 2.2 in equation 2.3 we have
After rearranging, it becomes

$$\sum_{l=0}^{p} w_n(l) E \{ x(n-l) x^*(n-k) \} = E \{ d(n) x^*(n-k) \}$$

2.5

The equation 2.5 can be represented in vector form as follows

$$R_s(n) w_n = r_{as}(n)$$

2.6

Where

$$R_s(n) = \begin{bmatrix}
E \{ x(n)x^*(n) \} & E \{ x(n-1)x^*(n) \} & \cdots & E \{ x(n-p)x^*(n) \} \\
E \{ x(n)x^*(n-1) \} & E \{ x(n-1)x^*(n-1) \} & \cdots & E \{ x(n-p)x^*(n-1) \} \\
\vdots & \vdots & \ddots & \vdots \\
E \{ x(n)x^*(n-p) \} & E \{ x(n-1)x^*(n-p) \} & \cdots & E \{ x(n-p)x^*(n-p) \}
\end{bmatrix}$$

2.7

is a $(p+1) \times (p+1)$ Hermitian matrix of autocorrelation and

$$r_{as}(n) = [E \{ d(n)x^*(n) \}, E \{ d(n)x^*(n-1) \}, \cdots, E \{ d(n)x^*(n-p) \}]^T$$

2.8

is a vector of cross-correlations between $d(n)$ and $x(n)$. In the case of jointly wide sense stationary (WSS) processes, equation 2.5 reduces to the Wiener-Hopf equations and the solution $w_n$ becomes independent of time. Solving each value of $n$ in equation 2.7 is time consuming, which is impracticable in digital hearing aid implementations. Hence, an iterative approach [145 & 136] based on steepest descent method is discussed in the next section.

### 2.2.1 The LMS algorithm

The LMS algorithm was first introduced by Widrow and Hoff in 1959 is simple, robust and is one of the most widely used algorithms for adaptive filtering and can be effectively used for reducing noise in digital hearing aid [111 & 134]. In the steepest descent adaptive filter, weight-vector update equation is given by
\[ w_{n+1} = w_n + \mu E\{e(n)x^*(n)\} \quad 2.9 \]

A practical limitation with this algorithm is that the expectation \( E[e(n)x^*(n)] \) is generally unknown. Therefore, it must be replaced with an estimate such as the sample mean

\[ \hat{E}\{e(n)x^*(n)\} = \frac{1}{L} \sum_{l=0}^{L-1} e(n-l)x^*(n-l) \quad 2.10 \]

Incorporating this estimate into the steepest descent algorithm, the update for \( w_n \) becomes

\[ w_{n+1} = w_n + \frac{\mu}{L} \sum_{l=0}^{L-1} e(n-l)x^*(n-l) \quad 2.11 \]

if we use a one-point sample mean \((L=1)\),

\[ \hat{E}\{e(n)x^*(n)\} = e(n)x^*(n) \quad 2.12 \]

In this case, the weight vector update equation assumes a particularly simple form

\[ w_{n+1} = w_n + \mu e(n)x^*(n) \quad 2.13 \]

The equation 2.13 is called LMS equation. The weight vector \( w_n \) in LMS algorithm is updated by using LMS equation [135].

### 2.2.2 Normalized LMS

As we have seen in the section 2.2.1, one of the difficulties in the design and implementation of the LMS adaptive filter is the selection of the step size \( \mu \). For stationary process, the LMS algorithm converges in the mean of

\[ 0 < \mu < \frac{2}{\lambda_{\text{max}}} \quad 2.14 \]

and converges in the mean square of

\[ 0 < \mu < \frac{2}{\text{tr}(R_x)} \quad 2.15 \]

The bound in the above equation can be calculated from

\[ \text{tr}(R_x) = (p+1)E\{|x(n)|^2\} \quad 2.16 \]
Therefore, the Condition for mean-square convergence may be replaced with

\[ 0 < \mu < \frac{2}{(p+1)E\{ |x(n)|^2 \}} \quad 2.17 \]

Where \( E\{ |x(n)|^2 \} \) is the power of input speech signal \( x(n) \). This power can be estimated using a time average such as

\[ \hat{E}\{ |x(n)|^2 \} = \frac{1}{p+1} \sum_{k=0}^{p} |x(n-k)|^2 \quad 2.18 \]

This leads to the following bound on the step size for mean-square convergence

\[ 0 < \mu < \frac{2}{x^H(n)x(n)} \quad 2.19 \]

Then, the time-varying step size is given by

\[ \mu(n) = \frac{\beta}{x^H(n)x(n)} = \frac{\beta}{\|x(n)\|^2} \quad 2.20 \]

Where \( \beta \) is a normalized step size. Replacing \( \mu \) in the LMS weight vector update equation with \( \mu(n) \) leads to the normalized LMS algorithm (NLMS), which is given

\[ w_{n+1} = w_n + \beta \frac{x^*(n)}{\| x(n) \|^2} e(n) \quad 2.21 \]

Normalization by \( \| x(n) \|^2 \) is to alter the magnitude, but not the direction, of the estimated gradient vector. In the LMS algorithm, the correction is applied to \( w_n \), is proportional to the input vector \( x(n) \). Therefore, when \( x(n) \) is large, the LMS algorithm experiences a problem with gradient noise amplification. Although the NLMS algorithm bypasses the problem of noise amplification, the similar problem occurs when \( \| x(n) \| \) becomes too small \([137]\). But, can be eliminated by adding small positive integer number \( \varepsilon \) as shown below

\[ w_{n+1} = w_n + \beta \frac{x^*(n)}{\| \varepsilon + x(n) \|^2} e(n) \quad 2.22 \]

The equation 2.22 represents the weight adaptation equation for normalized least mean square algorithm.
2.3 Adaptive Noise Cancellation Algorithms for digital hearing aid

The general problem of noise reduction is not new and has been addressed in great depth by statisticians, physicists, engineers, and others [4, 40, 75 & 116]. The problem is central to the field of signal processing. Adaptive noise cancellation algorithms can be effectively used for noise reduction of contaminated speech signal in digital hearing aid especially for SNHL [143 & 134].

2.3.1 Adaptive noise canceller with two microphones

In the adaptive noise cancellation process, the desired speech signal $d(n)$ is to be calculated from a noise-corrupted speech signal $x(n) = d(n) + v_1(n)$. In this method, reference signal, $v_2(n)$ is correlated with $v_1(n)$. This reference signal may be used to estimate the noise $v_1(n)$, and the estimate can be then be subtracted from $x(n)$ to get the estimate of $d(n)$.

$$d(n) - x(n) - v_1(n)$$

If $d(n)$, and $v_1(n)$ are jointly wide-sense stationary processes, and if the autocorrelation $r_{v_1}(k)$ and the cross-correlation $r_{v_2v_1}(k)$ are known, then filter can be designed to find the minimum means square estimate of $v_1(n)$. But, the desired speech signal $d(n)$ and the noise $v_1(n)$ are non-stationary signals and their autocorrelations are unknown [73 & 82]. Therefore, as an alternative to the Wiener filter, adaptive noise canceller is considered as shown in Fig. 2.2. If the reference signal $v_2(n)$ is uncorrelated with $d(n)$, then the minimization of mean square error $E(|e(n)^2|)$ is equivalent to minimizing

$$E(|v_1(n) - v_1(n)|^2).$$
In other words, the output of the adaptive filter is the minimum mean square estimate of the noise $v_1(n)$. If there is no information about desired speech signal $d(n)$ in the reference signal $v_2(n)$, then the adaptive filter can minimize noise, by estimating $v_1(n)$. Since the output of the adaptive filter is the minimum mean square estimate of $v_1(n)$, then it follows that $e(n)$ is the minimum mean square estimate of the desired speech signal $d(n)$. It is an efficient noise canceller and is implemented in digital hearing aid for reducing noise effects especially for SNHL persons [83 & 98].

**2.3.2 Single Microphone Adaptive Algorithm**

Under ideal conditions, at least one microphone (omni directional) must be placed at the noise source. If the ideal adaptive noise canceller is used with two microphones, one microphone picking up more speech than noise and the other microphone picking up more noise than speech, the noise will not be cancelled completely, but the level of the noise will be reduced [78, 145 & 144]. An improved speech-to-noise ratio will result, with improved intelligibility and can be effectively used for noise reduction in digital hearing aid for SNHL persons. Although these adaptive noise cancellation methods are extremely effective, they are restrictive in their requirements on the availability and placement of multiple
microphones. In these situations, adaptive filters can be employed with single microphone. Since, it is possible to derive a reference signal by simply delaying the input noisy speech signal \( x(n) = d(n) + v_1(n) \) as shown in Fig. 2.3.

\[
x(n) = d(n) + v_1(n)
\]

![Figure 2.3. Adaptive noise canceller with single microphone](image)

The desired speech signal \( d(n) \) is a narrowband signal and that \( v_1(n) \) is a broadband noise with

\[
E\{v_1(n)v_1(n-k)\} = 0; \quad |k| > k_0.
\]

If \( d(n) \) and \( v_1(n) \) are uncorrelated, then

\[
E\{v_1(n)x(n-k)\} = E\{v_1(n)d(n-k)\} + E\{v_1(n)v_1(n-k)\} = 0; \quad |k| > k_0
\]

Therefore, if \( n_0 > k_0 \) then the delayed process \( x(n-n_0) \) will be uncorrelated with the noise \( v_1(n) \), and correlated with \( d(n) \). Thus, \( x(n-n_0) \) may be used as a reference signal to estimate \( d(n) \) as shown in Fig. 2.3. In contrast to the adaptive noise canceller in Fig. 2.2, the adaptive filter in Fig. 2.3 produces an estimate of the broadband process, \( d(n) \) and the error \( e(n) \) corresponds to an estimate of the noise \( v_1(n) \). This adaptive structure can be effectively used for noise cancellation, but best suited for stationary signals [133]. In the case of non-stationary signals like speech signals, the delay would normally be a multiple of the pitch period [28, 39 & 141]. If, the delay is chosen properly, then this structure can be
effectively used for noise cancellation in digital hearing aids. In this work, the delay is approximately chosen, whose length is very much lesser than the length of the signal.

2.4 Performance measures of adaptive filters

Performance of the adaptive filters are measured, compared and analyzed with the help of following parameters.

a. Convergence rate: The convergence rate determines the rate at which the filter converges to its resultant state. Usually faster convergence rate is the desired characteristic of an adaptive system. Convergence rate is not, however, independent of all other performance characteristics. If the convergence rate is increased, the stability characteristics will decrease, making the system more likely to diverge instead of converge to the proper solution. Likewise, a decrease in convergence rate can cause the system to become more stable. In this work, convergence rate is measuring in terms of eigenvalue ratio.

b. Minimum mean square error (MSE): The MSE is a metric indicating how well a system can adapt to a given solution. A small minimum MSE is an indication that the adaptive system has accurately modeled, predicted, adapted and/or converged to a solution for the system. This parameter is indicating in terms of signal to noise ratio.

c. Computational complexity: Computational complexity is particularly important in real time adaptive filter applications. A highly complex algorithm will require much greater hardware resources.

d. Stability: Stability is probably the most important performance measure for the adaptive system. The algorithm convergence time and stability depends upon the ratio of the largest to the smallest eigenvalue associated with the correlation matrix of the input sequence. Therefore, stability of the algorithms is defined in terms of eigenvalue ratio.
e. **Filter length:** The filter length of the adaptive system is inherently tied to many of the other performance measures. The length of the filter specifies how accurately a given system can be modeled. The filter length affects the convergence rate, computation time, stability of the system at certain step sizes and also MSE. If the filter length of the system is increased, the number of computations will increase, decreasing the maximum convergence rate. Conversely, if the filter length is decreased, the number of computations will decrease, increasing the maximum convergence rate.

f. **Eigenvalue ratio:** Eigenvalue ratio or the eigenvalue spread is the ratio between the maximum eigenvalue and the minimum eigenvalue of the input autocorrelation matrix. The eigenvalue ratio $r$ can be calculated as

$$r = \frac{\lambda_{\text{max}}}{\lambda_{\text{min}}}$$  \hspace{1cm} (2.27)

Where $\lambda_{\text{max}}$ and $\lambda_{\text{min}}$ are the maximum and minimum eigenvalues, which found on the main diagonal of the autocorrelation matrix. Then the rate of convergence can be calculated as

$$C.\text{rate} = \frac{(r - 1)^2}{(r + 1)^2}$$  \hspace{1cm} (2.28)

From the above equation it is clear that, the convergence time decreases if the eigenvalue ratio increases and vice versa.

g. **Decorrelation efficiency:** The decorrelation efficiency is the ratio between the sum of off-diagonal elements of the autocorrelation matrix and the corresponding sum for matrix $T$. If the autocorrelation matrix of the signal is a Toeplitz matrix $R$, then the decorrelation efficiency $\eta_c$ is given by
\[ \eta_c = 1 - \frac{\sum_{i,j=1}^{\infty} R_{ij}}{\sum_{i=1}^{\infty} T_{ij}} \]

2.29

h. SNR: Amount of noise filtering can be measured from adaptive system with the help of input SNR and output SNR. Input SNR is the ratio between the power of input signal and power of noise at input. Output SNR is the ratio between the power of filtered signal and power of noise at output. In general SNR is defined as

\[ SNR = \frac{\sum_{n} x^2(n)}{\sum_{n} e^2(n)} \quad \text{and} \quad SNR(dB) = 10 \log_{10} \frac{\sum_{n} x^2(n)}{\sum_{n} e^2(n)} \]

(2.30)

Where, \( x(n) \) is the input signal and \( e(n) \) is the noise.

2.5 Results and evaluation

In this chapter normalized LMS and single source NLMS has been implemented for the enhancement of the speech signal in digital hearing aid for SNHL persons. The performance of both algorithms has been measured using output SNR, eigenvalue ratio, time plots and intelligibility tests.

2.5.1 Computational complexity

Computational complexity is particularly important in real time adaptive filter applications especially in digital hearing aid. Number of additions and multiplications required for implementing the algorithm is calculated to find out the computational complexity of the algorithm. The simplicity of the least means square algorithm comes from the fact that the update for the \( k^{th} \) coefficient, \( w_{n+1}(k) = w_n(k) + \mu e(n)x'(n-k) \). This
requires only one multiplication and one addition. Therefore, LMS adaptive filter having $p + 1$ coefficients requires $p + 1$ multiplication and $p + 1$ additions to update the filter coefficients. In addition, one addition is necessary to compute the error $e(n) = d(n) - y(n)$ and one multiplication is needed to find the product $\mu e(n)$. Finally, $p + 1$ multiplications and $p$ additions are necessary to calculate the output, $y(n)$ of the adaptive filter. Thus, a total of $2p + 3$ multiplications and $2p + 2$ additions per output point are required.

Compared with the LMS algorithm, the normalized LMS algorithm requires additional computation to evaluate the normalization term $\| x(n) \|^2$. If this term is evaluated recursively as follows

$$\| x(n+1) \|^2 = \| x(n) \|^2 + |x(n-1)|^2 - |x(n-p)|^2$$

Then the extra computation involves only two squaring operations, one addition, and one subtraction.

### 2.5.2 Performance evaluation by using output SNR, eigenvalue ratio and time plots

The algorithm is evaluated for corrupted speech signals with different types of noise like cafeteria, low frequency and babble noise with different SNR. The various parameters like $\beta$ and filter order were changed and the performance of the algorithm was evaluated. Results show that, both parameters SNR and eigenvalue ratio are strongly depending on $\beta$ and filter order.

The input signal is a speech sentence in English and is recorded with sampling frequency 22050 Hz in different noisy conditions to evaluate the performance of the algorithm. Performance of the algorithm was studied, for different values of $\beta$ and filter order. From the studies, we have noticed that for $\beta = 0.45$ and filter order = 32 normalized LMS gives better SNR and intelligibility improvement.
Figure 2.4 Original, contaminated and filtered signals of NLMS noise canceller.
Figure 2.5 Original, contaminated and filtered signals of single source noise canceller.
<table>
<thead>
<tr>
<th>Input SNR in dB</th>
<th>Output SNR in dB</th>
<th>Eigenvalue ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5</td>
<td>7.33</td>
<td>1069.43</td>
</tr>
<tr>
<td>0</td>
<td>9.32</td>
<td>1060.32</td>
</tr>
<tr>
<td>+5</td>
<td>11.15</td>
<td>1003.06</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Input SNR in dB</th>
<th>Output SNR in dB</th>
<th>Eigenvalue ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5</td>
<td>6.2</td>
<td>1129.67</td>
</tr>
<tr>
<td>0</td>
<td>8.51</td>
<td>1132.35</td>
</tr>
<tr>
<td>+5</td>
<td>11.15</td>
<td>1102.53</td>
</tr>
</tbody>
</table>

Table 2.1 Eigenvalue ratio and SNR of the output signal for direct LMS, NLMS and Single Source LMS.

For different input SNR, the output SNR and eigenvalue ratios are calculated as shown in Table 2.1. The eigenvalue ratio is calculated to find out how well the algorithm converges to the optimum Wiener solution. The main disadvantage of both the algorithms is, their high eigenvalue ratio. Because, filters having high eigenvalue ratio requires longer time to converge and vice versa.

Fig. 2.4 shows the time plots of pure signal, corrupted signal with -5dB SNR, and the NLMS filtered signal. Fig 2.5 shows the time plots of pure signal, corrupted signal and
filtered signal for single source noise canceller. Fig. 2.6 shows the autocorrelation of the input corrupted signal verses number of samples. The NLMS with two source gives better results compared to single source NLMS.

2.5.3 Intelligibility Test

In order to measure the performance of clinical intelligibility tests of the algorithms, listening tests were carried out. The tests were conducted on both hearing impaired and normal hearing persons. The experiment was carried out in a room whose size was about 4 m by 5 m. The room was carpeted but no attempt was made to improve the room acoustics otherwise. The main speaker and the noise source were placed 2.5 feet away from the microphones. For speech intelligibility test, we processed 10 sentences with different noise. These tests were performed on 15 subjects, 5 with normal hearing (Group 1), 5 with a mild to moderate SNHL (Group 2) and 5 with moderate to severe SNHL loss (Group 3).

In the experimental evaluation, the target source was a male speaker reading sentences and interference consisted of 3 different types of noise (1) cocktail party noise (2) five speaker babble (3 male and 2 female) (3) low frequency noise. The noise level is varied to get different SNR. The subjects were listened the original, the noisy and the filtered signals. The percentage of correct responses was recorded. The results are displayed in Tables 2.2, 2.3 and 2.4 for –5dB input SNR. The results indicate that a considerable improvement is obtained, particularly for moderate to severe SNHL subjects.

The result of recognition test of NLMS and single source noise canceller signals are displayed in Table 2.4. It is seen that after adaptive processing the intelligibility improvement is achieved in all the cases. NLMS filter showed an average intelligibility improvement of 1 % with normal subjects, 4 % with mild to moderate SNHL subjects and 6 % with moderate to severe SNHL subjects as compared to single source noise canceller with cocktail party noise.
<table>
<thead>
<tr>
<th>Group1</th>
<th>Group 2</th>
<th>Group 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>96 %</td>
<td>78 %</td>
<td>63 %</td>
</tr>
</tbody>
</table>

Table 2.2 Average intelligibility score for the noiseless signal

<table>
<thead>
<tr>
<th>Types of noise</th>
<th>Cocktail party noise</th>
<th>Babble noise</th>
<th>Low frequency noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group1</td>
<td>73 %</td>
<td>78 %</td>
<td>83 %</td>
</tr>
<tr>
<td>Group 2</td>
<td>31 %</td>
<td>34 %</td>
<td>38 %</td>
</tr>
<tr>
<td>Group 3</td>
<td>15 %</td>
<td>13 %</td>
<td>16 %</td>
</tr>
</tbody>
</table>

Table 2.3 Average intelligibility score for the signal plus noise

<table>
<thead>
<tr>
<th>Types of noise</th>
<th>Cocktail party noise</th>
<th>Babble noise</th>
<th>Low frequency noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group1 NLMS</td>
<td>94 %</td>
<td>93 %</td>
<td>94.5 %</td>
</tr>
<tr>
<td>Group1 NLMS with single source</td>
<td>93 %</td>
<td>92 %</td>
<td>93 %</td>
</tr>
<tr>
<td>Group2 NLMS</td>
<td>75 %</td>
<td>73 %</td>
<td>74.5 %</td>
</tr>
<tr>
<td>Group2 NLMS with single source</td>
<td>71 %</td>
<td>70.5 %</td>
<td>72 %</td>
</tr>
<tr>
<td>Group3 NLMS</td>
<td>63 %</td>
<td>61 %</td>
<td>64 %</td>
</tr>
<tr>
<td>Group3 NLMS with single source</td>
<td>57 %</td>
<td>53 %</td>
<td>58 %</td>
</tr>
</tbody>
</table>

Table 2.4 Intelligibility improvements for three groups of subjects.

2.6 Conclusion

Adaptive algorithms can be successfully used for noise reduction in digital hearing aid for SNHL persons. Off-line tests in different conditions show improvements in SNR up to 10.06 dB with NLMS-algorithm and up to 8.6 dB with single source NLMS for zero dB input SNR. In a more realistic environment, they may have the variations of ± 3 dB. But,
the results show that, both the algorithms have high eigenvalue ratio. Hence, they need more time to converge into the optimal solution.

In LMS filter, convergence rate is highly dependent on the conditioning of the autocorrelation matrix of its inputs. The mean square error of an adaptive filter trained with LMS, decreases over time as a sum of exponentials. The time constants of mean square error are inversely proportional to the eigenvalue of the autocorrelation matrix of the filter inputs. Therefore, small eigenvalue create slow convergence modes in the mean square error function. Large eigenvalue, on the other hand, put a limit on the maximum learning rate that can be chosen without encountering stability problems. Best convergence properties are obtained when all the eigenvalue are equal, that is, when the input autocorrelation matrix is proportional to the identity matrix. In that case, the inputs are perfectly uncorrelated and have equal power.

Convergence performance of the standard LMS algorithm can be improved by using frequency domain filtering, by exploiting the orthogonal property of DFT and related orthogonal transforms. Therefore in the next chapter, transform domain adaptive algorithms are implemented with less computational complexity, good decorrelation efficiency and good SNR and intelligibility improvement for SNHL persons.