Chapter 2
Adaptive Noise Cancellation to Speech Enhancement

Abstract This chapter focuses on the theory and implementation of (Hayes in Statistical digital signal processing and modeling, Wiley, 1996; Hadei 2010) adaptive noise cancellation (ANC) method for dual-channel speech enhancement. Existing gradient-based approaches for adaptive filtering in speech enhancement are explained in detail. This chapter discusses about the limitations of the gradient-based algorithms for IIR filters. It also presents the advantages of the heuristic optimization technique. The organization of the chapter is as follows. Section 2.1 explains the concepts of ANC. Section 2.2 briefly reviews the different gradient-based algorithms that are proposed to speech enhancement. Section 2.3 discusses about how the heuristic optimization methods are advantageous over gradient-based approaches for ANC.

2.1 Concepts of Adaptive Noise Cancellation

An adaptive noise canceller has been proposed by Widrow. It uses two or more microphones based on the availability of reference channel(s) which are characteristics of correlated samples or references of the contaminated noise. An adaptive filter utilizes the reference microphone output and produces an estimate of the noise. Its output is then subtracted from the primary microphone output (signal + noise). The overall output of the canceller is used to adjust the tap weights in the adaptive filter. Using an adaptation algorithm, ANC tends to minimize the mean square error value of the overall output. It gives the output which is the best estimate of the desired signal in the sense of minimum mean square error. Adaptive filters adjust their coefficients to minimize an error signal and can be realized as finite impulse response (FIR), infinite impulse response (IIR), lattice and transform domain filters. The most common of the adaptive algorithm is least mean square. The basic concept of adaptive noise cancellation (ANC) is based on two assumptions. These are as follows:

© The Author(s) 2016

P. Kunche and K.V.V.S. Reddy, *Metaheuristic Applications to Speech Enhancement*, SpringerBriefs in Speech Technology,
DOI 10.1007/978-3-319-31683-3_2

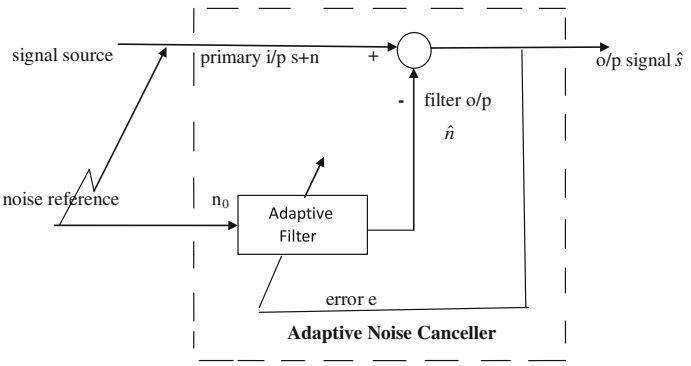


Fig. 2.1 Adaptive noise cancellation setup

- The signal and noise at the output of the primary microphone are uncorrelated.
- The noise at the output of the reference microphone is correlated with the noise component of the primary microphone output (Fig. 2.1).

As shown in the figure, an adaptive noise canceller (ANC) has two inputs—primary and reference. The primary input receives a signal s from the signal source that is corrupted by the presence of noise n uncorrelated with the signal. The reference input receives a noise n0 uncorrelated with the signal but correlated in some way with the noise n. The noise n0 passes through a filter to produce an output nˆ that is a close estimate of primary input noise. This noise estimate is subtracted from the corrupted signal to produce an estimate of the signal at ŝ, the ANC system output.

2.1.1 Adaptive Filters

An adaptive filter is a computational device that attempts to model the relationship between two signals in real time in an iterative manner. An adaptive filter is defined by four aspects.

1. The signal being processed by the filter;
2. The structure that defines how the output signal of the filter is computed from its input signal;
3. The parameters within this structure that can be iteratively changed to alter the filters input–output relationship;
4. The adaptive algorithm that describes how the parameters are adjusted from one time instant to the next.

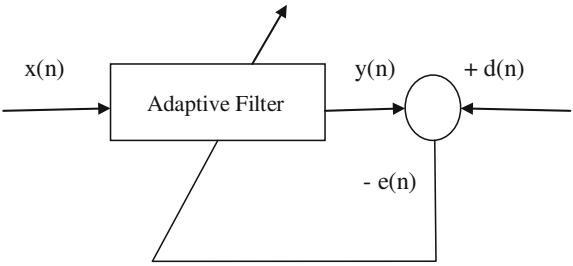


Fig. 2.2 Adaptive filter

The number and type of the parameters that can be adjusted is specified by choosing a particular adaptive filter structure. The adaptive algorithm is used to update the parameter values of the system and is often derived as a form of optimization procedure that minimizes an error criterion.

Figure 2.2 shows a block diagram in which a sample form of a digital input x(n) is fed into a device, called an adaptive filter, that computes a corresponding output sample y(n) at time n. The output signal is compared to a second signal d(n), called the desired response signal, by subtracting the two samples at time n. This difference signal is given by

$$e(n) = d(n) - y(n) \tag{2.1}$$

Here e(n) is known as error signal. The error signal is fed into a procedure that alters or adapts the parameters of the filter from time n to time instant (n + 1) in a well-defined manner. This process is called adaptation. Hence, adaptation refers to the method by which the parameters of the system are changed from the time index n to time index (n + 1).

The most general form of adaptive filter structure for many problems is to determine the best linear relationship between the input and the desired response signals. The linear filters typically take the form of a finite impulse response (FIR) or infinite impulse response (IIR).

2.1.2 IIR Filter

Linear digital filters classified into two groups based on their structure are IIR and FIR filters (Mitra and Kaiser 1993; Antoniou 1993). The present output of the IIR filter is dominated not only by present and past inputs, but also by the past outputs. IIR digital filters compute their outputs recursively and have feedback.

An IIR filter is a recursive filter where the current output depends on the previous outputs. The basic equation of this filter can be written as follows:

$$y(n) = \sum_{i=0}^{L} a_i x(n-i) - \sum_{i=1}^{Q} b_i y(n-i) \tag{2.2}$$

where a_i and b_i are the coefficients of the filter and $Q(\geq L)$ represents the order of the filter, which consequently determines the filter characteristics. The feedback feature makes IIR filters useful in high data-throughput applications that require low hardware usage. However, the feedback adds complexity to the filter design as it introduces phase distortion and finite word length effects, which may cause instability. The transfer function of the *Qth* IIR filter is given by

$$H(z) = \frac{A(z)}{B(z)} = \frac{\sum_{i=0}^{L} a_i z^{-i}}{1 + \sum_{i=1}^{Q} b_i z^{-i}} \tag{2.3}$$

The desired response of an adaptive filter is related in some way to the input signal and is made available to the filter. The characteristics of the adaptive filter are then modified so that the output of the adaptive filter resembles the desired response as closely as possible. The difference between the desired and adaptive filter response is error *e(n)* and is given by

$$e(n) = d(n) - y(n) \tag{2.4}$$

Ideally, the adaptive process becomes the one driving the error towards zero. In practice, however, this may not always be possible, and so an optimization criterion, such as the mean square error or some other measure of fitness, is employed.

Compared to FIR filters, IIR filters can obtain a comparable frequency response with lower filter order. On the other hand, IIR digital filters have the advantages of high selectivity and require fewer coefficients than FIR digital filters with similar performance. Consequently, producing IIR digital filters with good performance became a challenge to many researches.

2.1.3 Filter Modelling

The goal of the filter modelling is to alter the filter coefficients of a digital filter to match an unknown system transfer function. An adaptive algorithm tunes the parameters of the adaptive filter whose output gives the estimated noise. The algorithm continues to minimize the mean square error until the best estimate of the system parameters is obtained. In other words, the minimization of a performance function, typically the mean square error between filter output and desired response,

is attempted using a heuristic search algorithm. The objective function J in filter modelling problems is expressed as follows:

$$J = \frac{1}{L}\sum_{k=1}^{L}(\hat{y}(k) - y(k))^2 \tag{2.5}$$

where $y(k)$ is the noisy output of the actual system, $\hat{y}(k)$ is the output of the estimated filter, and L is the length of the input sequence. In some cases, noise-free $y(k)$ is received. This means that $y(k)$ is equal to $d(k)$, the desired output. In the presence of noise, $\hat{y}(k)$ is the estimation of the desired output.

2.2 Gradient-Based Algorithms to Speech Enhancement

2.2.1 LMS Algorithm

The LMS algorithm is basically a simplification of steepest-descent method, in which the gradient vector is estimated from the available data when we operate in an unknown environment. To develop an estimate of the gradient vector $\nabla J(n)$, the most obvious strategy is to substitute estimates of the correlation matrix R and cross-correlation vector p in the following equation

$$\nabla J(n) = -2p + 2Rw(n) \tag{2.6}$$

where the instantaneous estimates of R and p are given as

$$\hat{R}(n) = u(n) + u^H(n) \tag{2.7}$$

$$\hat{p}(n) = u(n) + d^*(n) \tag{2.8}$$

where $u(n)$ is the input vector and $d(n)$ is the desired response vector. Correspondingly, we obtain $\nabla J(n)$ as

$$\nabla J(n) = -2u(n) + d^*(n) + 2u(n)u^H(n)w(n) \tag{2.9}$$

The updating vector for steepest-descent algorithm is as follows:

$$w(n+1) = w(n) + \mu[p - Rw(n)] \tag{2.10}$$

Substituting the Eq. (2.8) for gradient vector in the steepest–descent algorithm, we get the following update vector rule for the tap-weight vectors

$$w(n+1) = w(n) + \mu.u(n)\left(d^*(n) - u^H(n)\hat{w}(n)\right) \tag{2.11}$$

where μ is the step size. The error signal $e(n)$ is defined as follows:

$$e(n) = d(n) - y(n) \tag{2.12}$$

The final update equation for the tap weight is given by

$$w(n+1) = w(n) + \mu.u(n)e(n) \tag{2.13}$$

2.2.2 Normalized LMS Algorithm

The adjustment applied to tap-weight vector (Widrow and Steam 1985; Goodwin and Sin 1985; Treichler et al. 1987) is directly proportional to tap-input vector $u(n)$. Therefore, when $u(n)$ is large, the LMS filters suffer from a gradient noise amplification problem. To overcome this difficulty, we may use the normalized LMS filter.

In structural terms, the normalized LMS filter is exactly the same as the standard LMS filter, but differ only in the way in which the weights are updated. The normalized LMS filter is manifestation of the principle of minimum disturbance. From the one iteration to the next, the weight vector of an adaptive filter should be changed in minimal manner, subject to minimum constraint imposed on updated filter's output. The tap-weight adaptation rule is given by

$$w(n+1) = w(n) + \frac{\tilde{\mu}}{\delta + \|u(n)\|^2}u(n)e^*(n) \tag{2.14}$$

where $\|u(n)\|^2$ is the total expected energy of the input signal $u(n)$, $\tilde{\mu}$ is the normalized step size, and δ is a positive scalar that controls the maximum step size μ.

2.2.3 RLS Algorithm

The recursive least squares (RLS) algorithm (Plackett 1950; Diniz 2002) is another algorithm for determining the coefficients of an adaptive filter. In contrast to the LMS algorithm, the RLS algorithm uses information from all the past input samples (and not only from the current tap-input samples) to estimate the (inverse of the) autocorrelation matrix of the input vector. The RLS algorithm is a recursive form of the least squares (LS) algorithm. It is recursive because the coefficients at time n are found by updating the coefficients at time $n-1$ using the new input data, but the

LS algorithm is a block update algorithm where the coefficients are computed from scratch at each sample time. To decrease the influence of input samples from the far past, a weighting factor for the influence of each sample is used. This weighting factor or forgetting factor λ is introduced in the cost function $C(n)$. The tap-weight update rule is given by

$$w(n+1) = w(n) + C^{-1}(n)u(n)e(n) \tag{2.15}$$

where $e(n)$ is the difference between the desired response and output produced by a filter, and $C(n)$ is the estimated autocorrelation matrix and is given by

$$C(n) = \sum_{i=0}^{n} \lambda^{n-1} u(i)u^{T}(i) \tag{2.16}$$

The parameter λ is the forgetting factor and $0 \leq \lambda \leq 1$.

2.3 Gradient-Based Algorithms Versus Stochastic Optimization Techniques

Gradient-based optimization techniques attempt to estimate the gradient of the error surface and proceed to an optimum solution by following the negative direction of this estimated gradient. These algorithms are well known, widely used and proven to be simple, effective and convergent local optimization techniques. The most notable of these algorithms is the least mean squares (LMS) algorithm (Haykin 2001). The problem is that gradient descent is a local optimization technique, which is limited in its performance because it is unable to converge to the global optimum on a multimodal error surface, if the algorithm is not initialized in the basin of attraction of the global optimum. Several modified gradient-based algorithms came into vogue when attempts are made to enable them to overcome local optima. One approach is to simply add noise or a momentum term (Haykin 2001) to the gradient computation of the gradient descent algorithm to enable it to be more likely to escape from a local minimum. This approach is only likely to be successful when the error surface is relatively smooth with minor local minima, or some information can be inferred about the topology of the surface such that the additional gradient parameters can be assigned accordingly.

Other approaches attempt to transform the error surface to eliminate or diminish the presence of local minima (Fan and Jenkins 1986), which would ideally result in a unimodal error surface. The problem with these approaches is that the resulting minimum transformed error used to update the adaptive filter can be biased from the true minimum output error and the algorithm may not be able to converge to the desired minimum error condition. These algorithms also tend to be complex, slow

to converge and may not be guaranteed to emerge from a local minimum. Some work has been done with regard to removing the bias of equation error in LMS (Fan and Jenkins 1986), (Ho et al. 1995) and (Kim and Song 1999) adaptive IIR filters, which add further complexity with varying degrees of success. Another approach (Blackmore et al. 1997) attempts to locate the global optimum by running several LMS algorithms in parallel, initialized with different initial coefficients. The notion is that a larger, concurrent sampling of the error surface will increase the likelihood that one process will be initialized in the global optimum valley. This technique does have potential, but it is inefficient and may still suffer the fate of a standard gradient technique in that it will be unable to locate the global optimum if none of the initial estimates is located in the basin of attraction of the global optimum. By using a similar congregational scheme, but one in which information is collectively exchanged between estimates and intelligent randomization is introduced, structured stochastic algorithms are able to hill climb out of local minima. This enables the algorithms to achieve better, more consistent results using a fewer number of total estimates.

2.4 Conclusions

Adaptive noise cancellation uses various minimization techniques or adaptive algorithms such as LMS, NLMS and RLS. These adaptive algorithms are gradient-based algorithms which are most commonly used due to their simplicity in computation and ease of implementation. The gradient-based algorithms are not suitable for the multimodal error surface, and they give only one possible solution for each iteration according to the generated error. This book aims to solve the problem of ANC by using stochastic and meta-heuristic optimization techniques rather than the conventional adaptive filtering approaches. The basics of the meta-heuristic optimization techniques and various proposed meta-heuristics to ANC for speech enhancement are discussed in the next chapters.

References

Antoniou A (1993) Digital filters: analysis, design, and applications. McGraw-Hill, New York, NY. ISBN:0-07-002117-1

Blackmore KL, Williamson RC, Mareels IMY, Sethares WA (1997) Online learning via congregational gradient descent. Math Control Sig Syst 10:331–363

Diniz PSR (2002) Adaptive filtering: algorithms and practical implementation, 2nd edn. Kluwer Academic Publisher, Norwell, MA

Fan H, Jenkins WK (1986) A new adaptive IIR filter. IEEE Trans Circ Syst CAS-33(10):939–947

Goodwin G, Sin K (1985) Adaptive filtering prediction and control. Englewood Cliffs, Prentice-Hall, NJ

Hayes MH (1996) Statistical digital signal processing and modeling. Wiley. ISBN:0-471-59431-8

Haykin S (2001) Adaptive filter theory, 4th edn. Prentice Hall
Ho KC, Chan YT (1995) Bias removal in equation-error adaptive IIR filters. IEEE Trans Sig Proc 43(1)
Kim HN, Song WJ (1999) Unbiased equation-error adaptive IIR filtering based on monic normalization. IEEE Sig Proc Lett 6(2)
Mitra SK, Kaiser J (1993) Handbook for digital signal processing. Wiley
Plackett RL (1950) Some theorems in least squares. Biometrika 37:149–157. ISSN 00063444
Treichler JR, Johnson CR, Larimore MG (1987) Theory and design of adaptive filters. Wiley
Widrow B, Stearns S (1985) Adaptive signal processing. Prentice Hall, Englewood Cliffs, NJ



http://www.springer.com/978-3-319-31681-9

Metaheuristic Applications to Speech Enhancement

Kunche, P.; Reddy, S.M.

2016, IX, 122 p. 50 illus., 40 illus. in color., Softcover
ISBN: 978-3-319-31681-9