ADAPTIVE CHANNEL EQUALIZER AND DTMF DETECTION

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ABSTRACT

DSP based equalizer systems have become ubiquitous in many diverse application including voice data and video communication via various transmission media. The effect of an equalization system is to compensate for transmission channel impairments such as frequency dependent phase and amplitude distortion.

Besides correcting for channel frequency response anomalies, the equalizer can cancel the effect of multi path signal components, which can manifest themselves in the form of voice echoes, video ghost or Raleigh fading conditions in mobile communication channels. Equalizers specifically designed for multi-path correction for often termed Echo cancellers or Deghosters. They may require significantly longer filter span than simple spectral equalizers, but the principle of operation are essentially the same.

Keywords: adaptive filter, DTMF, canceller, equalizer, APA, tap weights, LMS.

1.0 INTRODUCTION

Adaptive filtering techniques are necessary consideration when a specific signal output is desired but the coefficients of filter cannot be determined at the outset. Sometimes this is because of changing line or transmission. An adaptive filter is one, which contains coefficients that are updated by an adaptive algorithm to optimize the filter response to the desired performance criterion.

1.1. Adaptive filters

Adaptive filters are digital filters capable of self adjusting or updating their filter coefficients in accordance to their input signals.

The adaptive filter requires two inputs:

_ the input signal x(n)

_ the reference input d(n)

The new coefficients are sent to the filter from a coefficient generator. The coefficient generator is an adaptive algorithm that modifies the coefficients in response to an incoming signal. Adaptive filters have uses in a number of applications, including noise cancellation, linear prediction, adaptive signal enhancement, and adaptive control.

Figure-1 shows the block diagram of an adaptive filter model. The unknown system is modeled by an FIR filter with adjustable coefficients. Both the unknown system and FIR filter model are excited by an input sequence x(n). The adaptive FIR filter output y(n) is compared with the unknown system output d(n) to produce the error signal e(n). The error signal represents the difference between the unknown system output and the model output. The error e(n) is then used as the input to an adaptive control algorithm, which corrects the individual tap weights of the filter. This process is repeated through several iterations until the error signal e(n) becomes sufficiently small. The resultant FIR filter response now represents that of the previously unknown system.

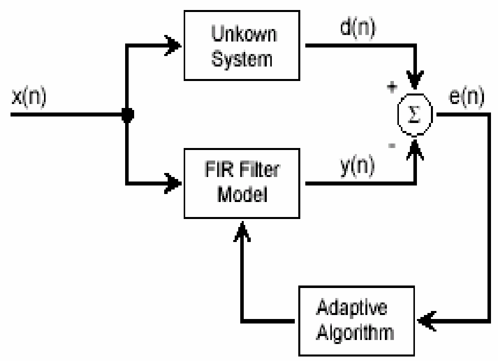

Figure-1. System identification model.

1.2. Dual tone multi-frequency (DTMF)

A DTMF signal corresponds o one of sixteen touchtone digits (0-9, A-D, #, *) and consists of a low-frequency tone and a high-frequency tone. Four low-frequency tones and four high-frequency tones are possible. Dual-tone multi-frequency (DTMF) signaling is used in telephone dialing, voice mail, and electronic banking systems.

DTMF detection amounts to detecting two sinusoids in noise subject to constraints on frequency resolution, time duration, and signal power. The key innovations are the use of two sliding windows and development of sophisticated timing tests. The detector requires no buffering of input data, and is simple enough to decode 24 telephone channels of a time-division multiplexed T1 telecommunications line using a single programmable fixed point digital signal processor (DSP).

2.0 PROCEDURE

2.1. Filtering techniques

The performance of an adaptive filtering algorithm is evaluated based on its convergence rate, misadjustment, computational requirements, and numerical robustness. An attempt to improve the performance by developing new adaptation algorithms and

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by using "unconventional" structures for adaptive filters is made.

The Normalized LMS algorithm is termed with Orthogonal Correction Factors (NLMS-OCF). The NLMSOCF algorithm updates the adaptive filter coefficients (weights) on the basis of multiple input signal vectors, while NLMS updates the weights on the basis of a single input vector. The well-known Affine Projection Algorithm (APA) is a special case of our NLMS-OCF algorithm.

2.1.1. Nlms algorithm

The Block diagram of system identification using adaptive filtering is shown in Figure-2. The objective is to change (adapt) the coefficients of an FIR filter, W, to match as closely as possible the Response of an unknown system, H. The unknown system and the adapting filter process the same input signal x [n] and have outputs d [n] (also referred to as the desired signal) and y [n].

2.1.2. Gradient-Descent adaptation

The adaptive filter, W, is adapted using the least mean-square algorithm, which is the most widely used adaptive ½ltering algorithm. First the error signal, e[n], is computed as e[n] = d [n]-y [n], which measures the divergence between the output of the adaptive filter and the output of the unknown system. On the basis of this measure, the adaptive filter will change its coefficients in an attempt to reduce the error. The coefficients update relation "is a function of the error signal squared" and is given by Eq.2.1.

$$h_{n+1}[i] = h_n[i] + \frac{\mu}{2}\left(-\left(\frac{\partial}{\partial h_n[i]}\left((|e|)^2\right)\right)\right)$$ Eq.2.1

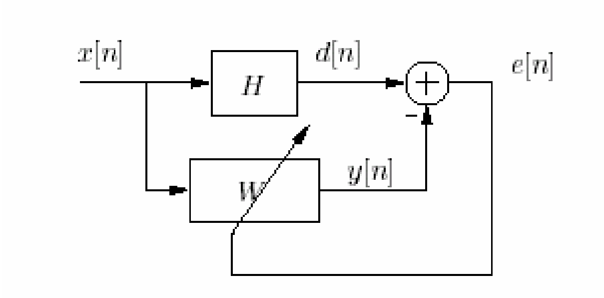

Figure-2. System identification block diagram.

The term inside the parentheses represents the gradient of the squared-error with respect to the ith coefficient. The gradient is a vector pointing in the direction of the change in filter coefficients that will cause the greatest increase in the error signal. Because the goal is to minimize the error, the eq.2.1.updates filters coefficients in the direction opposite to the gradient. So, the gradient term is negated. The constant μ is a step-size, which controls the amount of gradient information used to update each coefficient.

After repeatedly adjusting each coefficient in the direction opposite to the gradient of the error, the adaptive filter should converge; that is, the difference between the unknown and adaptive systems should get smaller and smaller.

To express the gradient decent coefficient update equation in a more usable manner, we can rewrite the derivative of the squared-error term as:

$$\begin{aligned}\frac{\partial}{\partial h[i]}\left((|e|)^2\right) &= 2\frac{\partial}{\partial h[i]}(e)e \\ &= 2\frac{\partial}{\partial h[i]}(d-y)e \\ &= \left(2\frac{\partial}{\partial h[i]}\left(d-\sum_{i=0}^{N-1}(h[i]x[n-i])\right)\right)(e)\end{aligned}$$ Eq2.2

$$\frac{\partial}{\partial h[i]}\left((|e|)^2\right) = 2(-(x[n-i]))e$$ Eq2.3

Which in turn gives us the final LMS coefficient update,

$$h_{n+1}[i] = h_n[i] + \mu e x[n-i]$$

Eq2.4

The step-size μ directly affects how quickly the adaptive filter will converge toward the unknown system. If μ is very small, then the coefficients change only a small amount at each update, and the filter converge slowly. With a larger step-size, more gradient information is Included in each update, and the filter converges more quickly; however, when the step-size is too large, the coefficients may change too quickly and the filter will diverge. (It is possible in some cases to determine analytically the largest value of μ ensuring convergence.)

2.2. DTMF Detection

DTMF detection algorithms have been largely based on the discrete Fourier transform (DFT). Given a sequence of N samples, the DFT uniformly samples the discrete-time Fourier transform of the sequence at N evenly-spaced frequencies, □ = 2□k / N, where k = 0,..., N–1. Each frequency bin has a width (resolution) of 2□/N. Each bin is centered at an integer multiple of 2□/N, which is an exact DTMF frequency only for an appropriate large N (e.g. 8000).

Although many values of N can meet the Bellcore frequency resolution and time duration specifications, no single value of N can meet the equivalent ITU specifications. Instead of computing all N DFT coefficients, detection of DTMF frequencies often uses a Instead of computing all N DFT coefficients, detection of DTMF frequencies often uses a bank of eight Goertzel filters, i.e., one filter per DTMF frequency. The Goertzel filter is typically implemented as a second-order IIR bandpass filter with the transfer function,

$$H_k(z)=\frac{1-e^{j2\pi k/N}z^{-1}}{1-2\cos\left(\frac{2\pi k}{N}\right)z^{-1}+z^{-2}}$$ Eq2.5

The Nth output sample of the Goertzel filter is the kth DFT coefficient. For the denominator section, the Goertzel filter requires N real multiplications, 2N real additions, and 3 words of memory. The numerator section is only computed on the nth input sample. The filter can be realized without input buffering because each sample can be processed when it is received. By setting k to yield an exact DTMF frequency of interest fi, i.e., k = N fi / fs, where fs is the sampling rate (8000 Hz), we implement the NDFT to detect energy at exact DTMF frequencies.

3.0 BLOCK DIAGRAM

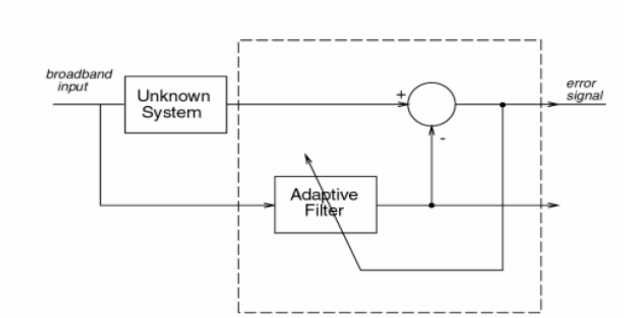

Figure-3. DMT: Equalization and approximation.

3.1. Equalization

In equalization, the received spectral coefficient blocks (i.e. after cyclic prefix removal and FFT) are adjusted to compensate for the frequency response of the channel (nothing can be done here about the additive noise). Due to the cyclic prefix1, each block has essentially undergone cyclic convolution with the channel's impulse response. In the frequency domain, this is the same as if the spectral coefficients were point wise multiplied by the frequency response of the channel. If the freq. response has no zeros and is known by the receiver, it is possible to perfectly remove the effect of the channel's filter. Since the channel point wise multiplied the blocks by its freq. response, all that needs to be done is multiply the blocks point wise by the 1 over the freq. response. Because we implemented the channel's impulse response as non-ideal low-pass, its freq. response has no zeros and equalization is rather trivial.

3.2. Approximation

After equalization, the effect of the channel's low-pass filter is removed, but the additive noise is still there. It manifests itself as causing the received constellation points to deviate from their location in the original constellation. To enable the bit stream to be recovered, a nearest-neighbor approximation is performed on each point. As long as the noise amplitude is small or the constellation points are far apart, it is unlikely that any single point will deviate enough from its original location such that it has a new nearest-neighbor. With high noise power, however, the points are scattered all over the constellation; the nearest neighbor in this case is unlikely to be the original point. In our system, we implemented this approximation with a parser and look up Table; we would examine each complex value

4.0 FREQUENCY RESPONSE OF EQUALIZER

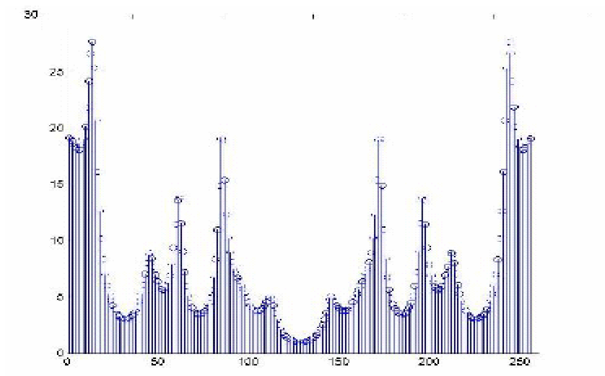

Figure-4. Transfer function of the equalizer.

This shows the frequency response of an equalizer. This gives the variation in the signal strength.

5.0 RESULTS

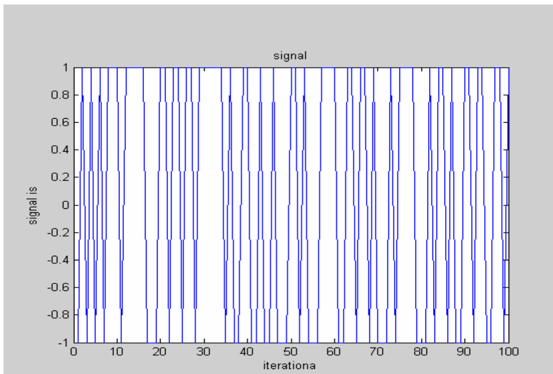

Figure-5.1. Signal.

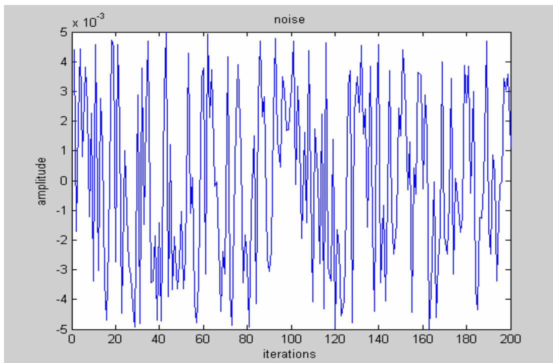

Figure-5.2. Noise.

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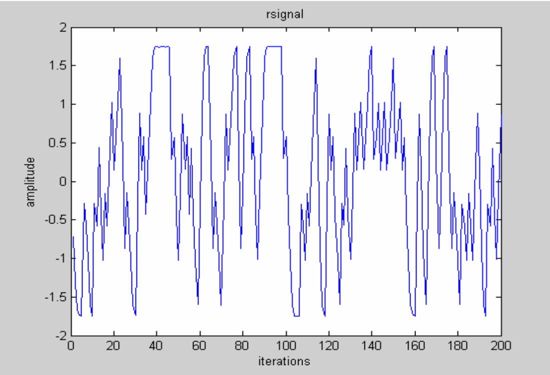

Figure-5.3. Received signal.

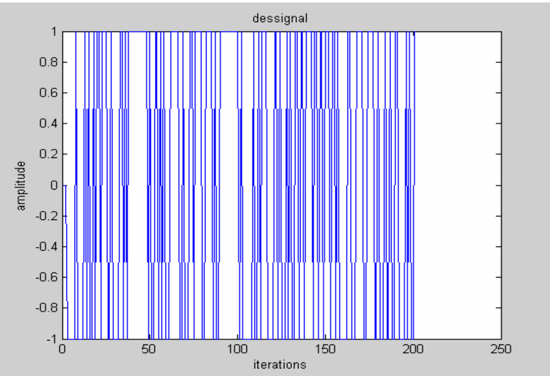

Figure-5.4. Desired signal.

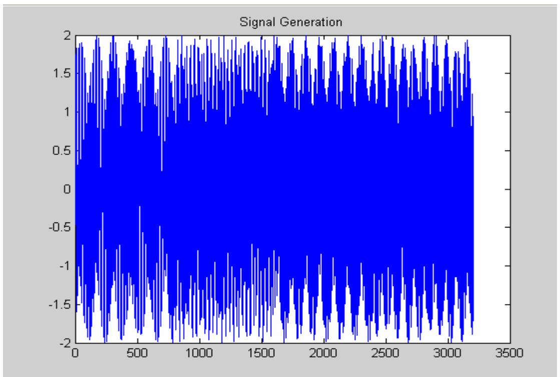

Figure-5.5. Signal generated.

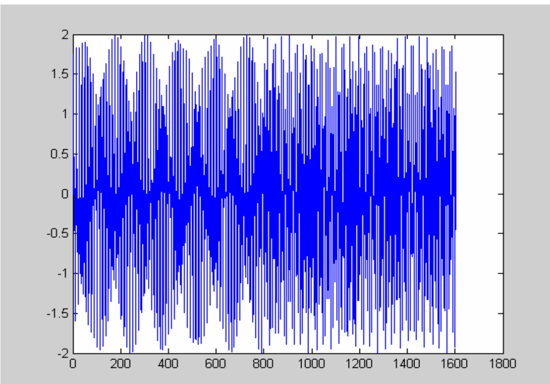

Figure-5.6. Desired signal after the reconstruction.

6.0 CONCLUSIONS

The purpose of an equalization system is to compensate for transmission channel impairments such as frequency dependent phase and amplitude distortion.

When designing an adaptive system, it is necessary to accept a number of trades-off between disparate requirements, which cannot be satisfied at the same time. For example the LMS-family algorithms are very simple, tractable and computationally efficient. But their essential disadvantage is the slow convergence rate and bigger steady-state error. On the other one side, RLS-family algorithms are computationally more complex and also structurally complicated. Here, the proper set-up and tuning of system parameters requires deeper experience in the domain of adaptive filtration. However, a great contribution can be addressed to precise adaptive mechanism with a low steady-state error and extremely high convergence rate.

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