CCD ANALOG ADAPTIVE SIGNAL PROCESSING*

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ABSTRACT

A CCD Adaptive Signal Processor is described which uses the "clipped-data" least-mean-square (LMS) error algorithm to optimize the selection of tap weights in a CCD filter. The filter is comprised of a basic linear combiner formed with a nondestructively tapped CCD analog delay line and electrically reprogrammable MOS analog conductances as the tap weights. Two methods of varying the analog conductance are discussed: (1) variable V_{GS} with fixed threshold voltage V_T and (2) variable V_T with fixed V_{GS}. The former is performed with a CCD bidirectional charge control weight adjustment, whereas the latter is accomplished with MNOS memory transistors. To demonstrate the feasibility of adaptive analog signal processing a 2-tap weight CCD adaptive filter is described and experimental results presented. Also presented is some discussion of the effort to construct a 16-tap all-monolithic CCD adaptive filter chip. Applications include optimum filtering, prediction, noise cancellation, and system modeling.

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1.0 Introduction

The history of adaptive signal processing might well begin with the introduction of the least squares estimation theory by Gauss[1] and Legendre.[2] Gauss introduced this technique to solve a large number of redundant equations to extract the "most probable values" of certain astronomical parameters. Modern adaptive filter theory begins with the work of Wiener[3] and Kolmogorov[4] on the prediction and filtering of stationary time series. The Wiener/Kolmogorov work provided the basic design criteria for optimal linear filters to suppress noise, perform signal prediction, and smooth statistically stationary signals. Kalman and Bucy[5] extended the work of Wiener and Kolmogorov to consider the design of time-varying filters for nonstationary signals with a priori information regarding the signal statistics. The so-called Kalman filter represents a recursive solution of Gauss's least-square estimation problem in which the computational benefits of modern digital computers are used to advantage.[6]

Adaptive filters are a class of "learning machines" in which the filter design (weight or parameter adjustments) is self-learning and based upon estimated (measured) statistical characteristics of the input and output signals. Adaptive filtering based on a recursive algorithm (correlation-cancellation loop) was employed in the RF antenna field in the 1950's.[7] Two groups, working independently, developed techniques for adaptive interference or clutter cancelling. One group worked on radar IF sidelobe clutter cancellers[8] with optimization achieved by an algorithm that maximized a generalized signal-to-noise ratio.[9] The other group worked on a self-optimizing array for control systems based on sampled signals and a least-mean-square (LMS) error algorithm.[10] These two adaptive algorithms, although arrived at with different approaches and different objectives, are nevertheless very similar since both derive their adaptive parameter adjustments by sensing the correlation between input signals. Thus, both algorithms use the covariance matrix describing the system inputs and both algorithms converge toward the optimum Wiener/Kolmogorov solution. In this paper, the LMS adaptive algorithm developed by Widrow and Hoff[11] in 1959 with modifications by Moschner[12] in 1970 is used.

The general form of an adaptive filter is limited by practical considerations since the inversion and storage of large matrices of data requires a sizeable volume of computer space and real-time signal processing is difficult to achieve. The iterative LMS algorithm requires very little computer time or memory and the algorithm is suitable for real-time processing of large amounts of data. With this algorithm the statistics of the signals are not measured explicitly to design the filter but, instead, through a recursive algorithm, the weight adjustments are made automatically with the arrival of each new data sample. Thus, the LMS algorithm allows the realization of an adaptive filter which can be used in real-time signal processing applications and may be implemented with analog circuit techniques. The CCD analog adaptive filter to be discussed here uses the "clipped data" LMS algorithm to allow ease of monolithic chip implementation with little sacrifice in system performance.

2.0 Analog Adaptive Filter Using the "Clipped Data" LMS Algorithm

Figure 1 illustrates a block diagram of an adaptive

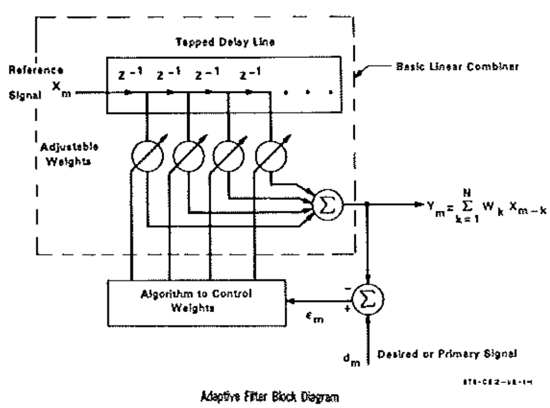

Figure 1. Adaptive Transversal Filter

filter. For sampled-data input signals, an error is formed at each clock according to the expression

$$\epsilon(m) = d(m) - y(m) \tag{1}$$

where d is the desired input, m is the clock index, and y is the weighted sum of the past N inputs, with N the length of the delay line. The error is used as the input to the algorithm which in turn adjusts the weight at each tap location to minimize the mean-square error.

The "clipped data" algorithm changes the weight of each tap location according to the equation

$$W_i(m+1) = W_i(m) + 2\mu\epsilon(m)\,\mathrm{sgn}\,X(m) \tag{2}$$

$$= W_i(o) + 2\mu \sum_{k=1}^{m} \epsilon(k)\,\mathrm{sgn}\,X_i(k)$$

where i is the tap location, μ is a constant which determines stability and convergence rate, ϵ is the instantaneous error defined by equation 1, X is the tap output, and sgn is the sign function. Equation 2 indicates that the algorithm retains full linearity of the error but requires a multiplier and integrator at each tap location. The multiplier is actually a branch operation which checks the sign of X and on this basis adds or subtracts the quantity $2\mu\ \epsilon(m)$ from the current tap weight to form the new weight value.

2.1 Analyses of Clipped Data LMS Algorithm for a 2-Tap Weight Adaptive Filter

In this section an analysis of a 2-tap weight adaptive filter using the clipped-data LMS adaptive algorithm is presented. Figure 2 illustrates a block diagram of the

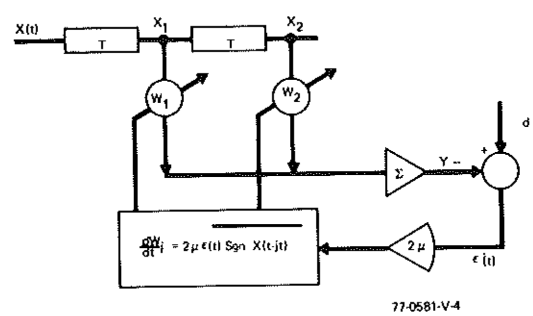

Figure 2. A 2-Tap Weight Adaptive Filter with Clipped Data LMS Algorithm Control

element to be analyzed with an input composed of a sinusoidal signal in the presence of white noise. The primary signal may be written as

$$d(t) = d_0 \cos(\omega t + \phi) \tag{3}$$

where ϕ is the relative phase shift with respect to the signal at tap 1. The tapped signals are,

$$X_1(t) = X_0 \cos(\omega t) + n_1(t) \tag{4}$$

$$X_2(t) = X_0 \cos[\omega(t - T)] + n_2(t)$$

where T is the time delay between tap positions, and $n_1(t)$ and $n_2(t)$ are uncorrelated noise sources at the tap positions. We will use a continuous time analysis in this section to illustrate the performance of the 2-tap weight adaptive filter. For continuous time the following expression for the weight factor, W, can be written

$$\frac{dW}{dt} = 2\mu P - 2\mu RW \tag{5}$$

where P = E [d(t)sgnX(t)] and R = E [X(t)sgnX(t)] define the matrix elements, and μ is the convergence factor. The matrix elements of the covariance matrix R become

$$E[X_1 \operatorname{sgn} X_1] = 2X_0/\pi + \sqrt{2/\pi}\,\sigma_n \tag{6}$$

$$E[n_1^2] = E[n_2^2] = \sigma_n^2$$

$$E[n_1 n_2] = E[X_1 n_1] = E[X_2 n_1] = E[X_1 n_2] = E[X_2 n_2] = 0$$

$$E[X_2 \operatorname{sgn} X_2] = E[X_1 \operatorname{sgn} X_1]\,;\; E[X_1 \operatorname{sgn} X_2]$$

$$= E[X_2 \operatorname{sgn} X_1] = \frac{2}{\pi} X_0 \cos[\omega T]$$

Calculation of the remaining steering vector matrix elements yield

$$E[d \operatorname{sgn} X_1] = \frac{2}{\pi} d_0 \cos[\phi]; E[d \operatorname{sgn} X_2] = \tag{7}$$

$$\frac{2}{\pi} d_0 \cos[\omega T + \phi]$$

Combining equations 6 and 7 results in the weight equation

$$\frac{d}{dt}\begin{pmatrix} W_1 \\ W_2 \end{pmatrix} = \frac{4\mu d_0}{\pi}\begin{pmatrix} \cos\phi \\ \cos(\omega T+\phi) \end{pmatrix} - 2\mu$$

$$\left(\begin{array}{c|c} \frac{2X_0}{\pi} + \sqrt{\frac{2}{\pi}}\,\sigma_n & \frac{2X_0}{\pi}\cos\omega T \\ \hline \frac{2X_0}{\pi}\cos\omega T & \frac{2X_0}{\pi} + \sqrt{\frac{2}{\pi}}\,\sigma_n \end{array}\right)\begin{pmatrix} W_1 \\ W_2 \end{pmatrix} \tag{8}$$

Equation 8 illustrates the cross-coupling between the taps due to the delay T. When $\omega = (2n + 1)\pi/2$, M = 0,1,2..., the system is decoupled and in so-called normal form. The weights may be transformed into a normal coordinate system and a transient and steady-state solution extracted. An interesting case arises when the system is coupled by a 90° phase shift between the taps to obtain a notch filter. Glover has analyzed this particular case and he showed that when a sum of sinusoids is applied to an adaptive filter, the filter converges to a dynamic solution in which the weights are time varying.[13] This time-varying solution gives rise to a tunable notch filter with a notch located at each of the reference frequencies. In this example, the desired, or primary, and reference frequencies were identical (i.e., $f_d = f_r$); however, when $f_d \neq f_r$, the weights have a dynamic steady-state response with an oscillation at the difference frequency ($f_d - f_r$) and the instantaneous response f_r. This time-varying solution should not be considered as noise in the adaptation process, since the time-varying weights modulate the reference frequency f_r and heterodyne it into the desired frequency f_d, thereby creating a notch effect.

When the system is decoupled and $f_d = f_r$, the steady-state weights approached their optical values

$$W_1(\text{op}) = \frac{d_0 \cos[\phi]}{X_0 + \sqrt{\pi/2}\,\sigma_n} \tag{9}$$

$$W_2(\text{op}) = \frac{-d_0 \sin[\phi]}{X_0 + \sqrt{\pi/2}\,\sigma_n}$$

with an exponential decay described by a characteristic time constant

$$\tau = \frac{1}{2\mu\left[\frac{2X_0}{\pi} + \sqrt{2/\pi}\,\sigma_n\right]}, \tag{10}$$

Several important consequences of the "clipped" data LMS algorithm may be seen from the above analysis:

(1) the final steady-state values of the weights are determined by the amplitude of the input signals rather than the power levels as in the linear LMS case.

(2) the influence of the noise on the final values is through σ_n rather than the variance σ_n^2 as in the LMS case.

(3) the characteristic time constant is also dependent upon amplitude rather than power levels.

Thus, the clipped data LMS algorithm, besides being easier to implement in integrated circuit form, is less dependent upon the fluctuation in input power levels. This is a direct consequence of the "limiter" function introduced by the sgn function in the comparators.

The adaptive filter may be operated as a simple single-frequency noise canceller in the case of 2-tap weights. A transfer function may be obtained for this mode of operation by considering the synchronously sampled system shown in figure 3. The primary, or desired, input may be any type of signal (i.e., stochastic, deterministic, periodic, transient, or combination thereof) while the input reference signal is a pure cosine signal $X_0 \cos[\omega t - \phi]$. The desired and reference signals are sampled synchronously at $f_c = 1/T$ with a 90° phase shift between taps X_1 and X_2. The algorithm for updating the weights is

$$W_1(m+1) = W_1(m) + 2\mu\epsilon(m)\,\mathrm{sgn}\,[X_1(m)] \tag{11}$$

$$W_2(m+1) = W_2(m) + 2\mu\epsilon(m)\,\mathrm{sgn}\,[X_2(m)]$$

The first step in the analysis is to consider the adaptive noise canceller as a feedback network with the filter output Y(m) disconnected, in the manner of Widrow, et. al.[14] Under these conditions, a unit impulse is applied at the desired input to create an error

$$\epsilon(m) = \delta(m-k) \begin{cases} 1 & m = k \\ 0 & m \neq k \end{cases} \tag{12}$$

The resulting pulse transfer function G(Z) is averaged over T/4 to obtain

$$G(Z) = \frac{8\mu X_0}{\pi} \; \frac{(Z\cos[\omega_0 T] - 1)}{Z^2 - 2Z\cos[\omega_0 T] + 1} \tag{13}$$

and since the closed-loop transfer function is $H(Z) = [1 + G(Z)]^{-1}$, the closed-loop zeroes are given as

$$Z = e^{\pm j\omega_0 T} \tag{14}$$

and poles from the solution of $1 + G(Z) = 0$. If the narrow-band approximation is used with $\mu X_0 < 1$, then the poles are inside the unit circle with a radial distance

$$\left(1 - 8\mu\frac{X_0}{\pi}\right)^{1/2} \cong 1 - 4\mu\frac{X_0}{\pi} \tag{15}$$

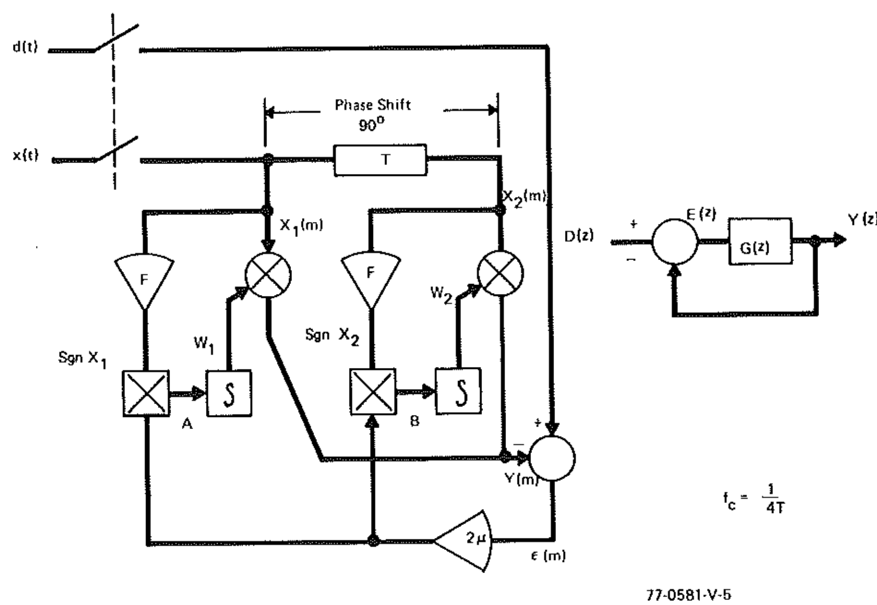

Figure 3. Single Frequency Adaptive Noise Canceller with Clipped Data LMS Algorithm

from the origin as indicated in figure 4. The angles of

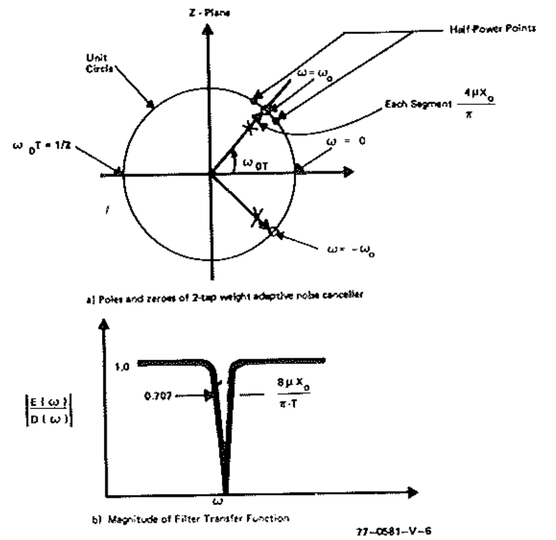

Figure 4. Characteristics of a 2-Tap Weight Adaptive Noise Canceller with Clipped Data LMS Algorithm

the poles are almost identical to those of the zeroes with a notch filter bandwidth of

$$\Delta\omega = \frac{8\mu X_0}{\pi T} \tag{16}$$

and $Q = \omega_0 / \Delta\omega$.

2.2 Monolithic CCD Adaptive Filter Design Considerations

A block diagram of the monolithic 16-tap analog adaptive filter is shown in figure 5. The analog delay line is a 2-1/2-phase CCD tapped delay line with a floating clock electrode sensor circuit[15] at each tap location to nondestructively sense the CCD signal charge and provide charge-to-voltage conversion. The CCD structure and timing is designed to maximize isolation between the clock signals and the signal sensing mode of the CCD.

The output of each tap location is a voltage which is converted to a weighted current, representing the required multiplication, via the drain-source conductance of a NMOS transistor biased in the triode region. In the triode region, the incremental drain-source current is given by

$$i_{ds} = K(V_{GS} - V_T)\, V_{ds} \quad (V_{ds} \cong 0) \tag{17}$$

$$= g_{ds}\, V_{ds}$$

where K is a constant dependent on device geometry and processing parameters, V_{GS} is the gate-source voltage (integrated value of $2\mu|\epsilon|$), V_T is the threshold voltage, v_{ds} is the drain-source voltage (delay line output), and g_{ds} is the drain-source conductance. Positive and negative weight values are achieved by using two transistors at each tap location, setting the conductance of one transistor to a fixed value, and allowing the conductance of the second device to vary via the adaptive algorithm. The required integrator is realized via the gate capacitance of the NMOS transistor weight. The incremental change in tap weights is achieved using the bidirectional charge controlled circuit described below.

The two currents from each tap are summed simultaneously with the weighted currents from the respective transistors at the other tap locations. The input nodes of two CMOS operational amplifiers serve as the two summing nodes. The two currents are converted to a voltage and further processed by a subtractor, comparator, absolute value circuit, and gain amplifier, as required by the "clipped data" LMS algorithm.

Referring to equation 2, the weight update algorithm requires a comparator at each tap location to form sgn X(m). The circuit complexity is reduced considerably by using a single comparator at the delay-line input and applying the comparator output (sgn X) to a digital shift register which is clocked in synchronism with the analog sample in the CCD. An Exclusive OR circuit provides the digital multiplication which provides the branch operation to increment or decrement the voltage of the NMOS weight.

On-chip timing is generated using three D-type flip-flops configured as a ripple counter to provide decoding waveforms for the NAND/NOR gates used in the combinatorial logic. The ability to update all the weights simultaneously relaxes the requirements of the clock drivers.

2.2.1 Methods for Achieving Programmable Weights

In order to achieve a variable V_{GS}, the error $\epsilon(mT)$ can be converted to digital form with an A/D converter, storage and accuracy can be achieved with accumulators, and finally, the multiplication can be ac-

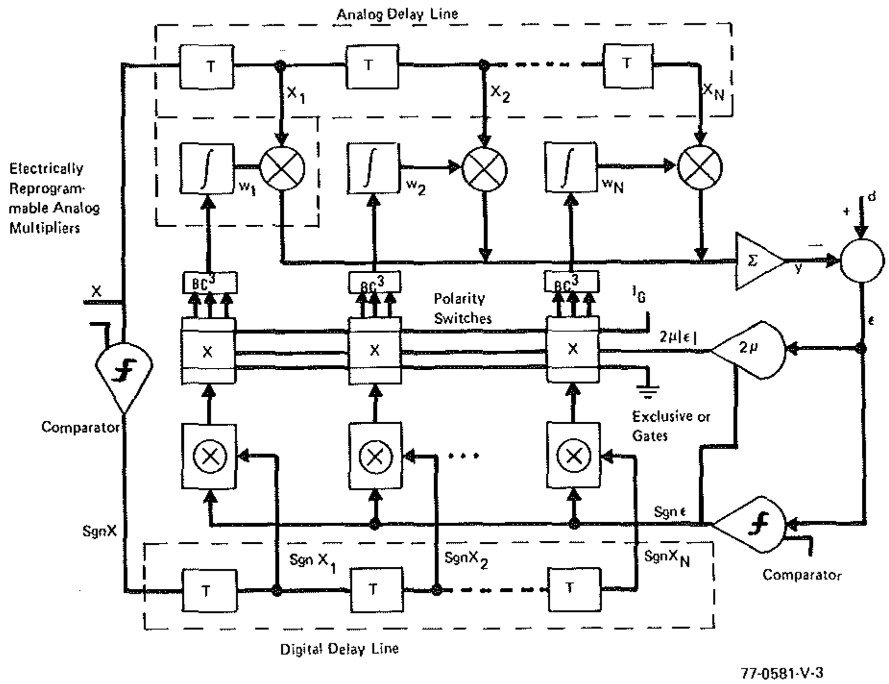

Figure 5. Monolithic CCD Analog Adaptive Filter

complished with multiplying digital-to-analog converters (MDAC's). This is an attractive approach because of the recent advancements in capacitor-weighted MDAC's.[16] However, unless the MDAC is shared over many taps, the complexity of the adaptive signal processor is increased.[17] In general, an MDAC for each tap weight is not too appealing an approach because of the chip area involved in the layout. In addition, the off-chip peripheral hardware is quite involved because of storage and accuracy requirements in the A/D conversion process. An 8-tap weight system has been built with this approach and it performed adaptive linear prediction with the clipped LMS algorithm.[17] However, the approach used lumped L-C delay lines with different dispersive characteristics, and a large amount of peripheral hardware was required for implementation.

Another method for achieving programmable weights is to replace the NMOS transistors described above with metal-nitride-oxide-silicon (MNOS) nonvolatile memory transistors. Memory is achieved in the MNOS transistor by electrically reversible tunneling of charge from the silicon semiconductor to deep traps near the SiO_2/Si_3N_4 interface. By the application of suitable voltages to the gate of the transistor, the threshold voltage can be changed in discrete increments. These changes can then be sensed as a change in the conductance of the transistor. This type of device has been used as the programmable tap weight and integrator, with a tapped CCD, to demonstrate in a hybrid form a 2-tap integrated circuit LMS adaptive filter.

A final approach to achieving programmable tap weights is the bidirectional charge-controlled circuit (BC^3). The technique uses stabilized charge injection to increment or decrement analog signal charge onto the node of a MOS-FET analog conductance. The concept is illustrated in figure 6. The analog, scaled error signal, $2\mu\epsilon$, is applied to a CCD storage or holding well and the control of the signal is accomplished by selecting the proper function of the G_1 and G_2 electrodes. The selection process involves the binary multiplication of

$$\mathrm{sgn}\,[\,\epsilon(mT)\,] \otimes \mathrm{sgn}\,[\,x(m-k)\,] \tag{18}$$

with an Exclusive OR gate as indicated in figure 5. The incremental voltage applied to the gate of the MOS-FET voltage-controlled analog conductance weight is

$$\Delta V = 2\mu\,|\,\varepsilon\,|\,\frac{C_H}{C} \tag{19}$$

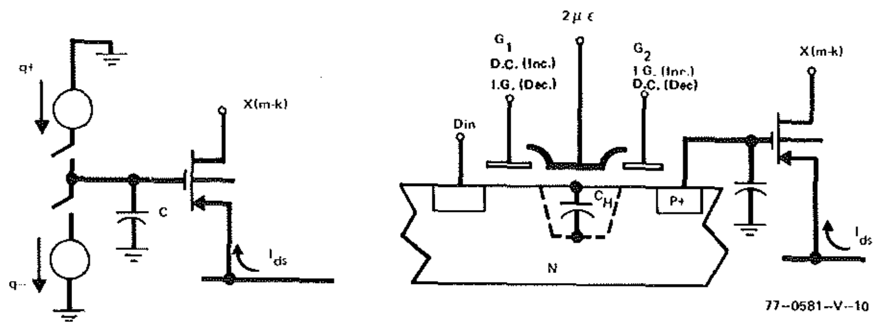

Figure 6. Bidirectional Charge Control for Incremental Adjustment of MOS-FET Analog Conductance Weight

where $|\epsilon|$ is formed with an absolute-value amplifier, and C_H is the holding well capacitance. The storage or integration of the weight values is performed with the on-chip capacitance C associated with the gate node of the MOS-FET weight. In order to achieve long-term weight retention, as might be necessary for some voice processing applications, either the C must be increased, which decreases the sensitivity of the weight to adjustment and increases the chip area for on-chip weighting, or some method of weight updating must be employed. One such method is to use an off-chip weight capacitance. Another method is to employ an A/D converter, memory, and a MDAC to sequentially update the weights in synchronization with the CCD clock.

3.0 Experimental Results

The feasibility of implementing the "clipped" LMS algorithm has been confirmed by fabricating and testing a 2-tap weight hybrid processor. The processor has been constructed using a basic linear combiner composed of a CCD serial in/serial out structure (see ref. 15), MNOS analog conductances, operational amplifiers, comparators, CMOS switches, and CMOS logic. A block diagram of the hybrid processor is shown in figure 7. The processor was configured, as shown in figure 8, to allow characteristic measurements to be made. Measurements were performed to determine the convergence factor, μ, as a function of processor transient response. The ability of the processor to track as a function of phase and amplitude variation in the desired channel (d of figure 8) was also confirmed.

The processor was then configured as a noise canceller. The block diagram of the arrangement and experimental results are presented in figure 9. The desired signal was corrupted by a narrow band tone 16 dB greater. After processing by the adaptive filter, the output interfering tone was 18 dB below the desired tone, representing a rejection of 34 dB.

4.0 Applications

There are a number of applications for adaptive filters with special need for real-time signal processing. Several applications are:

- Estimation/Prediction
- Filtering
- Spectral Analysis
- Data Compression
- Interpolation
- Multiple Linear Regression
- Echo Cancellation
- Speech Analysis
- Noise Cancellation
- Coherent Signal Processing
- Frequency Measurement
- System Modeling.

4.1 Adaptive Noise Cancellation

A very important application area is adaptive noise cancelling, such as the removal of interference in electrocardiographs, noise in speech signals, clutter cancellation in antenna sidelobe interference (or similar type systems with hydrophones, seismic/acoustic tranducers, electro-optical sensors, etc) and coherent signal processing when periodic signals must be separated from broadband interference, such as in spread spectrum systems. Cancellation of 60-Hz interference in conventional ECG, the donor ECG in heart transplants, and the maternal ECG in fetal electrocardiography is a straightforward use of the 2-tap adaptive noise canceller to reject the interference of a single frequency. The advantage of this technique is

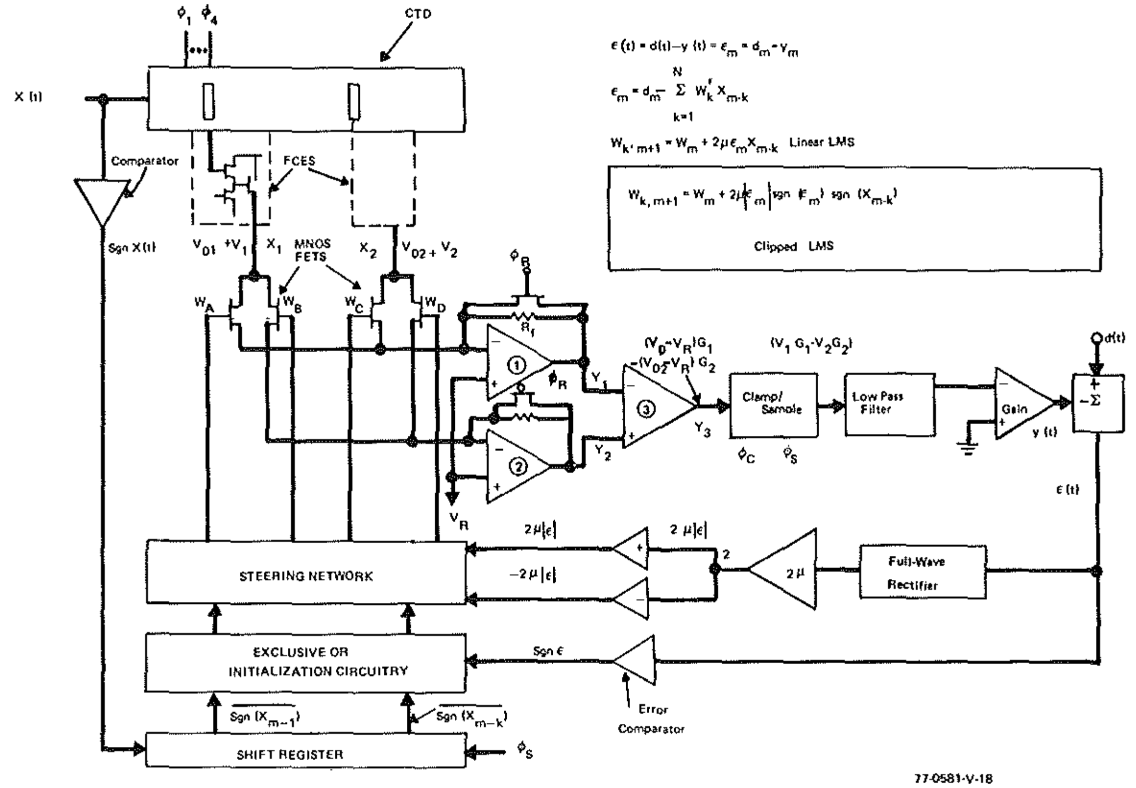

Figure 7. Adaptive Signal Processor Block Diagram (Clipped Data LMS Algorithm)

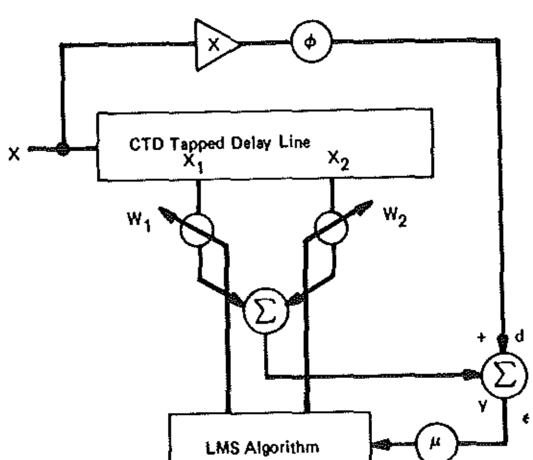

Figure 8. Configuration of Hybrid Adaptive Processor for Making Fundamental Performance Measurements

the cancellation of the interference even when the latter interfering signal frequency changes with time, since the reference input to the filter also changes.

A second area is the cancellation of noise in speech applications, such as the situation which arises in pilot communications with a high level of background engine noise. This interference contains strong periodic components in the speech frequency band and the intelligibility of the radio transmission is affected. A conventional filter would not suffice since the frequency and intensity of these interference signals vary with engine speed and load, in addition to the location of the pilots head.

A third area of noise cancelling is in adaptive cancellation of sidelobe interference in receiving arrays. For example, a sensor beamformer may be constructed with the adaptive noise canceller as shown in figure 10. The multiple reference inputs to the noise canceller are obtained from the beamformer element outputs prior to summation. The operation of the beamformer is

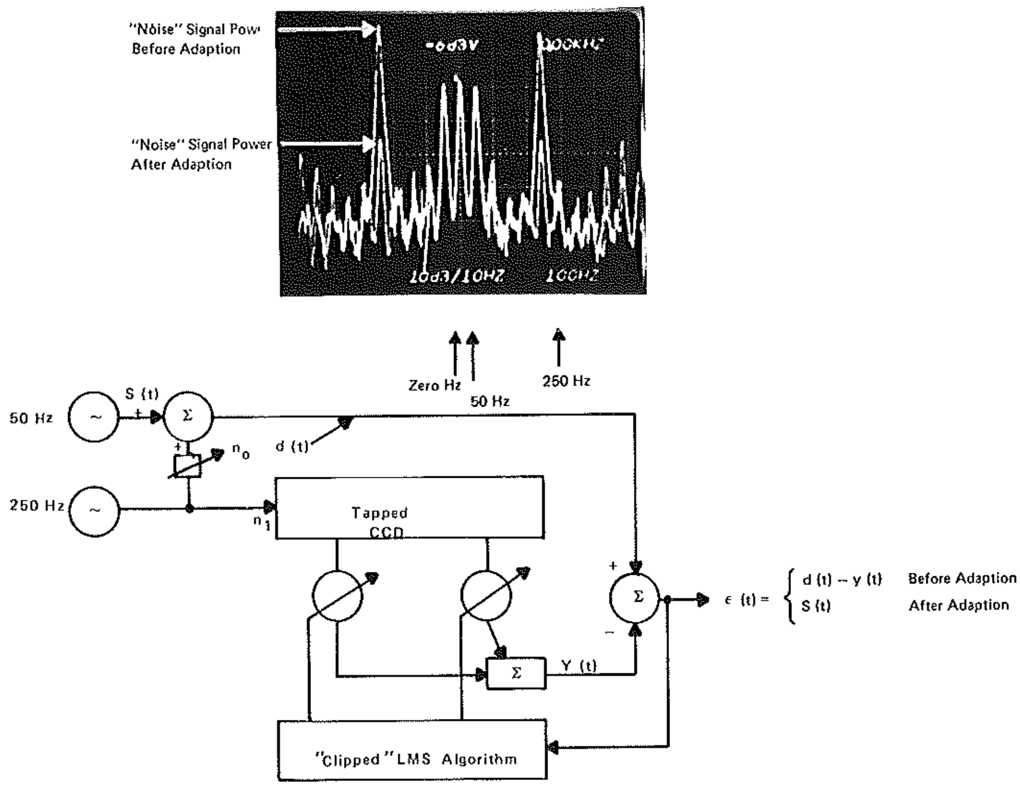

Figure 9. CCD Adaptive Noise Canceller with 2-Tap Adaptive Element

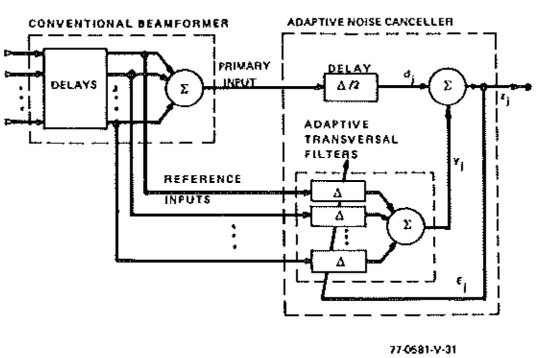

Figure 10. A Null-Constrained Adaptive Beamformer Array

constrained by the selection of the weighting coefficients of the adaptive filter taps. The gains of the control taps in the adaptive filter are constrained to zero in some manner so as to provide compensation for variations in element gain and phase, and to permit the reception of broadband signals over a desired angular sector.

A fourth area of interest is the separation of broadband and periodic signals as illustrated in figure 11. The insertion of a fixed delay in the reference path, as shown in figure 11a, decorrelates the broadband components while the narrow-band components remain correlated. This is an excellent method in the case when no external reference input is available, such as speech or music playback in the presence of tape hum

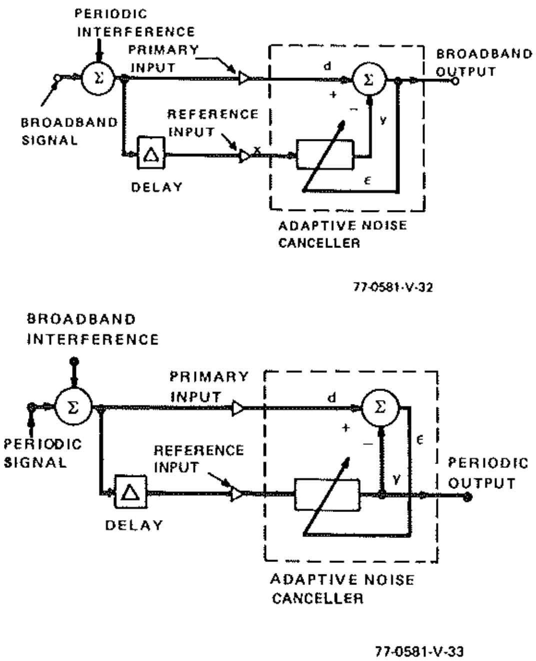

Figure 11. Separation of Broadband and Periodic Signals

or turntable rumble. Another area of application is in spread-spectrum communication. In this application, the narrow-band jamming signals can be separated from the broadband spread spectrum signal, and thus avoid compression of system dynamic range. Figure 11b illustrates the recovery of the periodic components and application, such as automatic signal seeking and the enhancement of low level sinusoidal signals buried in broadband noise. Thus, the adaptive filter can function as a coherent signal processor.

4.2 Adaptive Linear Prediction and Noise Cancellation for Narrow-Band Robust Voice Processing

A promising area for CCD adaptive filtering is in speech processing where redundancy in the spoken word has long been recognized by researchers. Electrical processing of speech which takes this redundancy into account can be used to substantially reduce the bandwidth required for speech transmission. For example, if speech is sampled and quantized at 56 k bits/sec (7 bits or 128 possible amplitude levels per sample at 8 kHz) for acceptable fidelity but the channel bandwidth restricts transmission to below 4 k bits/sec, then a speech compression ratio of approximately 15:1 is required. This low data rate would permit speech to be transmitted over high frequency radio or telephone links which have bandwidths barely wide enough for the original analog speech sounds. Such a narrow-band voice digitizer may be used in frequency division multiplexing for simultaneous transmission over wide-band channels. Narrow-band digitized speech lends itself to encryption for secure communication and provides a better S/N than a wide-band digitizer, particularly in RF transmission communication satellite links with limited or fixed available power.

"Speech compression, which maintains intelligibility, has always been difficult because speech consists of more than words and messages. Speech has the vocal timbre and conversational idiosyncrosies of the speaker and the emotion behind his words. It is normally constructed in an impromptu manner and delivered in a free and informal fashion. Speech flows in time as a continuation that a voice digitizer must process in real time, leaving no chance for later evaluation or correction. Although the information content of the message itself may be low (possibly below 100 bits/sec), transmission of the subtle vocal inflections requires a data rate of several thousand bits/sec."[18] Historically, speech compression and reconstruction began with the Dudley channel vocoder in 1936 in which the Fourier spectrum characteristics of speech determined the parameters of a filter bank. This filter bank approximated the vocal tract resonance characteristics of speech. It was excited by a pulse generator (variable period) to approximate the vowels or larynx vibration and a random noise generator to represent the consonants or fricative nasal sounds.

Another technique has proven quite successful in speech compression: linear prediction coding (LPC).[19] Linear prediction algorithms use time domain characteristics of the speech signal. The voice signal is analyzed as a linear combination of present and past values to form a set of prediction coefficients. If 10 to 12 consecutive samples of speech are taken (i.e., a speech segment of 1.25 to 1.5 milliseconds), then prediction coefficients can be generated which are the tap weights in an adaptive filter. Although only 10 to 12 prediction coefficients are needed, one must accumulate many speech samples (e.g., 100 to 200 samples) to determine these coefficients with some degree of accuracy. The accuracy of these measurements was discussed by Gauss with regard to highly redundant or over-determined equations and he formulated the method of least-squares. This method is used in the CCD adaptive filter.

Figure 12 illustrates a functional diagram of a conventional digital linear productive narrow-band voice processor. The major functional elements of this system are:

- Vocal tract analyzer
- Pitch extractor
- Voice/unvoice analyzer
- Synthesizer
- Encoder/decoder.

Many digital narrow-band voice systems using linear prediction algorithms have been analyzed and built over the last 5 years. The present major limitations to an all-digital approach are size, power dissipation, and cost. It is possible, however, that VLSI technology may impact some of these limitations in the future.
Figures 13 and 14 illustrate the use of the CCD adaptive filter as an analysis filter to generate the prediction coefficients $W_1 \ldots W_N$. The voice input is bandpass filtered and applied to the adaptive filter. The filter input is also used as the primary or desired signal to generate an error called the prediction residual. This error signal may then be used to extract the pitch period, amplitude, and voice/unvoice decision. The speech sample frame may be nominally 20 milliseconds in length and the error must converge to its minimum value within this time. Near the end of the time period, a unit pulse is inserted into the filter. The filter output is the impulse response of the filter. The converged weights are the predictive coefficients representing the state of the vocal tract. These coefficients can then be transformed to partial correlation coefficients for later transmission. The clipped data LMS algorithm has been computer simulated with the following constraints:[20]

- $W_k \leq 0.98$
- An increase of the unit circle (Z-domain) by 10 percent with scaling of the prediction coefficients
- 10 prediction coefficients of bit levels: 8,8,8,8,7,7,7,6,5,5
- Data rate of 3,600 bits/sec.

The prediction coefficients generated with the clipped data LMS algorithm and the above constraints were used to synthesize speech. Test sentences were employed and the playback of the reconstructed speech indicated good speech reproduction and quality, although the latter is a subjective parameter. Thus, a CCD adaptive filter with 10 weights operating at an 8-kHz sample rate is an excellent candidate for this particular application.

The use of the prediction residual of the analysis CCD adaptive filter as the pre-whitened input to a pitch extractor is an important application. The prediction residual signal is the voiced signal with the vocal tract contributions removed. Ideally, this signal corresponds to the source of voiced sounds caused by the vibrating vocal chords at the glottis. Linear prediction implementations usually have access to the prediction residual. However, those speech processing techniques which are based upon the short-time spectrum analysis (e.g., the channel vocoder) do not yield a whitened version of the voiced signal as a by-product of their pro-

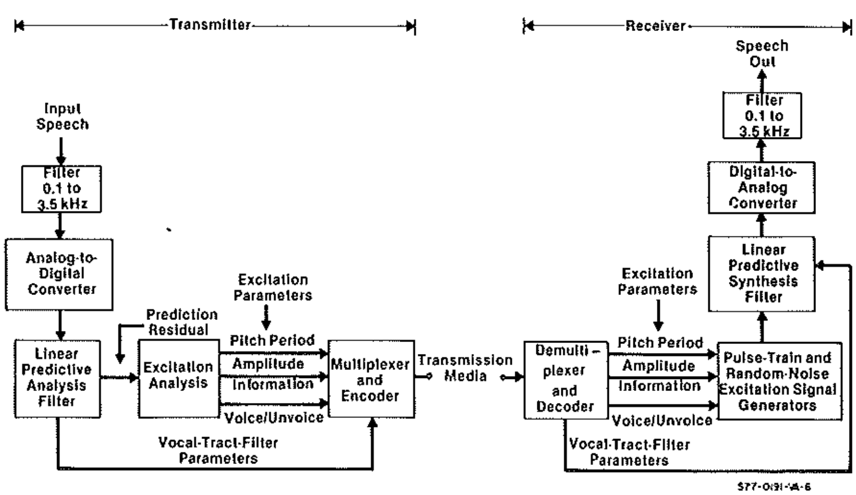

Figure 12. Narrow-Band Voice System

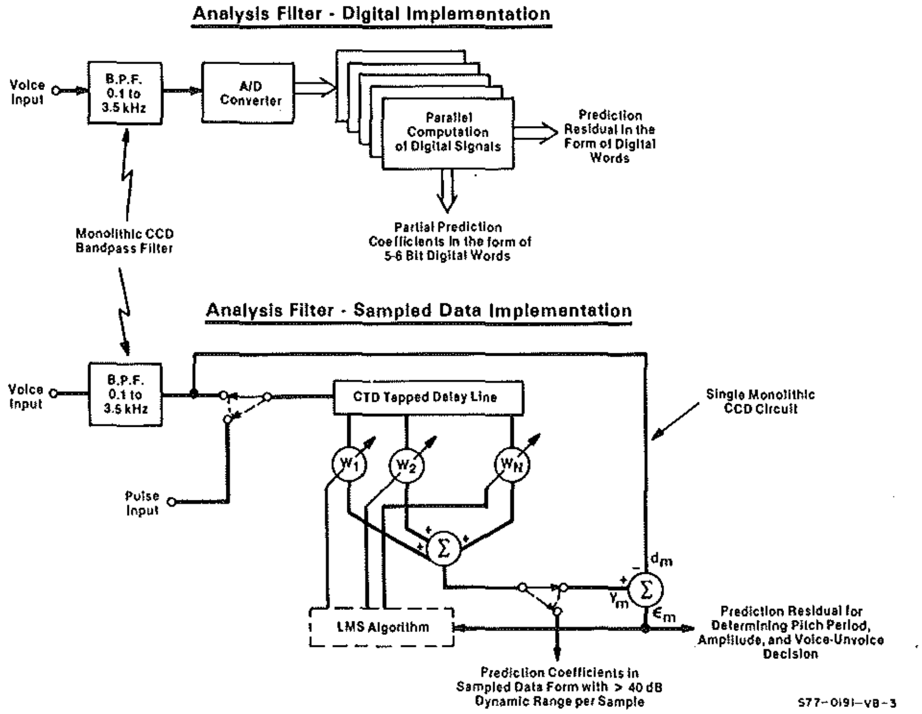

Figure 13. CCD Adaptive Filter for Linear Prediction Analysis of Speech

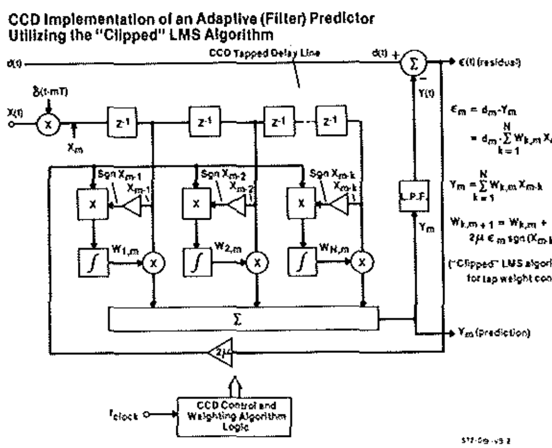

Figure 14. Narrow-Band Voice System

cessing. In these systems, a CCD adaptive filter simply used as a pre-whitener before pitch extraction by, for example, autocorrelation is extremely useful.

A major limitation to the use of LPC in practical acoustical environments is the degradation of synthesized voice quality due to the ambient acoustic noise background in the presence of the speaker. This speech quality degradation is due primarily to the vocal-tract analyzer's inability to compute accurate prediction coefficients of the "uncontaminated" speech. The residual or "whitened" speech signal of the analyzer is likewise contaminated, which causes errors in pitch extraction for LPC systems that synthesize pitch from the residual signal. Several techniques can be applied to improve LPC performance in a noisy acoustical environment. These methods may be classified into two broad areas: (1) acoustical and/or electrical interference mitigation prior to computation of the vocal-tract parameters, and (2) algorithms, such as SABER,[21] which attempt to separate the interference in the process of vocal tract computation. Electrical techniques, which mitigate interference prior to analysis, generally require two microphones. One microphone receives speech contaminated with ambient noise while the second microphone "receives" only the ambient noise. These signals are subsequently processed with an adaptive filter of the type described here for noise cancellation. In most practical environments it is difficult to arrange two strategically located microphones. A single microphone scheme can be implemented which will provide interference cancellation. This method assumes a "push-to-talk" microphone (i.e., similar to popular CB sets) is used and a time lapse of 200 to 300 milliseconds exists from activation of the microphone to the commencement of speech. A CCD adaptive filter, constructed of 6 to 20 taps, converges to a least-square estimate of the ambient noise within this 200- to 300-millisecond time lapse. Subsequently, the weights of the filter are fixed during the speech transmission and the filter serves to remove the background interference. One method for holding the weight values might be through the use of a digital memory coupled to MDAC's at the taps of the CCD. This technique assumes the noise environment is stationary in the period of speech transmission. In tests performed with the SABER algorithm, this requirement of noise stationarity did not limit the performance achieved in noise reduction. Figure 15 illustrates a robust LPC system block diagram which includes a noise canceller prior to the analyzer.

5.0 Conclusions

The description of the clipped LMS algorithm for adaptive signal processing has been presented along with a detailed analysis of a 2-tap weight adaptive filter. The 2-tap weight clipped, sampled data algorithm has been reduced to practice using a tapped CCD delay line, MNOS transistors for multiplication and integration, hybrid operational amplifiers, and CMOS logic elements. Experimental results show the algorithm is acceptable for analog LSI implementation. The basic components are amenable to monolithic fabrication. Numerous applications are presented for the CCD-LSI adaptive filter chip with special attention given to voice processing.

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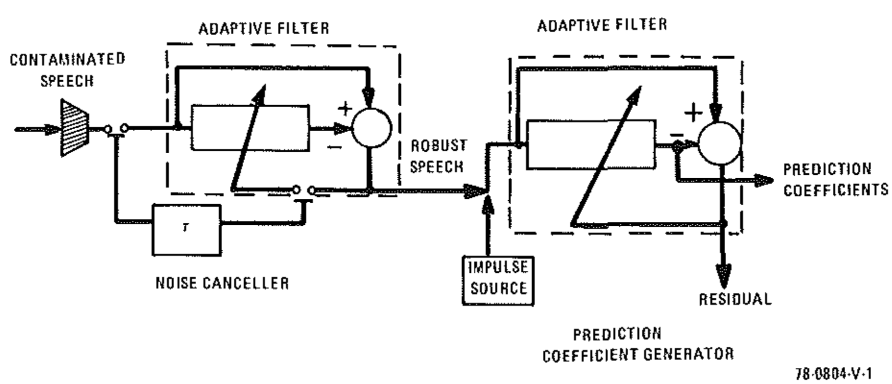

Figure 15. Robust LPC System Front-End

References

1. Gauss, K.G., *Theory of Motion of the Heavenly Bodies*, (Dover, New York, 1963).

2. Sorenson, H.W., "Least-Square Estimation: from Gauss to Kalman," *IEEE Spectrum*, p. 63, July 1970.

3. Wiener, N., *The Extrapolation, Interpolation, and Smoothing of Stationary Time Series*, Cambridge, Mass., MIT Press, (1949).

4. Kolmogorov, A., "Interpolation and Extrapolation von Stationaren Zufalligen Folgen," *Bull Acad. Sci, USSR, Ser. Math.*, 5,3, (1941).

5. Kalman, R. and Bucy, R., "New Results in Linear Filtering and Prediction Theory," Trans. *ASME (Ser. D) J. Basic Eng., 8395*, (1961).

6. Carlton, A.G. and Follin, J., "Recent Developments in Fixed and Adaptive Filtering," *AGARDograph, No. 21,* (1956).

7. Gabriel, W.F., "Adaptive Arrays - An Introduction," *Proc IEEE, 64*,239, (1976).

8. Howells, P.W., *Intermediate Frequency Sidelobe Canceller, U.S. Patent #3,202,990*, Aug. 24, 1965 (filed May 4, 1959).

9. Applebaum, S.P., "Adaptive Arrays," *Syracuse University Res. Corp. Rep SPL. Tr66-1*, Aug. 1966.

10. Widrow, B., "Adaptive Filters I: Fundamentals," *Stanford University Tech. Rept. No. 6764-6*, Dec. 1966.

11. Widrow, B. and Hoff, M., Jr., "Adaptive Switching Circuits," *IRE WESCON Conv. Rec., pt. 4*, 96, (1960).

12. Moschner, J.L., "Adaptive Filter with Clipped Input Data," *Stanford Lab. Rept. No. 6796-1*, June 1970.

13. Glover, J.R., "Adaptive Noise Cancelling of Sinusoidal Interference," Naval Underseas Center, San Diego, Calif. Rept #TN-1617, Dec. 1975 (Stanford University Ph.D. Thesis).

14. Widrow, B., et. al., "Adaptive Noise Cancelling: Principles and Applications," *Proc. IEEE, 63*, 1962 (1975).

15. White, M.H., Mack, I.A., Kub, F.J., Lampe, D.R., and Fagan, J.L., "An Analog CCD Transveral Filter with Floating Clock Electrode Sensor and Variable Tap Gain," *ISSCC 76 Technical Digest*, p. 194, Philadelphia, Pa.

16. McCreary, J.L. and Gray, P.R., "All MOS Charge Redistribution Analog-to-Digital Conversion Techniques - Part I," and Suarez, R.E., Gray, P.R., and Hodges, D.A., "All MOS Charge Redistribtion Analog-to-Digital Conversion Techniques - Part II," *IEEE J. of Solid-State Circuits, SC-10*, 371 (1975).

17. Morgan, D.R. and Craig, S.E., "Real-Time Adaptive Linear Prediction Using the Least Mean Square Gradient Algorithm," *IEEE Trans. on Acoustics, Speech and Sig. Proc., ASSP-24*, 494 (1976).

18. Kang, G.S., "Linear Prediction Narrow-Band Voice Digitizer," *EASCON 74*, Washington, D.C., Oct. 1974.

19. Atal, B.S. and Hanaver, S.L., "Speech Analysis and Synthesis by Linear Prediction of the Speech Wave," *J. of Acoust. Soc. Amer.*, Vol. 50, p 632. 1971.

20. Kang, G.S., private communication, 1977.

21. Ball, S., "Application of the SABER Method for Improved Spectral Analysis of Noisy Speech," *Tech. Report UUCS-77-107*, Aug. 1977.