PERIODIC DISTURBANCE CANCELLATION USING A GENERALIZED PHASE-LOCKED LOOP

R.J. Schilling,* A.F. Al-Ajlouni,** E.S. Sazonov,* and A.K. Ziarani*

Abstract

An effective technique for extracting an audio input from a composite signal that contains a nonstationary noise-corrupted periodic disturbance is presented. The proposed technique cancels the periodic disturbance using a synthesized signal whose parameters are adjusted adaptively. A combination of a generalized phase-locked loop (PLL) and an adaptive least mean square (LMS) method is used. The PLL creates a pair of basis signals that are phase-locked with the fundamental harmonic of the periodic disturbance. Harmonics generated from these basis signals are then used in the LMS method to minimize the average power of the residual nonperiodic signal. The virtue of this approach is that it does not depend on an explicit accurate estimate of the fundamental frequency of the disturbance. Furthermore, relatively large changes in the fundamental frequency can be tracked so long as they remain within the acquisition range of the PLL. Simulations and experimental results are presented that demonstrate the effectiveness of the proposed technique.

Key Words

Disturbance cancellation, phase-locked loop, least mean square, adaptive signal processing

1. Introduction

Noise-corrupted periodic disturbances occur in a wide variety of engineering applications [1]. Often the source of the disturbance is a rotating mechanical system where the fundamental frequency and the distribution of harmonics change with the speed of rotation [2–5]. In the area of power systems, the nonlinear load characteristics of power electronics induce harmonics in power systems [6]. By measuring the higher harmonics, one can determine the power quality [7–8]. Electromagnetic power line interference can cause periodic disturbances in biomedical instruments [9–10] and in communications systems [11].

* Electrical and Computer Engineering Department, Clarkson University, Potsdam, NY 13699; e-mail: schillin@clarkson.edu, esazonov@clarkson.edu, aziarani@clarkson.edu

** Hijjawi Faculty of Engineering Technology, Department of Communication Engineering, Yarmouk University, Irbid, Jordan; e-mail: alajloua@hotmail.com

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The focus of this paper is the cancellation of a periodic disturbance from a recorded composite signal that contains a noise-corrupted audio input such as speech. We assume that the periodic disturbance includes several harmonics, and that the fundamental frequency is unknown and may change with time. Several general approaches exist for measurement and rejection of periodic disturbances. When the fundamental frequency is constant, conventional offline techniques based on the discrete Fourier transform (DFT)can be effective [12]. For nonstationary periodic disturbances, adaptive notch filters can be used to extract the fundamental and higher harmonics [13–16]. Alternatively, adaptive nonlinear methods, such as those based on a generalized phase-locked loop (PLL)structure, can be used to lock onto the harmonics while simultaneously estimating amplitude, frequency, and phase [10, 17–20].

The approach proposed here is to use an active noise control technique, in the electrical domain rather than the acoustic domain, to synthesize a signal that causes destructive interference [21–22]. The parameters of the synthesized signal are adjusted adaptively to minimize the average power of the nonperiodic residual error. Narrowband active noise control techniques include both feedforward methods that employ a separate reference input that is correlated with the periodic disturbance, and feedback methods [23]. Indirect methods for periodic disturbance rejection separate the task of frequency tracking from the task of disturbance cancellation, while direct methods integrate these tasks [1, 24].

The proposed single-microphone approach is a direct method that uses a combination of a generalized PLL and an adaptive least mean square (LMS) system. Xiao *et al.* [25] have shown that LMS methods for estimating the harmonic components of a periodic signal are very sensitive to small errors in the estimate of the fundamental frequency, ω_0. Furthermore, direct estimation of ω_0 itself using LMS is inherently unstable and eventually exhibits a "run away" phenomenon unless the step size decreases very rapidly, and this leads to poor tracking of nonstationary signals [25]. Using a recursive formulation of the sine and cosine terms, Xiao *et al.* [25] were able to make the dependence on ω_0 appear less nonlinear through the use of intermediate frequency-dependent variables. Their approach was shown to work effectively for an initial frequency mismatch of 5%.

The technique described here is an alternative approach that leaves the determination of the fundamental frequency implicit. Instead, the PLL subsystem is used to produce a pair of basis signals that have the same period as the periodic disturbance. Using filtering and the Chebyshev polynomials of the first and second kinds, phase-locked harmonics are generated. An LMS algorithm is then employed to adjust the amplitudes of the harmonic components to minimize the average power of the residual nonperiodic signal. The virtue of this approach is that it does not depend on an explicit accurate estimate of the fundamental frequency. Furthermore, relatively large changes in the fundamental frequency can be tracked so long as they occur gradually and remain within the acquisition range of the PLL.

The remainder of this paper is organized as follows. Section 2 is a brief problem formulation. In Section 3 a generalized PLL is presented that produces a pair of phase-locked sine and cosine signals that form a basis for generating harmonics. Section 4 uses Chebyshev polynomials to generate harmonics and evaluates the distortion of the harmonics. Section 5 presents periodic disturbance cancellation that uses an LMS technique based on the PLL oscillator harmonics. It includes examples showing the effectiveness of the proposed approach. Section 6 is a brief summary of conclusions.

2. Problem Formulation

A audio signal can be extracted from a composite signal that includes a periodic disturbance by using a single-microphone configuration as shown in Fig. 1. Here the input signals are a periodic disturbance $x_p(k)$, a random white noise disturbance $v_{(k)}$, and an audio input $x_i(k)$ consisting of speech. Microphone M detects composite signal $x(k)$ that includes the audio input plus the disturbances:

$$x(k) = x_i(k) + x_p(k) + v(k) \tag{1}$$

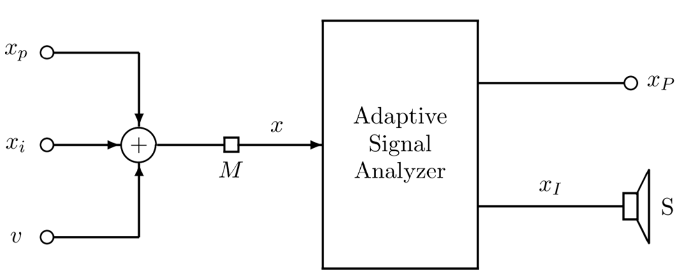


Figure 1. Periodic disturbance cancellation.

The design objective is to develop an adaptive signal analyzer that decomposes the composite signal into its periodic and nonperiodic components. Outputs $x_P(k)$ and $x_I(k)$ are estimates of the periodic disturbance $x_p(k)$ and the audio input $x_i(k)$, respectively. Speaker S reproduces the recorded composite signal, but with the periodic disturbance removed. An important special case of this problem arises when the audio input is absent with $x_i(k)=0$. Here the problem reduces to one of extracting a periodic signal from noise.

3. Generalized PLL

A combination of a generalized PLL and an adaptive LMS method is proposed to extract the periodic disturbance. The purpose of the PLL subsystem is to lock onto the fundamental harmonic of the periodic input and produce a pair of sine and cosine terms to serve as basis signals for generating higher harmonics used by the LMS method. Suppose f_s is the sampling rate and $T=1/f_s$ is the sampling interval. Let the input $u(k)$ consist of the samples of a sinusoid of amplitude A_0, frequency ω_0, and phase angle ϕ_0, plus a disturbance term $g(k)$ that may contain other periodic components such as higher harmonics plus random white noise.

$$\begin{aligned} u_0(k) &= A_0 \sin(k\omega_0 T + \phi_0) && (2)\\ u(k) &= u_0(k) + g(k) && (3)\end{aligned}$$

A generalized PLL or sinusoidal tracking algorithm (STA) capable of tracking the amplitude, frequency, and phase angle of the underlying sinusoidal signal $u_0(k)$ is presented in [16]. The discrete-time version of the generalized PLL consists of following third-order system.

$$\begin{aligned} A(k+1) &= A(k) + T\mu_1 e(k) x_2(k)\\ \omega(k+1) &= \omega(k) + T\mu_2 e(k) x_1(k)\\ \phi(k+1) &= \phi(k) + T\omega(k) + T\mu_2\mu_3 e(k) x_1(k)\\ e(k) &= u(k) - A(k) x_2(k)\\ x_1(k) &= \cos[\phi(k)]\\ x_2(k) &= \sin[\phi(k)] && (4)\end{aligned}$$

Here $\omega(0)=\omega_c$ plays the role of the center frequency of the traditional PLL. The system in (4) has been shown to be highly effective in tracking the amplitude, frequency, and phase of noise-corrupted nonstationary sinusoids [10, 17–19]. A stability analysis of the continuous-time case can be found in [17]. In general, the steady-state PLL frequency $\omega(k)$ is periodic but not constant. However, as long as the loop remains locked, the mean value satisfies $E[\omega(k)]=\omega_0$. Thus, in the steady state, $\omega(k)$ can be thought of as an unbiased estimate of the fundamental frequency [18]:

$$\omega(k) = \omega_0 + \Delta\omega(k) \tag{5}$$

The first loop gain parameter μ_1 controls the rate of convergence of the amplitude, $A(k)$, and it can be set independently of the others. Due to the relationship between frequency and phase, the remaining two loop gain parameters, μ_2 and μ_3, are interrelated as described in Ref. [18]. There is a trade off between transient performance or tracking speed which improves as the parameters are increased, and steady-state noise immunity which improves as the parameters are decreased.

To illustrate the variation in the PLL frequency, recall that the PLL center frequency is $f_c = 2\pi\omega_c$ Hz where $\omega(0) = \omega_c$. A lock range that is centered about f_c, but only includes the first harmonic, is $B = [(2/3)f_c, (4/3)f_c]$ Hz. Suppose $f_c = 300$ Hz and the sampling rate is $f_s = 8$ kHz. Consider the PLL input in (2) and (3) with $A_0 = 1$, $\omega_0 = f_0/(2\pi)$, and $\phi_0 = 0$. Suppose $200 \leq f_0 \leq 400$ Hz. Let the disturbance $g(k)$ consist of random white noise $v(k)$ with zero mean and variance σ_v^2. If $u_0(k)$ is regarded as the signal, then the signal-to-noise ratio (SNR) is as follows:

$$\text{SNR}_0 = 10\log_{10}\left\{\frac{E[u_0^2(k)]}{E[v^2(k)]}\right\} \text{dB} \tag{6}$$

Here the expected value operator $E[\,]$ is approximated with a time average. The variance of $v(k)$ was selected to produce $\text{SNR}_0 = 0$ dB which corresponds to significant noise. The loop gain parameters used for this and subsequent simulations were $\mu = [200, 40000, .02]$. The resulting PLL frequency estimates using five input frequencies uniformly spaced over $[200, 400]$ Hz are shown in Fig. 2. Note that $f(k) = 2\pi\omega(k)$ converges relatively quickly in each case (less than 1/8 s).

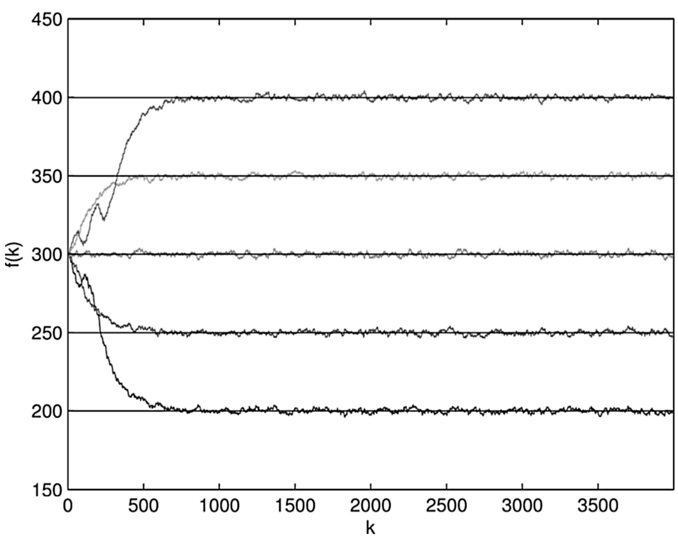


Figure 2. PLL frequencies for five sinusoidal inputs, $\text{SNR}_0 = 0$ dB.

4. Harmonic Distortion

The estimates of the input frequency represented by the PLL frequency might appear to be a reasonable choice for the fundamental frequency parameter, f_0, in an LMS algorithm. Unfortunately, the effectiveness of the LMS method for periodic disturbance cancellation is highly sensitive to the accuracy of f_0 [25]. An alternative approach is to exploit the fact that the loop oscillator outputs, $x_1(k) = \cos[\phi(k)]$ and $x_2(k) = \sin[\phi(k)]$, are phase-locked with the input $u(k)$ and therefore have periods that match. Of course the oscillator outputs are not purely sinusoidal due to the presence of the frequency variation $\Delta f(k)$. The distortion in $x_1(k)$ and $x_2(k)$ can be reduced by using a harmonic filter, $H_B(z)$. To isolate the fundamental harmonic, bandpass filters with a pass band of $B = [(2/3)f_c, (4/3)f_c]$ Hz can be used.

The filtered PLL oscillator outputs serve as basis signals for generating higher harmonics. To achieve this, two families of orthogonal polynomials are employed, the Chebyshev polynomials of the first and second kinds. The first two Chebyshev polynomials of the first kind are $T_0(x) = 1$ and $T_1(x) = x$, and the remaining Chebyshev polynomials are computed using the following recursive relationship:

$$T_i(x) = 2xT_{i-1}(x) - T_{i-2}(x) \quad i \geq 2 \tag{7}$$

The Chebyshev polynomials have many interesting characteristics, but the one that is relevant in this case is the following harmonic generating property:

$$T_i[\cos(\theta)] = \cos(i\theta) \quad i \geq 0 \tag{8}$$

Thus the ith even harmonic of the periodic disturbance can be approximated as $T_i[y_1(k)]$ where $y_1(k)$ is the filtered version of PLL oscillator output $x_1(k)$.

To generate the odd harmonics, the Chebyshev polynomials of the second kind are used. The first two Chebyshev polynomials of the second kind are $U_0(x) = 1$ and $U_1(x) = 2x$, and the remaining Chebyshev polynomials are computed using the same recursive relationship.

$$U_i(x) = 2xU_{i-1}(x) - U_{i-2}(x) \quad i \geq 2 \tag{9}$$

To generate the odd harmonics, the following characteristic of the Chebyshev polynomials of the second kind can be used:

$$\sin(\theta)U_{i-1}[\cos(\theta)] = \sin(i\theta) \quad i \geq 1 \tag{10}$$

It follows that the ith odd harmonic of the periodic disturbance can be approximated as $y_2(k)U_{i-1}[y_1(k)]$, where $y_1(k)$ and $y_2(k)$ are the filtered versions of PLL oscillator outputs, $x_1(k)$ and $x_2(k)$, respectively. Thus the approximations used for the even and odd harmonics are as follows:

$$C_i(k) = T_i[y_1(k)] \quad i \geq 0 \tag{11}$$

$$S_i(k) = y_2(k)U_{i-1}[y_1(k)] \quad i \geq 1 \tag{12}$$

Note that the maximum number of harmonics that can be used, while avoiding the effects of aliasing, is $N_{\max} = \text{floor}(0.5f_s/f_0)$. Both the PLL and the harmonic postfilters introduce phase shift in $C_i(k)$ and $S_i(k)$ relative to the sinusoidal input $u(k)$. To test the effectiveness of the approximations in (11) and (12), the square of the following error $e_i(k)$ was minimized by finding optimal values for b_1 and b_2:

$$z_i(k) = \cos(2\pi i f_0 kT) \quad i \geq 1 \tag{13}$$

$$e_i(k) = z_i(k) - [b_1C_i(k) + b_2S_i(k)] \quad i \geq 1 \tag{14}$$

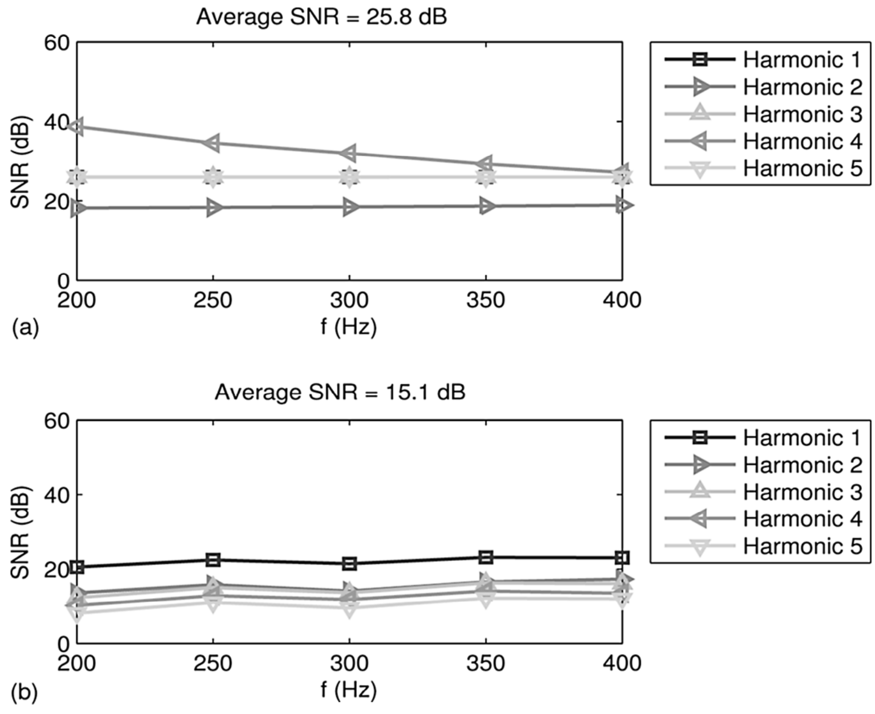


Figure 3. Signal-to-noise ratios of harmonics without postfilters, (a) $\text{SNR}_x = 50\,\text{dB}$ and (b) $\text{SNR}_x = 10\,\text{dB}$.

The harmonic signal-to-noise ratio, SNR_i, was then computed using the average power of $z_i(k)$ and the average power of $e_i(k)$:

$$\text{SNR}_i = 10\log_{10}\left\{\frac{E[z_i^2(k)]}{E[e_i^2(k)]}\right\} d\text{B} \quad i \geq 1 \tag{15}$$

In (15) the expected value operator E[ ] is approximated with a time average taken after the signals have reached steady state. The PLL oscillator outputs were evaluated using five input frequencies and five harmonics. The first case, shown in Fig. 3(a), corresponds to no postfilter and a relatively clean input signal u with a signal-to-noise ratio of $\text{SNR}_0 = 50\,\text{dB}$. The second case, shown in Fig. 3(b), corresponds to no postfilter and an input signal u with a reduced SNR of $\text{SNR}_0 = 10\,\text{dB}$. When the SNR of the input is reduced to 10 dB, the SNR of the harmonics decreases as expected. In this case the average SNR over five frequencies and five harmonics drops from 25.8 dB to 15.1 dB as the input SNR decreases by 40 dB.

The distortion in the harmonics can be reduced by postfiltering $x_1(k)$ and $x_2(k)$ with the harmonic bandpass filter $H_B(z)$. A fourth-order elliptic filter with a passband of $B = [(2/3)f_c,\ (4/3)f_c]$ Hz and a ripple of $\delta = 0.01$ was used. The case with an input SNR of 50 dB is shown in Fig. 4(a), and the case with an input SNR of 10 dB is shown in Fig. 4(b).

Note from Fig. 4(a) that for an input with a SNR of 50 dB, the harmonic SNR improves markedly with an average of 47.6 dB. However when the SNR of the input is reduced to 10 dB in Fig. 4(b), the postfilters achieve only a modest improvement to 16.2 dB in comparison with the 15.1 dB in Fig. 5. Thus the postfiltering of the PLL oscillator outputs does reduce distortion, but the effects become significant only when the SNR of the input is sufficiently high. A summary of the effects of input noise on the harmonic SNR both with and without postfilters is shown in Fig. 5. The upper curve represents the average SNR with postfilters, and the lower curve represents the average SNR without postfilters. It is clear that the benefits of postfiltering increase as the SNR of the input increases.

It should be pointed out that the harmonic generating properties of the Chebyshev polynomials are somewhat sensitive to the amplitudes of the inputs. As the postfilters modify the amplitudes as well as the phases, the signals $y_1(k)$ and $y_2(k)$ were normalized to have unit amplitude. It is possible that somewhat improved harmonic SNR might be achieved by reducing the bandwidth of the harmonic filter. However, this also reduces the range of input frequencies over which the periodic disturbance can be tracked. With a bandwidth of $B = [(2/3)f_c,(4/3)f_c]$ Hz, this allows for up to a ±33% variation in the input frequency. This is in contrast to the ±5% frequency mismatch presented in [25]. An alternative to using the Chebyshev polynomials is to generate the ith harmonic using $\cos[i\phi(k)]$and $\sin[i\phi(k)]$. However, in this case a total of $2N$ separate harmonic filters would be required to reduce distortion which significantly increases the order of the system.

5. Periodic Disturbance Cancellation

A compact formulation of the periodic disturbance, $x_p(k)$, can be obtained by introducing the following vector of even and odd harmonics:

$$h(k) = [C_0(k), \ldots, C_N(k), S_1(k), \ldots, S_N(k)]^T \tag{16}$$

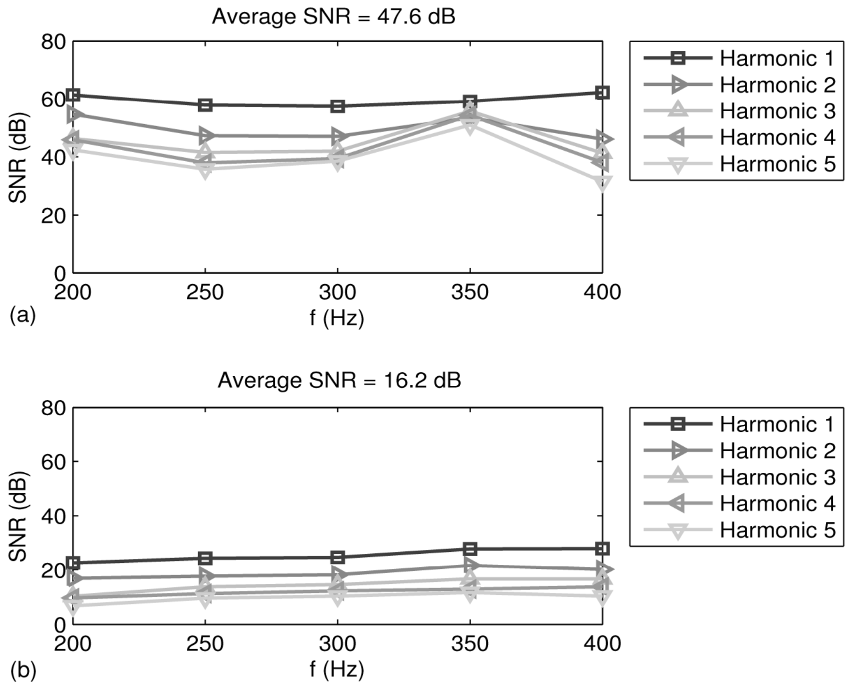


Figure 4. Signal-to-noise ratios of harmonics with fourth-order elliptic bandpass postfilters with ripple $\delta = 0.01$, (a) $\mathrm{SNR}_x = 50\,\mathrm{dB}$ and (b) $\mathrm{SNR}_x = 10\,\mathrm{dB}$.

Let $a \in R^{2N+1}$ denote the coefficient vector. Then the approximation to $x_p(k)$ using the first N harmonics is:

$$x_P(k) = a^T h(k) \tag{17}$$

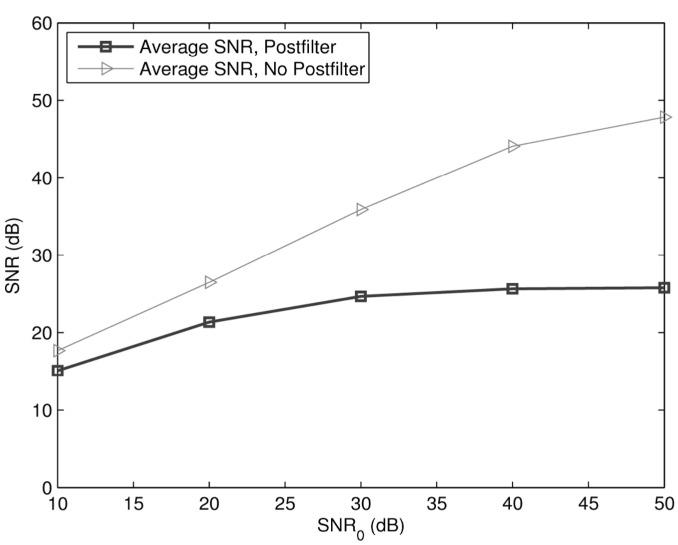


Figure 5. Average signal-to-noise ratios of harmonics with and without postfilters.

Optimal values for a can be obtained using the LMS method [26]. Recall from (1) that $x(k)$ is a composite signal that contains an audio input $x_i(k)$, the periodic disturbance $x_p(k)$, and random white noise $v(k)$. The objective is to minimize $E[e^2(k)]$ where $e(k)$ is the following error:

$$e(k) = x(k) - x_P(k) \tag{18}$$

If $E[e^2(k)]$ is approximated as $e^2(k)$ for the purpose of computing the gradient, then the steepest descent method results in the following LMS update formula where $\mu_4 > 0$ is the step size [26].

$$a(k+1) = a(k) + 2\mu_4 e(k) h(k) \tag{19}$$

Recall that the overall objective is to decompose the composite signal $x(k)$ into its periodic part $X_P(k)$ and its residual nonperiodic part $x_I(k)$. From (18) it is clear that minimizing $E[e^2(k)]$ effectively minimizes the average power of the nonperiodic part $x_I(k)$. The removal of the periodic disturbance can be quantified using the following measure:

$$E = 10 \log_{10} \left\{ \frac{E[\{x(k) - x_i(k)\}^2]}{E[\{x_I(k) - x_i(k)\}^2]} \right\} \mathrm{dB} \tag{20}$$

This represents the average power of the disturbance contained in $x(k)$ relative to the average power of the disturbance contained in $x_I(k)$.

As $v(k)$ has zero mean and is uncorrelated with $x_p(k)$, the numerator of (20) simplifies to $E[x_p^2(k)] + E[v^2(k)]$. When $x_P(k) = x_p(k)$, the cancellation is complete and the estimated audio input is $x_I(k) = x_i(k) + v(k)$. Thus the optimal denominator in (20)is $E[v^2(k)]$. The optimal value for periodic disturbance cancellation in the presence of random noise $v(k)$ is then as follows:

$$E_{\text{opt}} = 10\log_{10}\left\{1+\frac{E[x_p^2(k)]}{E[v^2(k)]}\right\}\text{ dB} \tag{21}$$

As an illustration, consider the case when the audio input is $x_i(k)=0$. Suppose the periodic input, $x_p(k)$, includes $H=6$ harmonics with the amplitude of the ith harmonic being $c_i=1/i$, and the phase angle θ_i being a random number in the range $[-\pi,\pi]$. The cancellation of $x_p(k)$ corresponding to an input signal-to-noise ratio of $\text{SNR}_0=20\,\text{dB}$ is shown in Fig. 6. Here the LMS step size was $\mu_4=0.001$. Five frequencies were considered and the number of PLL harmonics included $N=2,4,6$. Also shown is the optimal cancellation E_{opt}. As the number of PLL harmonics N is increased the cancellation E increases. The average cancellation reaches a maximum of 89.6% of E_{opt} when $N=H$, and remains essentially the same for $N>H$. The cancellation in this instance is somewhat improved for frequencies above the center frequency of the PLL.

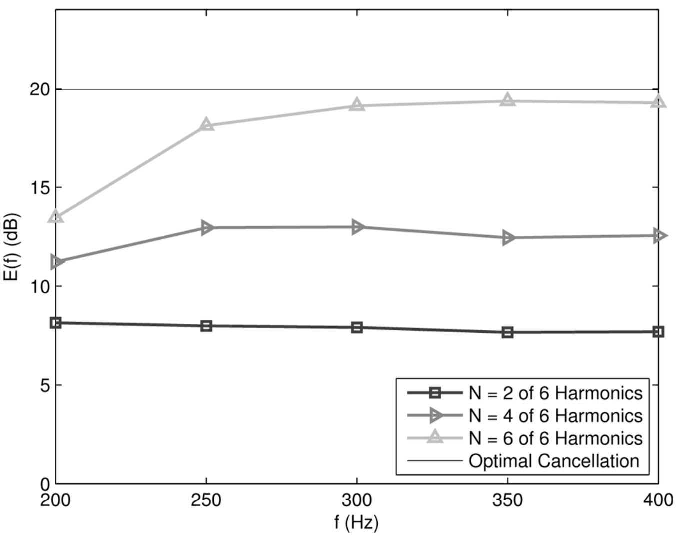


Figure 6. Disturbance cancellation using different numbers of PLL harmonics, $\text{SNR}_0=20\,\text{dB}$, postfilter.

Some periodic disturbances are nonstationary or vary with time. To test the effectiveness of the proposed technique to track a changing disturbance, a multifrequency chirp signal with a triangular frequency profile of amplitude Δf was used. As the input frequency changes with time, the measure of disturbance cancellation introduced in (20) is modified to $E_L(k)$ by approximating the expected value using a window of width L samples:

$$E_L[x^2(k)] = \left(\frac{1}{L}\right)\sum_{i=0}^{L-1} x^2(k-i) \tag{22}$$

Random noise was also added to yield an SNR for the input of $\text{SNR}_0=20\,\text{dB}$. A plot of the PLL frequency $f(k)$ and the triangular input frequency $f_0(k)$ is shown in Fig. 7. After a very brief transient, it is clear that $f(k)$ faithfully tracks $f_0(k)$ indicating that the PLL remains locked. Fig. 8 displays the corresponding periodic disturbance cancellation

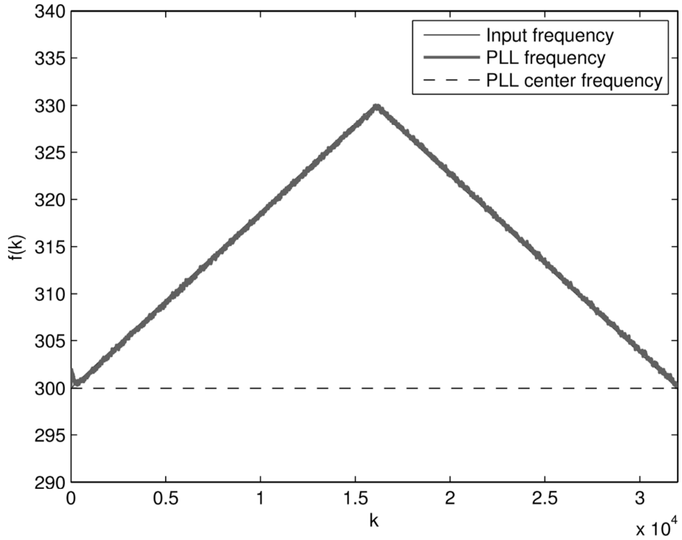


Figure 7. PLL frequency during a multifrequency chirp with $\text{SNR}_0=20\,\text{dB}$.

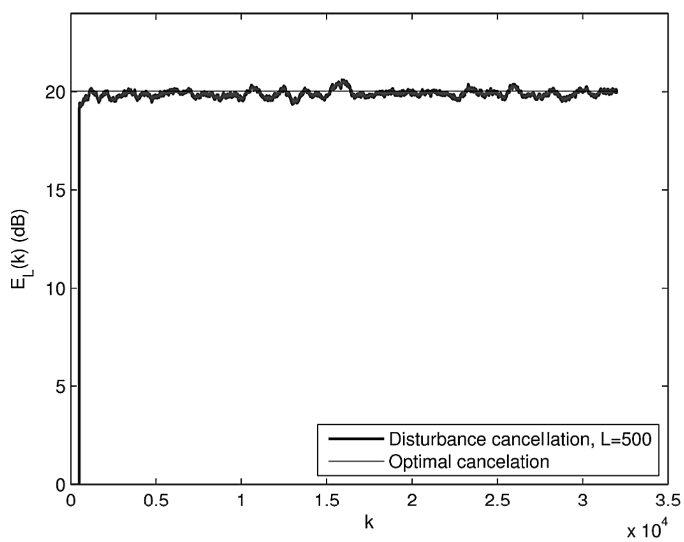


Figure 8. Disturbance cancellation during a multifrequency chirp with $\text{SNR}_0=20\,\text{dB}$ and $L=500$ samples.

E_L using a window of width $L=500$ with a signal length of $p=32,000$. Also shown for comparison is the optimal cancellation, E_{opt}, corresponding to complete removal of the chirp signal. An excellent average cancellation of 99.2% of the optimal value was achieved using a second-order elliptic bandpass postfilter. When a fourth-order elliptic postfilter is used, the average disturbance cancellation decreases to 79.8% of the optimum. Given the nonstationary nature of the periodic input, this decrease may be due to sluggish transient behaviour of the postfilter. The maximum deviation of $\Delta f=30\,\text{Hz}$ represents a 10% variation in the input frequency, and the rate of change of the input frequency was 5% per second.

Next consider the original problem posed in Fig. 1, namely the decomposition of a complete composite signal $x(k)$ into periodic and nonperiodic components. As the input $x(k)$ now has three components, consider the following measures of the average power of the audio input $x_i(k)$ relative to the periodic disturbance $x_p(k)$ and the random noise $v(k)$, respectively:

$$\mathrm{SNR}_{ip} = 10\log_{10}\left\{\frac{E[x_i^2(k)]}{E[x_p^2(k)]}\right\}\ \mathrm{dB} \tag{23}$$

$$\mathrm{SNR}_{iv} = 10\log_{10}\left\{\frac{E[x_i^2(k)]}{E[v^2(k)]}\right\}\ \mathrm{dB} \tag{24}$$

A recorded audio input x_i consisted of the phrase "alpha, beta, gamma, delta." The periodic disturbance had a constant fundamental frequency of $f_0 = 315\,\mathrm{Hz}$ and included $H = 5$ harmonics with the amplitude of the ith harmonic being $c_i = 1/i$ and the phase angle θ_i being a random number in the range $[-\pi, \pi]$. The SNR for the periodic disturbance was $\mathrm{SNR}_{ip} = -10\,\mathrm{dB}$, and the SNR for the random white noise disturbance was $\mathrm{SNR}_{iv} = 10\,\mathrm{dB}$. The number of PLL harmonics was $N = 5$, and a second-order elliptic postfilter was used.

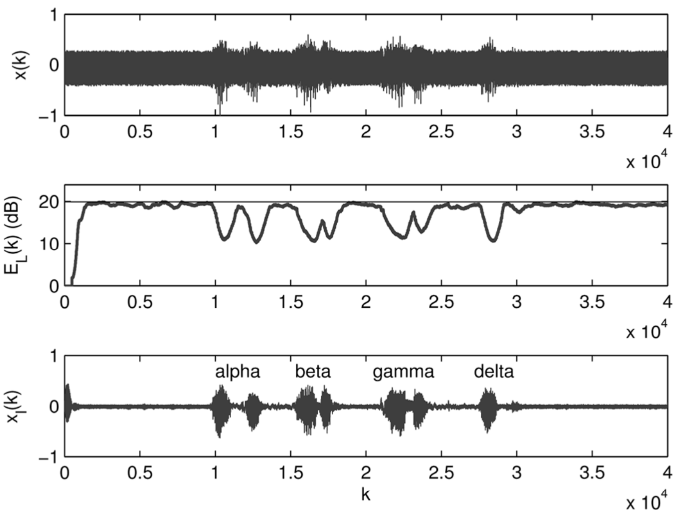


Figure 9. Periodic disturbance cancellation during speech, $\mathrm{SNR}_{ip} = -10\,\mathrm{dB}$, $\mathrm{SNR}_{iv} = 10\,\mathrm{dB}$.

The composite signal before and after cancellation of the periodic disturbance is shown in Fig. 9. The top plot shows the original audio input $x_i(k)$ corrupted with both a periodic disturbance $x_p(k)$and white noise $v(k)$. The middle plot shows the amount of periodic disturbance cancellation as measured in (20) but using (23) with $L = 500$. Also shown for comparison is the optimal cancellation, E_{opt}. Note that after a fairly brief transient the cancellation approaches its optimal value until the audio input appears. Each time a word is spoken, cancellation drops down to about half the optimum value with the minimum being $E_{\min} = 10.3\,\mathrm{dB}$. During brief pauses between the words and after the last word the cancellation returns to near optimal values. The average cancellation during the speech segment was 16.2 dB. The fact that the cancellation is less effective during speech is to be expected. Unlike white noise, certain phonemes in speech have significant periodic content and sometimes correlate with periodic disturbances depending on the pitch of the speaker. The last plot shows the residual nonperiodic signal, $x_I(k)$, with the periodic disturbance removed. Listening to $x(k)$ and then $x_I(k)$ in succession, it is clear that the signal $x_I(k)$ sounds cleaner even though there is still white noise $v(k)$ corrupting the original audio input $x_i(k)$.

6. Conclusions

An effective technique for extracting an audio input from a composite signal that contains a nonstationary noise-corrupted periodic disturbance was presented. The proposed approach uses an active noise control technique to cancel the periodic disturbance, in the electrical domain, using a synthesized signal whose parameters are adjusted adaptively. A combination of a generalized PLL and an adaptive LMS method is used. The PLL creates a pair of basis signals that are phase-locked with the fundamental harmonic of the periodic disturbance. After filtering with an elliptic bandpass filter, higher harmonics are generated from these basis signals using the Chebyshev polynomials of the first and second kinds. These harmonics are then used in the LMS method to minimize the average power of the residual nonperiodic signal. The virtue of this approach is that it does not depend on an explicit accurate estimate of the fundamental frequency of the disturbance. Furthermore, relatively large changes in the fundamental frequency can be tracked so long as they remain within the acquisition range of the PLL. Simulations and experimental results with recorded sounds were presented to demonstrate the effectiveness of the proposed technique.

References

[1] M. Bodson, Rejection of periodic disturbances of unknown and time-varying frequency, *International Journal of Adaptive Control and Signal Processing*, *19*, 2005, 67–88.

[2] D. Chen & H. Paden, Adaptive linearization of hybrid step motors: Stability analysis, *IEEE Transactions on Automatic Control*, *38*(6), 1993, 874–887.

[3] A. Sacks, M. Bodson, & P. Khosla, Experimental results of adaptive periodic disturbance cancellation in a high performance magnetic disk drive, *Journal of Dynamic Systems, Measurement, and Control*, *118*(9), 1996, 416–424.

[4] Y. Xu, M. de Mathelin, & D. Knittel, Adaptive rejection of quasi-periodic tension disturbances in the unwinding of a circular roll, *Proc. American Control Conf., Anchorage*, AK, 2002, 4009–4014.

[5] H.-Y. Ahn, Y. Chen, & H. Dou, State-periodic adaptive compensation of cogging and coulomb friction in permanent magnet linear motors, *IEEE Transactions on Magnetics*, *41*(1), 2005, 90–98.

[6] H. Rudnick, J. Dixon, & L. Moran, Delivering clean and pure power,*IEEE Power and Energy Magazine*, *1*(5), 2003, 32-40.

[7] M.W.M. Grady & S. Santoso, Understanding power system harmonics, *IEEE Power Engineering Review*, *21*(11), 2001, 8–11.

[8] E.L. Owen, A history of harmonics in power systems," *IEEE Industry Applications Magazine*, *4*(1), 1998, 6–12.

[9] M.F. Chimeno & R. Pallas-Areny, A comprehensive model for power line interference in biopotential measurements, *IEEE Transactions on Instrumentation and Measurement*, *49*(3), 2000, 535–540.

[10] A.K. Ziarani & A. Konrad, A nonlinear adaptive method of elimination of power line interference in ECG signals, *IEEE Transactions on Biomedical Engineering*, *49*(6), 2002, 540–547.

[11] G. Keratiotis, L. Lind, J.W. Cook, M. Patel, P. Whelan, D. Croft, & P. Hughes, A novel method for periodic interference suppression on local telephone loops, *IEEE Transactions on*

Circuits and Systems I: Fundamental Theory and Applications, *47*(7), 2000, 1096–1100.

[12] T.A. George & D. Bones, Harmonic power flow determination using the fast Fourier transform, *IEEE Transactions on Power Delivery*, *6*(2), 1991, 530–535.

[13] S. Bittanti, M. Campi, & S.M. Savaresi, Unbiased estimation of a sinusoid in colored noise via adaptive notch filters, *Automatica*, *33*(2), 1997, 209–215.

[14] M.V. Dragosevic & S.S. Stankovic, An adaptive notch filter with improved tracking properties, *IEEE Transactions on Signal Processing*, *43*(9), 1995, 2068–2078.

[15] G. Li, A stable and efficient adaptive notch filter for direct frequency estimation, *IEEE Transactions on Signal Processing*, *45*(8), 1997, 2001–2009.

[16] S.M. Savaresi, Funnel filters: A new class of filters for frequency estimation of harmonic signals, *Automatica*, *33*(9), 1997, 1711–1718.

[17] M. Karimi-Ghartemani & A.K. Ziarani, Periodic orbit analysis of two dynamical systems for electrical engineering applications, *Journal of Engineering Mathematics*, *48*, 2003, 135–154.

[18] M. Karimi-Ghartemani & A.K. Ziarani, Performance characterization of a non-linear system as both an adaptive notch filter and a phase-locked loop, *International Journal of Adaptive Control and Signal Processing*, *18*, 2004, 23–53.

[19] M. Karimi-Ghartemani & M.R. Iravani, Measurement of harmonics/inter-harmonics of time-varying frequencies, *IEEE Transactions on Power Delivery*, *20*(1), 2005, 2331.

[20] B. Wu & M. Bodson, A magnitude/phase-locked loop approach to parameter estimation of periodic signals, *IEEE Transactions on Automatic Control*, *48*(4), 2003, 612–618.

[21] R.J. Schilling, P. Zulch, J.J. Carroll & R. Mukundan, Active noise control using a dual feedforward approach, *International Journal of Systems Science*, *27*(10), 1996, 905–915.

[22] R.J. Schilling, A. Al-Ajlouni, J.J. Carroll, & S.L. Harris, Active control of narrowband acoustic noise of unknown frequency using a phase-locked loop, *International Journal of Systems Science*, *29*(3), 1998, 287–295.

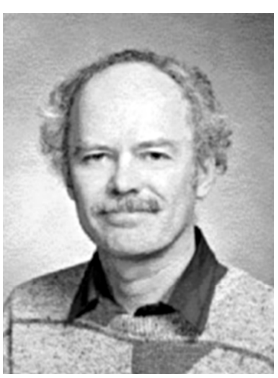
[23] S.M. Kuo & D.R. Morgan, *Active noise control systems: Algorithms and DSP implementations* (New York: Wiley, 1996).

[24] B. Wu & M. Bodson, Multi-channel active noise control for periodic sources – indirect approach, *Automatica*, *40*(2), 2004, 203–212.

[25] Y. Xiao, R.K. Ward, L. Ma, & A. Ikuta, A new LMS-based Fourier analyzer in the presence of frequency mismatch and applications, *IEEE Transactions on Circuits and Systems-I: Regular Papers*, *52*(1), 2005, 230–245.

[26] B. Widrow & S.D. Stearns, *Adaptive signal processing* (Englewood Cliffs, NJ: Prentice Hall, 1985).

Biographies



Robert J. Schilling received his B.E.E. degree in Electrical Engineering from his University of Minnesota, Minneapolis, in 1969 and his M.S. and Ph.D. degrees in Electrical Engineering from the University of California, Berkeley, in 1970 and 1973, respectively. He was a lecturer in the Department of Electrical Engineering and Computer Science at the University of California, Santa Barbara, from 1974 to 1978. In 1978, he joined the Department of Electrical and Computer Engineering at Clarkson University in Potsdam, NY, where he is currently a full professor. He has authored four textbooks in the areas of engineering analysis, robotics, numerical methods, and digital signal processing. His current research interests include adaptive signal processing, active noise control, and control and identification of nonlinear systems.

Ahmad F. Al-Ajlouni received his M.S. degree in Electrical Engineering from Manhattan College, New York, NY, in 1989, and Ph.D. degree in Electrical and Computer Engineering from Clarkson University, Potsdam, NY, in 1997. Dr. Al-Ajlouni is now an associate professor at the Department of Communication Engineering – Hijjawi Faculty of Engineering Technology, Yarmouk University, Irbid-Jordan. His research interests are in the areas of data compression, digital signal processing, active noise control, nonlinear system identification, artificial intelligence, and engineering education.

Edward S. Sazonov (M'02) received his Diploma of Systems Engineer from Khabarovsk State University of Technology, Russia, in 1993 and his Ph.D. degree in Computer Engineering from West Virginia University, Morgantown, WV, in 2002. Currently he is an associate professor in the Department of Electrical and Computer Engineering, Potsdam, NY. His research interests are focused on the area of ambient intelligent systems, including sensor network applications in bioengineering and structural health monitoring, self-powered devices and energy harvesting, and ambient and wearable intelligent devices.

Alireza K. Ziarani received his B.Sc. degree in electrical and communication systems engineering from Tehran Polytechnic University, Tehran, Iran, in 1994, and his M.A.Sc. and Ph.D. degrees in electrical engineering from the University of Toronto, Toronto, ON, Canada, in 1999 and 2002, respectively. Prior to joining Indiana-based Sona Dyamics in 2008 where he is currently employed, he was an associate professor of electrical and computer engineering at Clarkson University, Potsdam, NY. His research interests include nonlinear adaptive signal processing, biomedical engineering, non-destructive testing of materials, and the theory of differential equations.