ACTIVE FEEDBACK NOISE CONTROL IN THE PRESENCE OF IMPULSIVE DISTURBANCES

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ABSTRACT

The problem of active feedback control of a narrowband acoustic noise in the presence of impulsive disturbances is considered. It is shown that, when integrated with appropriately designed outlier detector, the proposed earlier feedback control algorithm called SONIC is capable of isolating and rejecting noise pulses. According to our tests this guarantees stable and reliable operation of the closed-loop noise cancelling system.

***Index Terms*—** Active noise control, rejection of impulsive disturbances, adaptive signal processing.

1. INTRODUCTION

Active control of acoustic noise is based on the principle of destructive interference: the unwanted sound is locally "silenced" by means of generating the anti-sound – the sound wave with the same amplitude as the cancelled one, but opposite polarity. Active noise control (ANC) is particularly useful in the range of low frequencies (roughly, up to 500 Hz) where conventional methods of suppression of acoustic noise, incorporating sound absorbers, are not used because of physical constraints and/or cost inefficiency [1]–[4].

In spite of the fact that the ANC technique has been in use for more than 30 years, and has resulted in many interesting applications, such as attenuation of low-frequency noise in ventilation ducts [5]–[7], active headsets [8]–[10], active noise-canceling car mufflers [11]–[14], and systems that create quiet zones inside cars, trains, airplanes and operator cabins [15]–[19], it still remains an area of intensive research, addressing several new challenges – for an interesting overview of current research topics see e.g. [20].

Active noise cancellers are traditionally divided into feedforward, feedback and hybrid systems. A feedforward system utilizes a reference signal, i.e., a signal strongly correlated with the disturbance, measured by a sensor placed close to the source of unwanted sound. Since the acoustic delay, with which the disturbance reaches the cancellation point, is longer than the delay with which the reference signal is transmitted to the control unit, the controller has the advantage of knowing the signal correlated with the disturbance ahead of time. This allows one to attenuate wideband disturbances. Most of the feedforward ANC systems incorporate the filtered-x least mean squares (FxLMS) algorithm or its modifications [1]–[4].

In the case of feedback ANC systems, the control signal depends solely on the measurements provided by the error microphone placed at the cancellation point – this solution is therefore restricted to mitigation of predictable, i.e., narrowband disturbances. Among the most popular feedback approaches are those based on the internal model principle [21], [22], phase-locked loop control [23], [24] and self-tuning regulation [25]–[27].

Finally, the so-called hybrid ANC systems combine the feedforward and feedback mechanisms mentioned above [28]–[30].

In ANC systems, impulsive noise constitutes either a measurable unwanted sound (such as factory noise of impulsive nature, due to hammering, welding, transportation etc.) that should be cancelled, or an unmeasurable and unpredictable external/internal disturbance (such as digital transmission errors, spurious sounds caused e.g. by hit, mechanical tension or thermal effects, sounds generated by the surrounding environment etc.) which cannot be reduced but may negatively influence operation of the control loop.

Cancellation of impulsive noise using feedforward ANC systems has attracted a great deal of attention in recent years. It resulted in a number of modified FxLMS algorithms [31]–[35] which, unlike the original scheme, are robust to impulsive noise (since impulsive noise is often modeled as a process without finite second order moments, and the FxLMS algorithm tries to minimize the variance of the error signal, without such modifications the stability of the closed-loop system cannot be guaranteed).

The problem of "robustification" of feedback ANC systems is less explored, even though equally important. This paper intends to fill this gap. We will focus on the self-optimizing narrowband interference cancelling (SONIC) algorithm proposed in [25], capable of reducing nonstationary harmonic noise under plant (secondary path) uncertainties. We will show that, when integrated with an appropriately designed outlier detector, SONIC can work reliably in the presence of impulsive disturbances, both short (typical of digital errors) and long (typical of mechanical impacts).

2. PROBLEM FORMULATION

Denote by $t = \ldots, -1, 0, 1, \ldots$ the normalized (dimensionless) discrete time, and by q^{-1} the backward shift operator $q^{-1}x(t) = x(t-1)$. We will consider the problem of reduction of a nonstationary complex-valued narrowband interference $c(t)$ observed, in the presence of impulsive disturbances $\delta(t)$, at the output of a linear stable plant with unknown or partially unknown transfer function $K(q^{-1})$. In acoustical applications such a plant is usually referred to as a secondary path. More specifically, we will assume that the open-loop system description has the form

$$y(t) = K(q^{-1})u(t-1) + c(t) + v(t) + \delta(t) \tag{1}$$

where $y(t)$ denotes the complex-valued system output, $u(t)$ denotes the input (control) signal and $v(t)$ is a wideband measurement noise – zero-mean circular white sequence with variance σ_v^2. Similar to

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[25], for the purpose of deriving the robust control algorithm, we will assume that the interference signal $c(t)$ obeys the following narrowband random-walk model

$$c(t) = e^{j\omega_0} c(t-1) + e(t) \tag{2}$$

where $\omega_0 \in [0, \pi)$ is a known angular frequency and $e(t)$ denotes circular white noise, independent of $v(t)$, with variance σ_e^2. According to (2), when $e(t) \equiv 0$, the signal $c(t)$ can be written down explicitly as $c(t) = c_0 e^{j(\omega_0 t + \phi_0)}$, i.e., it is a complex sinusoid (cisoid) with constant amplitude $c_0 > 0$, initial phase shift ϕ_0, and constant frequency ω_0. The signal governed by the perturbed model (2) can be therefore characterized as a nonstationary cisoid with a slowly drifting amplitude and with instantaneous frequency that fluctuates (due to the local phase changes) around its nominal value ω_0.

The only assumption made about the unknown plant is that it has nonzero gain at the frequency ω_0: $k_p = K(e^{-j\omega_0}) \neq 0$. We will not make any specific assumptions about the sequence of noise pulses $\delta(t)$, except that it is sparsely distributed in time.
We will look for a feedback controller minimizing the mean-squared value of the cancellation error $\xi(t) = c(t) - K(q^{-1})u(t-1)$: $\mathrm{E}[|\xi(t)|^2] \to \min$.

3. SONIC CONTROLLER

In the absence of impulsive disturbances the task formulated in Section 2 can be solved using the SONIC algorithm proposed in [25].

In order to understand how SONIC operates, note that when the true plant gain k_p is known, and $\delta(t) \equiv 0$, the cancelling algorithm can be designed in a very simple form

$$\begin{aligned} \widehat{c}(t+1|t) &= e^{j\omega_0}[\widehat{c}(t|t-1) + \mu_0 y(t)] \\ u(t) &= -\frac{\widehat{c}(t+1|t)}{k_p} \end{aligned} \tag{3}$$

where $\mu_0 > 0$ denotes a real-valued small adaptation gain. The design is based on the observation that, since linear systems basically scale and shift sinusoidal inputs, it holds that $K(q^{-1})u(t-1) \cong k_p u(t-1)$. Moreover, under Gaussian assumptions imposed on $v(t)$ and $e(t)$, and optimal choice of μ_0 (which can then be interpreted as the steady state gain of a Kalman-predictor-based interference tracker), the controller (3) can be shown to be optimal in the mean-squared sense.

It is straightforward to show [25] that if the true plant gain k_p appearing in (3) is replaced with the nominal plant gain k_n, different from k_p ($\beta = k_p/k_n \neq 1$), and at the same time the real-valued gain μ_0 is replaced with the complex-valued gain $\mu = \mu_0/\beta$, the resulting algorithm performs identically as (3). Since for the unknown plant the value of the modeling error β is not known, in the SONIC algorithm such a complex-valued gain is adjusted automatically using the recursive prediction error (RPE) approach - μ is updated recursively so as to minimize the local measure of fit made up of exponentially weighted "squared" system outputs

$$V(t, \mu) = \sum_{\tau=1}^{t} \rho^{t-\tau} |y(\tau, \mu|^2$$

where the forgetting constant ρ ($0 < \rho < 1$) determines the effective summation range. This allows one to simultaneously: account for the unknown (possibly time-varying) characteristics of the controlled dynamic process, and optimize cancelling performance.

The SONIC algorithm can be summarized as follows

$$\begin{aligned} z(t) &= e^{j\omega_o}\left[(1 - c_\mu) z(t-1) - c_\mu \frac{y(t-1)}{\widehat{\mu}(t-1)} \right] \\ r(t) &= \rho r(t-1) + |z(t)|^2 \\ \widehat{\mu}(t) &= \widehat{\mu}(t-1) - \frac{z^*(t) y(t)}{r(t)} \\ \widehat{c}(t+1|t) &= e^{j\omega_o}[\widehat{c}(t|t-1) + \widehat{\mu}(t) y(t)] \\ u(t) &= -\frac{\widehat{c}(t+1|t)}{k_n} \end{aligned} \tag{4}$$

where $r(t) = V''(t, \widehat{\mu}(t-1))$, $z(t) = \partial y(t, \widehat{\mu}(t-1))/\partial\mu$ denotes the sensitivity derivative and $c_\mu > 0$ is a small positive constant (see [25] for tuning recommendations).

It can be shown that, for a nonstationary harmonic signal governed by (2), the disturbance rejection scheme based on (4) converges in the mean to the optimal solution [25].

4. ROBUST OPEN LOOP ESTIMATION

Impulsive disturbances can significantly deteriorate performance of active noise cancelling systems since they interfere with their internal adaptation mechanisms. In the case of SONIC, large values of the output signal $y(t)$, caused by the presence of noise pulses $\delta(t)$, may perturb operation of the loop used for tuning μ [governed by the first three recursions of (4)]. This in turn may adversely affect the controller's cancelling efficiency.

To get some insights that will be useful for designing a robust control algorithm, consider a somewhat simpler problem of estimation of a narrowband signal $c(t)$, governed by (2), based on its noisy measurements

$$s(t) = c(t) + v(t) + \delta(t). \tag{5}$$

When both $v(t)$ and $e(t)$ are normally distributed, and noise pulses (often called outliers) are absent, the estimation of $c(t)$ can be carried out using a Kalman filter. In the presence of impulsive disturbances this standard solution can be robustified by incorporating the device known as outlier detector. Denote by $d(t)$ the true pulse location function

$$d(t) = \begin{cases} 1 & \text{if} \quad \delta(t) \neq 0 \\ 0 & \text{if} \quad \delta(t) = 0 \end{cases}$$

and by $\widehat{d}(t)$ – decision made by the outlier detector. The outlier detection alarm will be triggered at the instant t [$\widehat{d}(t) = 1$] if the magnitude of the corresponding prediction error $\varepsilon(t) = s(t) - \widehat{c}(t|t-1)$ exceeds η times its standard deviation $\sigma_\varepsilon(t)$ (under Gaussian assumptions $\eta = 3$ is a typical choice, resulting in the well-known "3-sigma" outlier detection rule); otherwise $\widehat{d}(t)$ will be set to zero. Following [36], $\{\delta(t)\}$ will be regarded as a sequence of zero-mean normally distributed random variables, independent of $\{v(t)\}$ and $\{e(t)\}$, with variance given by

$$\sigma_\delta^2(t) = \begin{cases} 0 & \text{if} \quad \widehat{d}(t) = 0 \\ \infty & \text{if} \quad \widehat{d}(t) = 1 \end{cases} .$$

Such variance scheduling guarantees that measurements regarded as outliers have no influence on the process of estimation of $c(t)$ – they are treated as if they were missing. The corresponding combined estimation/detection algorithm has the form:

Prediction

$$\widehat{c}(t|\,t-1) = e^{j\omega_o}\widehat{c}(t-1|\,t-1)$$
$$p(t|t-1) = p(t-1|t-1) + \sigma_e^2$$
$$\varepsilon(t) = s(t) - \widehat{c}(t|\,t-1)$$
$$\sigma_\varepsilon^2(t) = p(t|t-1) + \sigma_v^2$$

Outlier detection

$$\widehat{d}(t) = \begin{cases} 0 & \text{if} \quad |\varepsilon(t)| \leq \eta\sigma_\varepsilon(t) \\ 1 & \text{if} \quad |\varepsilon)(t)| > \eta\sigma_\varepsilon(t) \end{cases} \tag{6}$$

Filtration

Case 1: if $\widehat{d}(t) = 0$ then

$$g(t) = \frac{p(t|t-1)}{\sigma_v^2 + p(t|t-1)}$$
$$\widehat{c}(t|\,t) = \widehat{c}(t|\,t-1) + g(t)\varepsilon(t)$$
$$p(t|t) = p(t|t-1)[1-g(t)]$$

Case 2: if $\widehat{d}(t) = 1$ then

$$\widehat{c}(t|\,t) = \widehat{c}(t|\,t-1)$$
$$p(t|t) = p(t|t-1)$$

where $\widehat{c}(t|t-1)/\widehat{c}(t|t)$ denote *a priori* / *a posteriori* estimates of $c(t)$, and $p(t|t-1)/p(t|t)$ – the corresponding error variances.

When no noise pulses are detected [$\widehat{d}(t) \equiv 0$], the algorithm summarized above is identical with the classical Kalman predictor/filter. In this case it holds that

$$\widehat{c}(t+1|\,t) = e^{j\omega_o}[\widehat{c}(t|\,t-1) + g(t)\varepsilon(t)]. \tag{7}$$

Note that the estimation formula used in the SONIC algorithm resembles that presented above – the adaptation gain $\mu(t)$ plays in (5) the same role as the Kalman gain $g(t)$ in (7), and the regulation error $y(t)$ is the substitute of the prediction error $\varepsilon(t)$.

Note also that if detection alarm is on at the instant t, i.e., $\widehat{d}(t) = 1$, the subsequent noise variance update in (4) takes the form

$$\begin{aligned}\sigma_\varepsilon^2(t+1) &= p(t+1|t) + \sigma_v^2 = p(t|t-1) + \sigma_v^2 + \sigma_e^2 \\ &= \sigma_\varepsilon^2(t) + \sigma_e^2.\end{aligned} \tag{8}$$

5. ROBUST SONIC

The proposed outlier-resistant SONIC algorithm implements the disturbance rejection mechanisms incorporated in the robust Kalman filter/predictor (6).

First of all, as already mentioned in Section 4, in the feedback control system the output signal $y(t)$ plays the analogous role as the prediction error signal $\varepsilon(t)$ in the open loop system configuration. For this reason outlier detection will be based on monitoring $y(t)$.

When noise pulses are absent, the local estimate of the variance of $y(t)$ can be evaluated recursively as an exponentially weighted average of the past values of $|y(t)|^2$

$$\widehat{\sigma}_y^2(t) = \lambda\widehat{\sigma}_y^2(t-1) + (1-\lambda)|y(t)|^2 \tag{9}$$

where λ, $0 < \lambda < 1$, denotes the forgetting constant. This estimate will play the same role as the prediction error variance $\sigma_\varepsilon^2(t)$ evaluated (analytically) in (6).

In order to incorporate the variance update rule (8), applicable when the noise pulse is detected, one needs an estimate of the mean-squared rate of signal change $\sigma_e^2 = \mathrm{E}[|c(t) - e^{j\omega_0}c(t-1)|^2]$. Using the approximation $c(t) - e^{j\omega_0}c(t-1) \cong \widehat{c}(t) - e^{j\omega_0}\widehat{c}(t-1)$, and noting that, according to (4), it holds that $|\widehat{c}(t) - e^{j\omega_0}\widehat{c}(t-1)|^2 = |\widehat{\mu}(t)y(t)|^2$, one arrives at the following local exponentially weighted estimate of σ_e^2, analogous to (9)

$$\widehat{\sigma}_e^2(t) = \lambda\widehat{\sigma}_e^2(t-1) + (1-\lambda)|\widehat{\mu}(t)y(t)|^2. \tag{10}$$

Finally, to avoid "accidental acceptances" of corrupted measurements placed in the middle of long-lasting noise pulses of complicated shapes, one can request that detection alarm should not be terminated unless m measurements in a row are accepted, where m denotes the user-dependent integer number.

The robust SONIC algorithm can be summarized as follows:

Outlier detection

$$\widehat{d}_0(t) = \begin{cases} 0 & \text{if} \quad |y(t)| \leq \eta\widehat{\sigma}_y(t-1) \\ 1 & \text{if} \quad |y(t)| > \eta\widehat{\sigma}_y(t-1) \end{cases}$$

$$\widehat{d}(t) = \begin{cases} 0 & \text{if} \ \ \widehat{d}_0(t) = \ldots = \widehat{d}_0(t-m+1) = 0 \\ 1 & \qquad \text{otherwise} \end{cases}$$

Estimation

Case 1: if $\widehat{d}(t) = 0$ then

$$z(t) = e^{j\omega_o}\left[\,(1-c_\mu)z(t-1) - c_\mu\frac{y(t-1)}{\widehat{\mu}(t-1)}\,\right]$$
$$r(t) = \rho r(t-1) + |\,z(t)|^2$$
$$\widehat{\mu}(t) = \widehat{\mu}(t-1) - \frac{z^*(t)y(t)}{r(t)}$$
$$\widehat{c}(t+1|\,t) = e^{j\omega_o}[\,\widehat{c}(t|\,t-1) + \widehat{\mu}(t)y(t)\,]$$
$$\widehat{\sigma}_e^2(t) = \lambda\widehat{\sigma}_e^2(t-1) + (1-\lambda)|\widehat{\mu}(t)y(t)|^2$$
$$\widehat{\sigma}_y^2(t) = \lambda\widehat{\sigma}_y^2(t-1) + (1-\lambda)|y(t)|^2$$

Case 2: if $\widehat{d}(t) = 1$ then

$$z(t) = e^{j\omega_o}z(t-1)$$
$$r(t) = r(t-1)$$
$$\widehat{\mu}(t) = \widehat{\mu}(t-1)$$
$$\widehat{c}(t+1|\,t) = e^{j\omega_o}\widehat{c}(t|\,t-1)$$
$$\widehat{\sigma}_e^2(t) = \widehat{\sigma}_e^2(t-1)$$
$$\widehat{\sigma}_y^2(t) = \widehat{\sigma}_y^2(t-1) + \widehat{\sigma}_e^2(t)$$

Control

$$u(t) = -\frac{\widehat{c}(t+1|\,t)}{k_\mathrm{n}}\,. \tag{11}$$

6. SIMULATION RESULTS

Two simulation experiments were performed to check performance of the proposed algorithm. The secondary path was simulated using a finite impulse response of a real acoustic duct, established under 8-kHz sampling – see Fig. 1. The cancelled narrowband signal was generated according to

$$c(t) = [1 + a\cos(\omega_1 t)]\sin(\omega_0 t), \ \ \omega_1 \ll \omega_0 \tag{12}$$

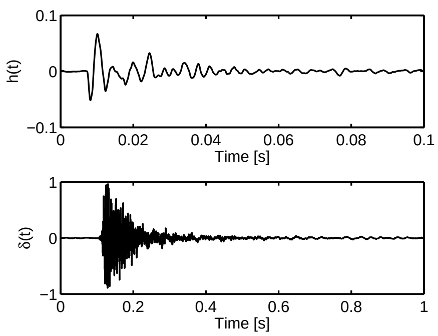

Fig. 1. Secondary path of a ventilation duct (top plot) and a typical acoustic disturbance generated by hitting the outer surface of the duct (bottom plot).

i.e., it was a real-valued sinusoidal signal with slowly varying amplitude. Note that the model (12) differs from the complex-valued "narrowband random walk" model (2), assumed for design purposes. The wideband noise $v(t)$ was Gaussian with $\sigma_v = 0.01$.

Since SONIC was designed for systems with complex-valued inputs and outputs, the generated real-valued signals $c(t)$, $v(t)$ and $\delta(t)$ were converted to the complex format by adding zero imaginary parts. For cancellation purposes the real part of the complex-valued signal $u(t)$ worked out by SONIC was used: $u_\mathrm{R}(t) = \mathrm{Re}[u(t)]$. A more sophisticated approach to cancellation of real-valued signals was described in [27].

The SONIC algorithm was used with the following settings: $c_\mu = 0.0005$, $\rho = 0.99995$, $\lambda = 0.999$. While the true plant gain at the frequency ω_0 was equal to $k_\mathrm{p} = 1.9 + 0.48j$, the nominal gain was set to $k_\mathrm{n} = \beta k_\mathrm{p}$, where $\beta = 0.9e^{j\pi/6}$. Additionally, to avoid erratic behavior during initial transients, the following constraint was enforced (when necessary): $|\widehat{\mu}(t)| \leq 0.01$.

Experiment 1

In this experiment the sequence $\{\delta(t)\}$ was made up of rectangular pulses of fixed height A, random duration (varying between 1 and 1000), random location, and random sign. The cancelled signal was generated using (12) with $a = 0.05$ and $\omega_0 = 0.157$, $\omega_1 = \omega_0/400$. Under 8-kHz sampling the latter values correspond to 200 Hz and 0.5 Hz, respectively. Detection threshold was set to $\eta = 3$ and the width of the detection window – to $m = 1$.

Figure 2 shows typical results obtained for $A = 1$. Note that when the robust version of SONIC is not used, noise pulses cause local bursts of the cancellation error $\xi(t)$, which in the real-valued case is defined as $\xi(t) = c(t) - K(q^{-1})u_\mathrm{R}(t-1)$. The time-averaged values of the mean-squared cancellation errors observed for three different pulse heights A=0.25, 1.0, 10.0 were: 4.5 $\cdot 10^{-4}$, 7.1 $\cdot 10^{-1}$, 2.2 $\cdot 10^{0}$ for the original SONIC, and 8.1 $\cdot 10^{-6}$, 8.6 $\cdot 10^{-6}$, 1.7 $\cdot 10^{-5}$ for the robust SONIC, respectively. Note that while for the original SONIC algorithm the error variance grows rapidly with A, for the robust SONIC it is almost insensitive to the pulse height.

Experiment 2

In our second experiment we checked robustness of the SONIC-based ANC system to some real-world disturbances – a sequence of artifacts generated by hitting the outer surface of a duct with a metal bar. Since such disturbances form long-lasting oscillatory patterns (see Fig. 1), the decision window width was set to $m = 320$ (which corresponds to 0.04 s). Additionally, a higher detection threshold was used: $\eta = 4$. Fig. 3 shows the results obtained, for a stationary interference signal $c(t) = \sin(\omega_0 t)$, $\omega_0 = 0.157$, for two versions of the algorithm. Again, the robust version of SONIC is doing much better than its original version.

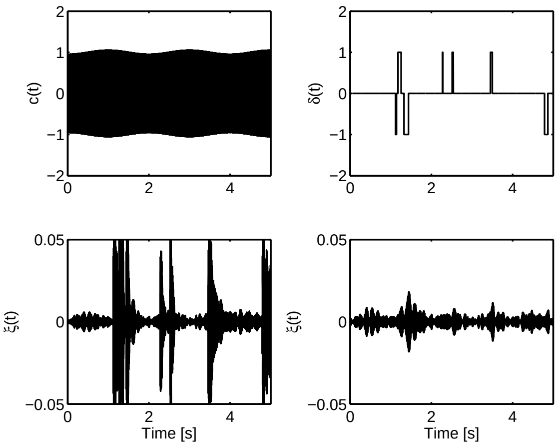

Fig. 2. Nonstationary narrowband interference (top left) corrupted by impulsive disturbances (top right) and the corresponding cancellation errors yielded by the original SONIC (bottom left, clipped) and the robust SONIC (bottom right) controllers.

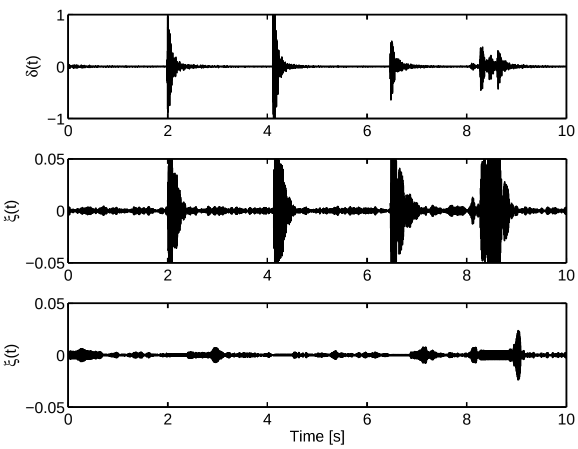

Fig. 3. Cancellation errors yielded by the original SONIC controller (central plot, clipped) and the robust SONIC controller (bottom plot) in the presence of artifacts caused by a series of mechanical impacts (top plot).

7. CONCLUSIONS

While the problem of cancellation of impulsive noise using feedforward ANC systems has attracted a great deal of attention in recent years, the design of feedback ANC systems that are robust to impulsive disturbances seems not to have been considered yet. In this paper we show how one can robustify the recently proposed feedback scheme, known as self-optimizing narrowband interference canceller (SONIC).

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