ROBUST ADAPTIVE NOISE CANCELLER ALGORITHM WITH SNR-BASED STEPSIZE CONTROL AND NOISE-PATH GAIN COMPENSATION

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ABSTRACT

This paper proposes a robust adaptive noise canceller algorithm with SNR-based stepsize control and noise-path gain compensation. The stepsize for coefficient adaptation is controlled with an estimated SNR for low distortion of the output signal and a small residual noise. A second SNR estimate, which is the output over an adjusted reference input, initially controls the stepsize to promote coefficient growth, followed by a more accurate first SNR estimate defined as the output over the noise replica. The power gap between the reference input and the noise replica is compensated for by a factor estimated during an initial target-signal absence. Switchover from the second to the first SNR estimate takes place when the coefficient growth is saturated to guarantee robustness to different noise-path gains. Evaluations with clean speech and noise recorded at a busy station demonstrate that conventional algorithms exhibit initial increase in the coefficient error and never reach the switchover status at a high SNR whereas the proposed algorithm achieves as much as 8dB smaller coefficient error than that without gain compensation.

Index Terms— Signal enhancement, Noise canceller, SNR estimate, Switchover, Stepsize

1. INTRODUCTION

Adaptive noise cancellers (ANCs) [1]-[5] are more suitable for signal enhancement than noise suppressors [6]-[18] when SNR (signal-to-noise ratio) is relatively low. Successful applications include a mobile phone handset [19, 20], a personal robot [22, 23], and a hearable device [24]. An adaptive filter generates a noise replica to be subtracted from the primary microphone signal and the coefficients are updated with the noise-cancelled signal, which consists of pure error and the target signal. The target signal is not correlated with the error and interferes coefficient adaptation, leading to distortions in the target signal and insufficient noise cancellation [5].

It was shown [5],[20]-[23],[31] that an estimated SNR as a power ratio of the ANC output to the noise replica is useful to make the stepsize small to offset the interference by the target signal to the pure error. Initially, however, the estimated SNR equals infinity because its denominator is the adaptive-filter output and division-by-zero happens with zero initial coefficients. Such an SNR value results in a near-zero stepsize and coefficients hardly grow. A solution to this problem is to switch the SNR estimate [25] from a temporary estimate as a power ratio of the primary to the reference input signal to the SNR estimate used in [5],[20]-[23],[31]. A shortcoming is that this initial SNR estimate is interfered by the noise in the numerator, which makes the obtained SNR bigger than the true value, resulting in slow coefficient growth. A better solution is to replace its numerator by the ANC output so that the interference by the noise reduces with coefficient adaptation [26]. Nevertheless, the switchover timing in [25, 26] is determined by the intersection of the two SNR estimates. This condition is not satisfied in reality because the real noise-path impulse response is lossy and its gain is smaller than unity. A new measure for switchover-timing identification is needed.

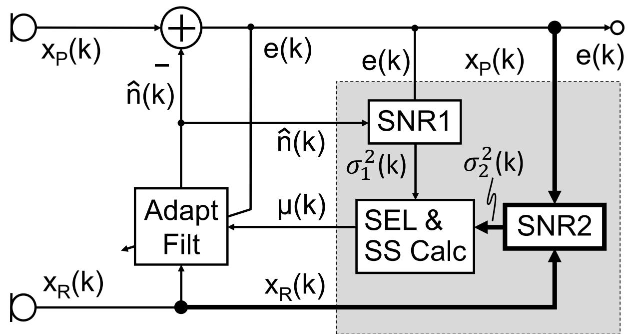

Fig. 1. Conventional noise canceller with SNR-estimate switchover [26].

This paper proposes a robust adaptive noise cancellers algorithm with SNR-based stepsize control and noise-path gain compensation. The switchover is defined by convergence of the adaptive filter coefficients and an initial SNR estimation is made more accurate by an estimated noise-path gain so that the stepsize is appropriately controlled for a wide range of impulse-response gains. The following section investigates the conventional algorithm [26] and clarifies its switchover problem dependent on the noise-path gain, followed by the proposed algorithm with noise-path gain compensation and switchover based on coefficient convergence in Section 3. In Section 4, evaluation results are demonstrated to show robust adaptation by the proposed algorithm compared to the conventional algorithms.

2. CONVENTIONAL NOISE CANCELLER WITH SNR ESTIMATION FOR STEPSIZE CONTROL [25]

Figure 1 depicts a block diagram of a conventional noise canceller with SNR-estimate switchover [26]. When SNR2 is disabled, Fig. 1 represents the original noise canceller with an SNR based stepsize control [20]. In either case, the noise cancelled signal $e(k)$ is expressed by

$$
\begin{aligned}
e(k) &= x_P(k) - \hat{n}(k) \\
&= s_1(k) + \Delta n(k), && (1)\\
\Delta n(k) &= n(k) - \hat{n}(k) \\
&= n(k) - \boldsymbol{w}^T(k)\boldsymbol{x}_R(k), && (2)\\
\boldsymbol{w}(k) &= [w(k,0), w(k,1), \cdots, w(k, L-1)]^T && (3)\\
\boldsymbol{x}_R(k) &= [x_R(k-L+1), x_R(k-L+2), \cdots, x_R(k)]^T && (4)
\end{aligned}
$$

where $x_P(k), x_R(k), s_1(k), n(k)$, and $\hat{n}(k)$ are the primary- and the reference-microphone signals, the target signal, noise to be cancelled in $x_P(k)$, and a noise replica (adaptive filter output). $\{\cdot\}^T$ is a vector transpose. $w(k,l)$ is the l-th filter coefficient at time k with $0 \leq l \leq L-1$ and constitutes a filter-coefficient vector $\boldsymbol{w}(k)$.

With $\hat{n}(k)$ and $e(k)$, an estimated SNR, $\sigma_1^2(k)$, is calculated by (5) as the output of SNR1 in Fig. 1 and converted to a stepsize $\mu(k)$ by an appropriate function $f\{\cdot\}$ as in (6).

$$
\begin{aligned}
\sigma_1^2(k) &= e^2(k)/\hat{n}^2(k), && (5)\\
\mu(k) &= f\{\sigma_1^2(k)\} \cdot \mu_0. && (6)
\end{aligned}
$$

μ_0 is the NLMS (normalized least mean-square) stepsize that satisfies $0 < \mu_0 < 2$. A function $f\{\cdot\}$ is designed as a monotonically decreasing function of $\sigma_1^2(k)$ such that a high SNR with a strong target signal interference returns a small value for stable adaptation. Adaptive filter coefficients $w(0,i)$ are initialized to zero for $i = 0, 1, \cdots, L-1$. Therefore, from (1) and (2), $e(k) = x_P(k)$ continues and no coefficient grows because $\Delta n(k) = n(k)$ does not get closer to zero. $\sigma_1^2(k) = \infty$ and it does not initially work at all as an SNR estimate.

Introduction of another SNR estimate, $\sigma_2^2(k)$ in (7),

$$
\sigma_2^2(k) = e^2(k)/x_R^2(k), \tag{7}
$$

alleviates this problem [26]. Because $e^2(1) = x_P^2(1)$, $\sigma_2^2(k)$ starts with a value depending on the primary and the reference signals, which grows coefficients. Thus, $\sigma_2^2(k)$ decreases as $e^2(k)$ decreases with adaptation. Use of $\sigma_2^2(k)$ makes $\sigma_1^2(k)$ change via a nonzero $\hat{n}^2(0)$. When $\sigma_1^2(k)$ becomes comparable to $\sigma_2^2(k)$, the SNR estimate switches over from $\sigma_2^2(k)$ to $\sigma_1^2(k)$. However, in reality, this switchover condition is hardly satisfied.

Let us investigate a ratio $\sigma_d^2(k)$

$$
\sigma_d^2(k) = \frac{\sigma_1^2(k)}{\sigma_2^2(k)} = \frac{x_R^2(k)}{\hat{n}^2(k)} \tag{8}
$$

to see if $\sigma_1^2(k)$ is comparable to $\sigma_2^2(k)$. $\sigma_d^2(k) = 1$ means their agreement. A mathematical expectation of (8) with (2) leads to

$$
E[\sigma_d^2(k)] \approx \frac{E[x_R^2(k)]}{E[\hat{n}^2(k)]} = \frac{E[x_R^2(k)]}{E[\boldsymbol{w}^T(k)\boldsymbol{x}_R(k)\boldsymbol{x}_R^T(k)\boldsymbol{w}(k)]} \tag{9}
$$

Applying $\boldsymbol{w}(k) \approx \boldsymbol{h}$ near convergence, where $\boldsymbol{h}$ represents the impulse response of the noise path, (9) becomes

$$
E[\sigma_d^2(k)] \approx \frac{E[x_R^2(k)]}{E[\boldsymbol{h}^T\boldsymbol{x}_R(k)\boldsymbol{x}_R(k)^T\boldsymbol{h}]} = \frac{E[x_R^2(k)]}{\boldsymbol{h}^T E[\boldsymbol{x}_R(k)\boldsymbol{x}_R(k)^T]\boldsymbol{h}} \tag{10}
$$

When $x_R(k)$ is white,

$$
E[\boldsymbol{x}_R(k)\boldsymbol{x}_R(k)^T] = E[x_R^2(k)] \cdot \boldsymbol{I}, \tag{11}
$$

where $\boldsymbol{I}$ is the identity matrix. With (11), (10) reduces to

$$
E[\sigma_d^2(k)] \approx \frac{E[x_R^2(k)]}{E[x_R^2(k)]\boldsymbol{h}^T\boldsymbol{I}\boldsymbol{h}} = \frac{1}{||\boldsymbol{h}||^2}. \tag{12}
$$

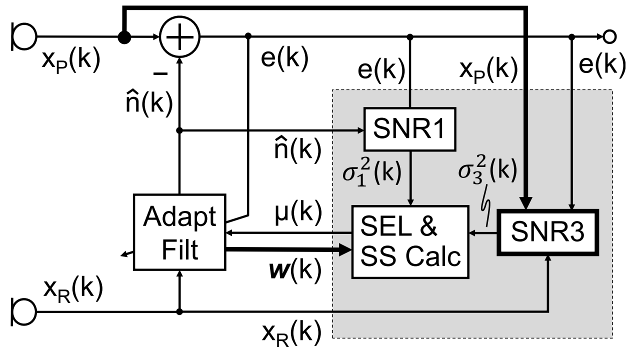

Fig. 2. Proposed noise canceller with SNR-estimate switchover.

(12) clearly shows that $E[\sigma_d^2(k)] = 1$ is not satisfied unless $||\boldsymbol{h}||^2 = 1$. The noise path is a passive circuit with $||\boldsymbol{h}||^2 < 1$ and $\sigma_d^2(k)$ converges to a value larger than 1. The conventional algorithm [26] never switches over from $\sigma_2^2(k)$ to $\sigma_1^2(k)$.

3. PROPOSED ALGORITHM

3.1. Switchover from the first to the second SNR estimate

The no-switchover problem [26] arises from a power gap in (8) between $x_R^2(k)$ and $\hat{n}^2(k)$. It is a natural consequence to introduce a compensation factor $\eta(k)$ to replace $\sigma_2^2(k)$ in (7) with $\sigma_3^2(k)$ in (13).

$$
\sigma_3^2(k) = \frac{e^2(k)}{\eta(k) \cdot x_R^2(k)}. \tag{13}
$$

$\eta(k) = ||\boldsymbol{h}||^2$ for a white $n(k)$ and can be estimated during absence of $s_1(k)$ otherwise. Moreover, evolution of $\sigma_3(k)$ and its approach to $\sigma_1(k)$ originate from coefficient growth. Therefore, it is more straightforward to evaluate saturation of the coefficient-vector norm $||\boldsymbol{w}(k)||^2$ for a switchover timing instead of $\sigma_d(k)^2$.

Figure 2 illustrates a blockdiagram of the proposed algorithm. A derivative $\delta(k)$ of $||\boldsymbol{w}(k)||^2$, which can be approximated by a slope as

$$
\delta(k) = \frac{\mathrm{d}}{\mathrm{dk}} E[||\boldsymbol{w}(k)||^2] \approx \frac{E[||\boldsymbol{w}(k)||^2] - E[||\boldsymbol{w}(k-M)||^2]}{M}, \tag{14}
$$

is introduced to determine a switchover timing, where M is a positive integer. Mathematical expectations are generally approximated by their time averages assuming ergodicity.

$$
E[||\boldsymbol{w}(k)||^2] \approx \frac{1}{M} \sum_{l=k-M+1}^{k} ||\boldsymbol{w}(k)||^2. \tag{15}
$$

For switchover of SNR estimates, from $\sigma_3^2(k)$ to $\sigma_1^2(k)$, a flag $\xi(k)$ is utilized with $\xi(0) = 0$ and ϵ as a constant close to zero as

$$
\xi(k) = \begin{cases} 1 & \delta(k) < \epsilon \quad and \quad \xi(k-1) = 0 \\ \xi(k-1) & otherwise \end{cases}. \tag{16}
$$

The final SNR estimate $\sigma^2(k)$ is obtained by

$$
\sigma^2(k) = \{1 - \xi(k)\}\sigma_3^2(k) + \xi(k)\sigma_1^2(k). \tag{17}
$$

Crosstalk has been untouched so far, however, it is negligeble with a presence of an acoustic barrier between the primary and the auxiliary microphone such as mobile phones [5, 20] and TV receivers [21]. Otherwise, application of the proposed techniques to crosstalk resistant structures such as CTRANC [27, 28], CRANC [29], and PFCC [5, 30, 31] is straightforward.

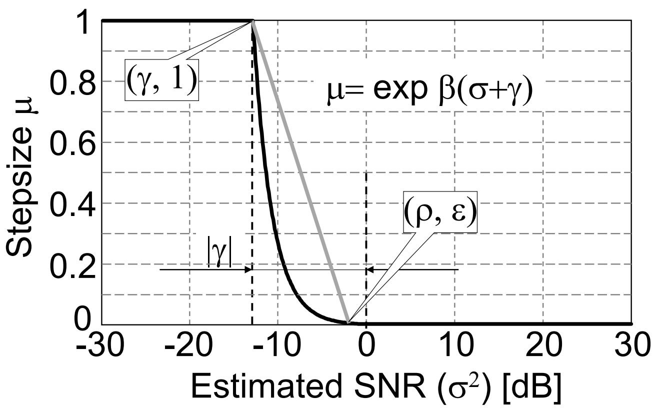

Fig. 3. SNR-dependent stepsize.

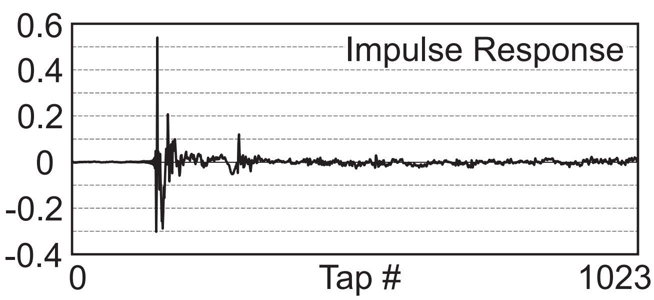

Fig. 4. Impulse response from the noise source to the primary microphone ($\boldsymbol{h}$ in Fig. 1). $||\boldsymbol{h}||^2 = 1$ or 0 dB here and will be scaled.

3.2. Coefficient update with a new SNR estimate $\sigma^2(k)$

$\sigma^2(k)$ is converted to a stepsize $\mu(k)$ [20] by

$$\mu(k) = \max\{\min\{\alpha \exp\beta(\sigma^2(k) + \gamma), \alpha\}, \epsilon\}, \qquad (18)$$

where $\alpha = 1$ in this paper. The function $\mu(k)$ in (18) is illustrated in Fig. 3. Equation (18) indicates that the stepsize $\mu(k)$ is a decreasing exponential function with a ceiling α and a floor ϵ. It is shifted by γ to the left. $\mu(k)$ transfers from the exponential function to the floor $\epsilon = \exp\beta(\rho + \gamma)$ at ρ. Compared to an approximating linear function that connects (γ, 1) and (ρ, ϵ), this function takes a small stepsize more often in the transition range between γ and ρ. This fact guarantees higher stability for coefficient adaptation. Parameters in (18) were optimized for a wide range of real signals with different SNRs, noises, and crosstalk levels and have proven insensitive.

A coefficient vector $\boldsymbol{w}(k)$ is updated by the NLMS algorithm [32] as

$$\boldsymbol{w}(k+1) \quad = \quad \boldsymbol{w}(k) + \mu(k) \cdot \frac{e(k)\boldsymbol{x}_R(k)}{||\boldsymbol{x}_R(k)||^2}, \qquad (19)$$

where $\boldsymbol{x}_R(k)$ is a reference signal vector of the same size as the filter coefficient vector $\boldsymbol{w}(k)$.

4. EVALUATION

Evaluations were performed using male speech and a re-recorded station noise sampled at 8 kHz for $s_1(k)$ and $n_0(k)$. Re-recording was performed in a listening room with a mobile phone handset fixed

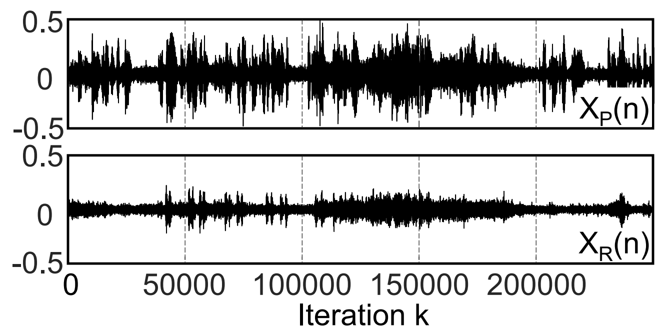

Fig. 5. Input signals, $x_P(k)$ and $x_R(k)$, generated with speech and station noise and adjusted to an SNR of 0 dB.

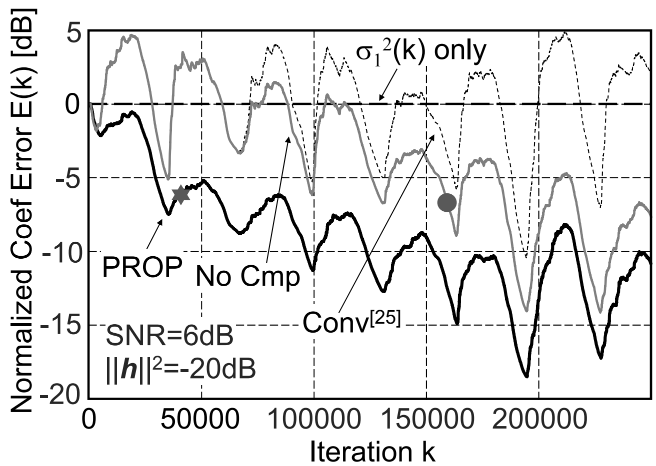

Fig. 6. Comparison of NCE for noise and speech inputs at SNR=6dB (at primary microphone) and with $||\boldsymbol{h}||^2 = -20$ dB. Ensemble average of 20 independent runs.

to a mouth simulator stand [19]. Six loudspeakers were arranged irregularly in distance and facing direction around the stand to implement diffuse noise nature. Convolution of the station noise or the male speech and an impulse response of length $L = 1024$ was added to 20 independent male speech signals for the primary signal. Figure 4 illustrates the impulse response from the noise source to the primary microphone identified in the same setting as in [19]. Parameters for coefficient adaptation were set as in [20]. $\boldsymbol{w}^2(k)$ were averaged over L samples before the use in (15) and $M = 4 \times L$. Figure 5 depicts one of the primary signals $x_P(k)$ and the reference signal $x_R(k)$ for the male speech and the station noise at an SNR of 0 dB.

Figures 6 compares a normalized coefficient error (NCE) $E(k)$

$$E(k) = 10\log_{10}\{||\boldsymbol{h} - \boldsymbol{w}(k)||^2/||\boldsymbol{h}||^2\} \qquad (20)$$

as a measure of adaptive filter convergence for $||\boldsymbol{h}||^2 = -20$ dB at SNR=6 dB with the conventional algorithms [3, 26] and the proposed algorithm with (PROP) and without (No Cmp) noise-path gain compensation by $\eta(k)$. $\eta(k)$ was estimated as $x_P(k)^2/x_R(k)^2$ with averages of 128 samples in the initial absence of $x_P(k)$. A fat solid line, a fat gray line, and a slim dashed line represent the NCE by the proposed algorithm with and without gain compensation and that by the conventional algorithm [26]. A gray hexagram and a gray circle represent estimated-SNR switchover points. Only the NCE with the proposed algorithm (PROP) keeps decreasing whereas the proposed

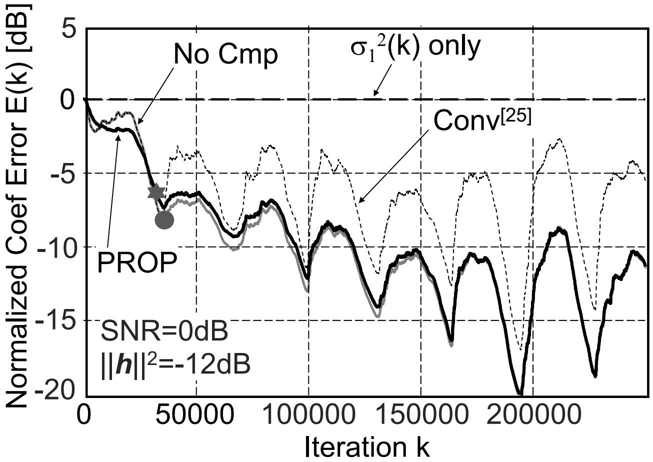

Fig. 7. Convergence characteristics of NCE for noise and speech inputs at SNR=0dB (at primary microphone) and with $||\boldsymbol{h}||^2 = -12$ dB. Ensemble average of 20 independent runs.

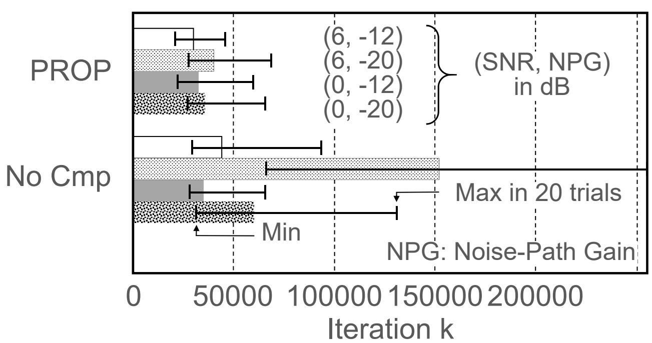

Fig. 8. Comparison of the time till estimated-SNR switchover point. It takes longer time till switchover without noise-path gain compensation (No Cmp) and exhibits a bigger variance for different SNRs and noise-path gains. Based on 20 independent runs.

algorithm without gain compensation (No Cmp) and conventional algorithm [26] all exhibit increasing error in the initial period. This difference mostly comes from gain compensation to fill the gap between the powers of the reference input and the true noise. NCE by conventional algorithms with $\sigma_1(k)^2$ only [3, 5, 20] does not change at all as pointed out in the Introduction. NCE by the proposed algorithm is as much as 8dB lower than conventional algorithms.

Figure 7 corresponds to Fig. 6 with SNRs of 0 and $||\boldsymbol{h}||^2 = -12$dB. The NCE by the proposed algorithms is comparable to that by the same algorithm without compensation with some superiority in the initial stage. NCE by the conventional algorithm is still as much as 6dB larger than that by the proposed due to missing detection of a changeover.

Figure 8 shows comparison of the time till estimated-SNR switchover point. The proposed SNR algorithm (PROP) provides robust adaptation with constant switchover timing and a small variance for SNR=6 and 0dB with the noise-path gain (NPG) of -12 and -20dB. Gain compensation by $\eta(k)$ demonstrates a significant effect clearly observed by comparison of PROP and No Cmp.

Figure 9 depicts the primary signal $x_P(k)$ and the reference signal $x_R(k)$ for speech-speech inputs. They have significant overlaps,

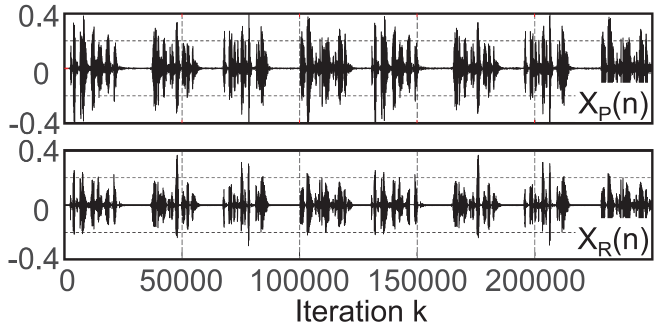

Fig. 9. Input signals, $x_P(k)$ and $x_R(k)$, generated with speech signals and adjusted to an SNR of 0 dB.

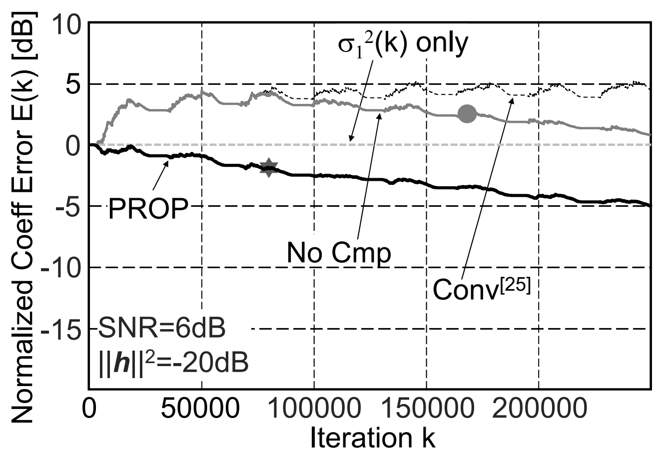

Fig. 10. Convergence characteristics of NCE for speech-speech input at SNRs of 6dB (at primary microphone) and with $||\boldsymbol{h}||^2 = -20$ dB. Ensemble average of 20 independent runs.

which is hard for the adaptive filter to converge without a good adaptation algorithm.

NCE by the conventional algorithm [26] and the proposed algorithm with (PROP) and without (No Cmp) are compared in Fig. 10 for speech inputs of $s_1(k)$ and $n(k)$. It is equal to Fig. 6 except that both input signals are speech. The results in Fig. 10 are more favorable to the proposed algorithm. The effect of noise-path gain compensation is more significant than in Fig. 6 and only the NCE by the proposed algorithm decreases.

5. CONCLUSION

A robust noise canceller algorithm with SNR-based stepsize control and gain compensation has been proposed. A second and a first SNR estimate have been used to define the stepsize one after the other for robust adaptation independent of the noise-path gain. The noise-path gain compensation provides quick initial convergence before switchover to a first SNR estimate upon coefficient-growth saturation. Evaluations with recorded speech and station noise demonstrate that the proposed algorithm provides as much as 13 dB better coefficient error than the conventional algorithm including 8dB by the gain compensation even when conventional algorithms exhibit initial coefficient-error increase and never reach the switchover.

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