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2020

Wen, S., Gan, W.-S., & Shi, D. (2020). Using empirical wavelet transform to speed up selective filtered active noise control system. *The Journal of the Acoustical Society of America*, 147(5), 3490–3501. doi:10.1121/10.0001220

<https://hdl.handle.net/10356/142538>

<https://doi.org/10.1121/10.0001220>

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Using empirical wavelet transform to speed up selective filtered active noise control system

Shulin Wen,^{a)} Woon-Seng Gan,^{b)} and Dongyuan Shi

Digital Signal Processing Lab, School of Electrical & Electronic Engineering, Nanyang Technological University, Singapore, Singapore

ABSTRACT:

The gradual adaptation and possibility of divergence hinder the active noise control system from being applied to a wider range of applications. Selective active noise control has been proposed to rapidly reduce noise by selecting a pre-trained control filter for different primary noise detected without an error microphone. For stationary noise, considerable noise reduction performance with a short selection period is obtained. For non-stationary noise, more restrictive requirements are imposed on instant convergence, as it leads to faster tracking and better noise reduction performance. To speed up a selective filtered active noise control system, empirical wavelet transform is introduced here to accurately and instantaneously extract the frequency information of primary noise. The boundary of the first intrinsic mode function of random noises is extracted as the instant signal feature. Primary noise is attenuated immediately by picking the optimal pre-trained control filter labeled by the nearest boundary. The storage requirement for a pre-trained control filter library is reduced. Instant control is obtained, and the instability caused by output saturation is overcome. With more concentrated energy distribution, better noise reduction performance is achieved by the proposed algorithm compared to conventional and selective active noise control algorithms. Simulation results validate these advantages of the proposed algorithm. © 2020 Acoustical Society of America.

<https://doi.org/10.1121/10.0001220>

(Received 30 December 2019; revised 20 April 2020; accepted 21 April 2020; published online 14 May 2020)

[Editor: Jordan Cheer]

Pages: 3490–3501

I. INTRODUCTION

Active noise control (ANC) is widely used to attenuate low frequency noise, below 1000 Hz (Kuo and Morgan, 1999). The theoretical foundation of ANC grounded on adaptive signal processing is fully elaborated in Kuo and Morgan (1996) and Nelson and Elliott (1991). Currently, ANC has been applied to headphones and automobiles (Elliott and Nelson, 1993). In order to maintain the stability of these commercial products and remove the tedious adaptation procedure of an adaptive ANC algorithm, a fixed filter is a more practical choice for these real applications. However, only a certain kind of noise could be attenuated to the expected level with a fixed filter. For those unexpected noises, the noise reduction performance may not be good enough. Meanwhile, system instability for a practical non-stationary signal and a long adaptation procedure are the two main obstacles in the way of implementing a conventional adaptive ANC system to a wider range of applications.

Many studies have been carried out to improve the robustness of the ANC system by posing restrictions on system parameters, such as step size and filter length (Leboucher *et al.*, 2002; Kong and Kuo, 1999; Elliott *et al.*, 1992; Slock, 1993). But the concrete constraints could only be derived with the assumption that the input signal is white Gaussian noise (WGN), which is not suitable for

unpredictable non-stationary practical noises. Other works (Bai and Wu, 1997; Chambers and Avlonitis, 1997; Elliott and Boucher, 1994; Fraanje *et al.*, 2004, 2007; Song and Zhao, 2018) try to relax the convergence restrictions by adding and controlling different forms of effort weighting terms based on robust regression theories (Hoerl and Kennard, 1970; Tibshirani, 2004; Zou and Hastie, 2005). However, system stability is only ensured for specific cases and the shortened gradual convergence still cannot be neglected. In real implementation, it is an advantage for the ANC system to gain instant control without any human intervention and remain constantly stable. With the aim of achieving immediate control with high robustness, selective active noise control (SANC) is proposed in Shi *et al.* (2018) and Ranjan *et al.* (2016). It is a hybrid of a fixed filter and adaptive ANC algorithm, which benefits rapid control from a fixed filter and flexibility for varying noises from an adaptive ANC algorithm. In Ranjan *et al.* (2016), the whole noise sample is analyzed ahead of the control to identify the noise type, which makes it impractical to implement in practice. A more efficient and workable SANC system structure is proposed in Shi *et al.* (2018). A series of WGN noises with the same central frequency point and different frequency bandwidths are pre-trained to obtain the optimal control filter labeled with a frequency index vector. Once the noise signal is sensed, it will be transformed from time-domain to frequency-domain using fast Fourier transform (FFT). After an inner comparison with the average mean value, the corresponding frequency index vector is generated. It will be

^{a)}Electronic mail: alicia.wen@ntu.edu.sg, ORCID: 0000-0002-8277-5664.

^{b)}ORCID: 0000-0002-7143-1823.

compared with that of every WGN noise in the library. Each comparison will produce a similarity ratio (SR). The control filter with the highest SR is selected to control the input noise. This whole selection process is defined as “frequency-band-match” method in Shi *et al.* (2018). Considerable control performance is directly obtained after a short time of selection. The robustness of the ANC system is improved as well. It works well for the stationary noise cases. When it comes to non-stationary noises, in order to track the signal variability, a continuous selection is needed, which would result in a heavy computation burden, and the short-time selection would degrade the final non-stationary noise reduction performance.

In order to reduce the computational complexity of the SANC algorithm, the block-by-block updating mechanism replaces the sample-by-sample way. This algorithm is proposed in Shi *et al.* (2018) and termed as SANC_DU here. But this would lengthen the selection time. To further reduce the selection time and achieve better noise reduction performance for non-stationary noise, empirical wavelet transform (EWT) is introduced into SANC to extract signal features in Wen *et al.* (2020). The EWT proposed in Gilles (2013) is based on wavelet transform (WT) and the concept of empirical mode decomposition (EMD) (Huang *et al.*, 1998). It decomposes a short time period signal into a limited number of narrow sub-bands termed intrinsic mode function (IMF). Different from the sub-band method, the central frequency and bandwidth for each sub-band are varying and dependent on the signal characteristics. Other than the conventional applications, such as signal reconstruction, de-noising, diagnose, and classification (Chen *et al.*, 2019; Li *et al.*, 2019; Liu *et al.*, 2018; Deng *et al.*, 2018), EWT is adopted here to extract the boundary for the first IMF of noise signal online, and directly generates the opposite signal to attenuate the noise. This EWT based SANC algorithm is termed as SANC_EWT. The concept of SANC_EWT is roughly presented in Wen *et al.* (2020). In this paper, more concrete structure descriptions and performance analyses are elaborated. In order to maintain a high noise reduction performance with real primary and secondary paths, a more complicated meaningful boundary search process is adopted other than the simple maxima sorting method. In order to enable the algorithm processing simple tonal and chirp signal, the feature extracting process is revised as well.

The processing flow of the SANC_EWT system is summarized as follows. Different WGN noises are pre-trained to get the optimal control filters. These optimal control filters labeled with the first boundary value form the pre-trained optimal control filter library. Once the primary noise is sensed, its first IMF and its corresponding boundary are extracted by EWT. Subsequently, the pre-trained control filter labeled with the boundary nearest to the extracted boundary will be selected to attenuate the noise immediately.

Stability over output saturation of the SANC_EWT algorithm is compared with that of a fixed filter, conventional FxLMS, SANC, and SANC_DU algorithms.

Comparisons over the storage requirement for pre-trained library and selection time are done between the SANC, SANC_DU, and SANC_EWT algorithms. Simulations are conducted with both stationary and non-stationary noise input to investigate the noise reduction performance, convergence speed, and stability of the newly proposed algorithm.

The rest of the paper is organized as follows. The theoretical backgrounds EWT and data analysis are presented in Sec. II. The newly proposed SANC_EWT algorithm is elaborated and analyzed in Sec. III. Simulation results of the comparisons between fixed filter, conventional FxLMS, SANC, SANC_DU, and SANC_EWT algorithms are presented in Sec. IV. Conclusions are made in Sec. V.

II. THEORETICAL BACKGROUNDS

The SANC algorithm proposed in Shi *et al.* (2018) is quite effective for a stationary signal. If the stationarity is known as *a priori* knowledge, we could just analyze a period of the noise samples to obtain the frequency band information, and then assign a pre-trained optimal filter for noise control. But if the primary noise is fast varying non-stationary, the short selection time of the SANC would cause the degradation of noise reduction performance. In a real application scenario, noises are mostly unpredictable and non-stationary. Therefore, for real-time practical implementation, we should extract the noise signal feature online accurately and assign the proper control filter right after identification within a short stimulated time period. Stability without human intervention is required.

A. Theoretical backgrounds of EWT

Conventional FFT is an efficient method to extract frequency information from periodic, time-invariant, and stationary signal, which is adopted in Shi *et al.* (2018). For signal energy concentrated in time for transient, non-stationary, or time phenomena, wavelet is more appropriate (Burrus *et al.*, 1998). Since most of the practical noises are non-stationary and transient, WT could be used to extract their instantaneous features for practical implementation of SANC. EWT is a popular signal reconstruction and decomposition method based on WT and the concept of EMD (Huang *et al.*, 1998). EWT can decompose a short period of signals into a limited number of IMFs.

The core concept of EWT is derived from the Littlewood-Paley and Mayer's wavelets. The definitions of its empirical scaling function and empirical wavelets are stated as

$$\hat{\phi}_n(\omega) = \begin{cases} 1, & \text{if } |\omega| \leq \omega_n - \tau_n \\ \cos \left[\frac{\pi}{2} \beta \left(\frac{1}{2\tau_n} (|\omega| - \omega_n + \tau_n) \right) \right], & \text{if } \omega_n - \tau_n \leq |\omega| \leq \omega_n + \tau_n \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$\hat{\psi}_n(\omega) = \begin{cases} 1, & \text{if } \omega_n + \tau_n \leq |\omega| \leq \omega_{n+1} - \tau_{n+1} \\ \cos \left[\frac{\pi}{2} \beta \left(\frac{1}{2\tau_{n+1}} (|\omega| - \omega_{n+1} + \tau_{n+1}) \right) \right], & \text{if } \omega_{n+1} - \tau_{n+1} \leq |\omega| \leq \omega_{n+1} + \tau_{n+1} \\ \sin \left[\frac{\pi}{2} \beta \left(\frac{1}{2\tau_n} (|\omega| - \omega_n + \tau_n) \right) \right], & \text{if } \omega_n - \tau_n \leq |\omega| \leq \omega_n + \tau_n \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

A commonly used function $\beta(x)$ is expressed as

$$\beta(x) = x^4(35 - 84x + 70x^2 - 20x^3), \quad (3)$$

where $\hat{\phi}_1(\omega)$ and $\hat{\psi}_n(\omega)$ together form the filter bank for signal decomposition. The filter bank of the EWT decomposition is illustrated in Fig. 1. Local maximum sorting in decreasing order is adopted in Gilles (2013) to find the boundaries for bank filter building. Only a limited number of boundaries is picked to avoid over-segmentation. The definition of EWT is stated as

$$\mathcal{W}_f^e(n, t) = \int f(\tau) \overline{\psi_n(\tau - t)} d\tau = (\hat{f}(\omega) \overline{\hat{\psi}_n(\omega)})^\vee, \quad (4)$$

and the approximation coefficients by an inner product with scaling function is expressed as

$$\mathcal{W}_f^e(0, t) = \int f(\tau) \overline{\phi_1(\tau - t)} d\tau = (\hat{f}(\omega) \overline{\hat{\phi}_1(\omega)})^\vee, \quad (5)$$

where $\psi_n(\omega)$ and $\phi_1(\omega)$ are defined in Eqs. (1) and Eqs. (2), respectively. Operation $\vee$ and $\wedge$ mean Fourier transform and its inverse. Operation $\bar{}$ refers to conjugation operation.

B. Signal analysis with EWT

First, we use EWT defined in Eqs. (4) and (5) to decompose different kinds of noises so as to investigate the underlying signal characteristics of different kinds of stationary and non-stationary noises. We randomly pick 512 samples as a frame for each of these noises to analyze.

1. Stationary noise signal

For stationary type, tonal noises and WGN noises are the most common stationary noise types that the ANC system is concerned about. Sine tone noise (500 Hz) is picked as an example. The EWT decomposition result of 500 Hz

FIG. 1. Filter bank of EWT decomposition.

tonal noise is presented in Fig. 2. Since only one maximum point exists in the frequency of a sine tonal signal, this maximum point is the only boundary. It is the cutoff frequency for both the first and second IMF, as shown in Fig. 1. Thus, the energy of the first IMF and the second IMF are the same. Actually, they both represent the energy of signal energy at the maximum frequency point.

As for WGN noises, we use EWT to extract features of different bandlimited WGN noises with different bands within the ANC concerning frequency range (100–1000 Hz). Part of the typical results is presented in Fig. 3. The EWT analysis results show that when the frequency band is narrower, signal energy focuses on the first IMF; when the frequency band becomes broader, signal energy is spread to more IMFs.

2. Non-stationary noise signal

For non-stationary noises, chirp signal and some practical noises are taken into consideration. A chirp signal with varying frequency from 100 to 500 Hz is decomposed by EWT. The decomposition result is presented in Fig. 4. As the frequency of the chirp signal is increasing all the time, for each frame only one maximum exists. The first IMF and the second IMF have overlap parts as presented in Fig. 1, which results in the energy of the second IMF is almost half of the first IMF.

Non-stationary noises are ubiquitous in our urban environment. In particular, noises caused by passing aircraft, construction work, and heavy traffic causes health problems for urban residents. Most of the signal energy of these practical noises is distributed at a low-frequency part. It has been explained in Bolin *et al.* (2011) and Leventhall (2004) how low-frequency noise affect human's health. Noises for an aircraft A320 passing by, a bulldozer, and engine noise caused by rotary component on Soundsnap (2007) are adopted to be decomposed by EWT. Even though all of them are non-stationary processes, most of the processing results show that the signal energy concentrates on the first IMF. The energy of the rest of the IMFs could be neglected.

FIG. 2. (Color online) EWT decomposition results of 500 Hz tonal noise.

(a)

(b)

FIG. 3. (Color online) EWT decomposition results of bandlimited WGN noises: (a) 200–400 Hz; (b) 100–700 Hz.

FIG. 4. (Color online) EWT decomposition results of 100–500 Hz chirp noise.

Still, during some short periods, the noise energy spreads to more than one IMF. Part of the decomposition results are presented in Fig. 5.

III. SANC_EWT ALGORITHM

Based on the analyses above, we note that the first IMF always has a high energy level for the nonstationary

(a)

(b)

(c)

FIG. 5. (Color online) EWT decomposition results for non-stationary practical noises: (a) Aircraft A320 pass-by noise; (b) bulldozer noise; (c) engine noise.

practical noises. This gives us a hint of only attenuating the first IMF of a random signal. As presented in Fig. 1, the first IMF extracted by EWT is a low-pass signal. The first boundary, ω_1 , used to separate the first IMF with the rest of the IMFs in Eq. (1), as defined in the following, could be used to represent the first IMF:

$$\omega_1 = \frac{\pi f_1}{f_s}. \quad (6)$$

Therefore, the higher frequency bound of this low-pass signal is

$$f_1 = \frac{\omega_1 \times f_s}{\pi}. \quad (7)$$

Thus, combined with the concept of the SANC algorithm, this simple higher frequency boundary for the first IMF f_1 could be used as the indicating parameter, other than the complex frequency index vector. The concrete system structure of the SANC_EWT system is proposed and presented in Fig. 6, based on the system structure of SANC in Shi *et al.* (2018). The parts different from the SANC algorithm are highlighted with red blocks. The processing procedure of the SANC_EWT algorithm is expounded as follows. Different bandlimited WGN noises with the same lower frequency boundary in the concerned frequency range are pre-trained to obtain the optimal control filters labeled by their higher frequency boundary. When the noise is detected, the higher frequency boundary for the first IMF is extracted. This boundary will be matched with the boundaries in a control filter library. Then the control filter labeled by the boundary nearest to the extracted boundary is directly assigned to attenuate disturbance.

The boundaries determine the cutoff frequency of each IMF. How to segment the Fourier spectrum is crucial to EWT, as it could separate different portions of the spectrum which correspond to different IMFs. The general definition of the boundaries in Gilles (2013) is the local maxima of the

FIG. 6. (Color online) System structure of the SANC_EWT system.

frequency points. It is extremely simple and computationally cost effective. However, these simple local maxima are not meaningful enough for segmenting. Thus, a Gaussian kernel is introduced to place the spectrum into a higher dimensional vector space. After clustering using a Gaussian kernel, the Otsu algorithm is adopted to further extract the key boundaries that minimize the intra-class variance. The process of boundary extraction is plotted in Fig. 7.

The key part to distinguish different ANC algorithms from each other is the control mechanism. In order to differentiate SANC_EWT from other algorithms, we compare its control mechanism with that of fixed filter, conventional FxLMS, SANC, and SANC_DU algorithms based on the simplified ANC system structure plotted in Fig. 8.

For current ANC commercial products, such as headphones, a fixed filter is mostly employed for its simplicity and high robustness. The control filter remains the same all the time for all noise cases.

For conventional FxLMS, an error signal is an essential input sensed by an error microphone as feedback to adjust the control filter. The residual error signal in time domain is commonly defined as

$$e(n) = d(n) - s(n) * y(n), \quad (8)$$

where $d(n)$ is the disturbance signal, and $y(n)$ is the output signal of secondary speaker. And $y(n)$ is defined as

$$y(n) = w^T(n)x(n), \quad (9)$$

FIG. 7. Meaningful boundary extraction process.

FIG. 8. Simplified ANC system structure.

where $s(n)$ is the impulse response of the secondary path $S(z)$, $w(n)$ is the coefficient vector of $W(z)$, and $x(n)$ is the reference signal. For a conventional FxLMS algorithm, the weight vector $w(n)$ of the control filter is updated based on the least mean square error criterion and gradient descent. The updated equation for conventional FxLMS is

$$w(n+1) = w(n) + \mu x'(n)e(n), \quad (10)$$

where $x'(n) = \hat{s}(n)e(n)$, and $\hat{s}(n)$ is the impulse response of the estimated secondary path $\hat{S}(z)$.

For SANC, SANC_DU, and SANC_EWT, the error signal is no longer needed for the control filter updating, which means we can remove the error microphone, thereby simplify the system setup. The weight updating procedure is replaced by the signal feature extraction and feature match in the library.

In SANC, the frequency point information of the last comb of the reference signal is calculated through FFT every sampling interval. After inner comparison with the average mean value, a sequence of Boolean number is generated as the frequency index vector of the real-time signal. Then, it is compared with all the frequency index vectors in the pre-trained library. The SRs corresponding to each comparison are generated as the results. Eventually, the control filter with the highest SR is picked to conduct the control.

The processing flow of SANC_DU and SANC are quite similar; the only difference is that the control filter is updated only once for each block. Assuming the block size is B , the computation consumed by the control filter update for SANC will be divided by B in SANC_DU.

In SANC_EWT, the reference signal is decomposed by EWT. The higher frequency boundary of the first IMF f_1 is adopted as the representative feature of the reference signal. The extracted boundary f_1 will match with all the boundaries in the library, and the control filter with the boundary nearest to f_1 will be picked to generate the anti-noise. More detailed analyses of SANC_EWT on selection time, stability, and storage requirement for a pre-trained library are elaborated hereinafter.

A. Selection time

The idea of selecting the pre-trained optimal control filter of the SANC algorithm is intended to remove the gradual adaption of a conventional FxLMS algorithm. It is shown in Shi *et al.* (2018) that a short-time period of selection still exists in the SANC algorithm. The underlying cause for this

short-time selection is its control filter updating mechanism. Specifically, the SANC algorithm only updates the last comb of the control filter for one sampling interval. Initially, some inappropriate control filter may have a last comb filter with a higher SR compared to the most suitable control filter. This will make the SANC algorithm jump between different control filters for a while. If the signal is stationary, the SANC algorithm will finally choose the most appropriate control filter. This constant control filter rotation may degrade the noise reduction performance for varying non-stationary noise control. As for SANC_DU, if the block size equals the filter length, the selection time of SANC_DU is the same as that of SANC, as well as the computational complexity. If the block size is quite large for the sake of reducing the computational complexity, this will lengthen the selection time in turn.

However, for SANC_EWT, the EWT directly extracts the feature of a real-time noise signal. The only delay simply equals the length of the control filter, which is negatable concerning the high sampling rate for a real application scenario. Instant control is supposed to be obtained by SANC_EWT.

B. Stability over output saturation problem

In real application scenarios, the sound pressure level (SPL) of the noise could be unexpectedly high. For this situation, conventional FxLMS will adaptively increase the weight coefficients of a control filter to generate an output signal with high enough power to attenuate the primary noise. But the secondary speaker may not be able to produce this high-power output signal due to the output constraints. It could deteriorate both noise reduction performance and residual sound quality, and even lead to divergence, which needs to be avoided in real application scenarios (Shi *et al.*, 2017; Costa *et al.*, 2001; Tobias and Seara, 2002). However, the control filters adopted by SANC, SANC_DU, and SANC_EWT are previously trained with controllable band-limited WGN noises based on the system setup. The coefficients of the control filter will not grow without limit. Thus, instability caused by output saturation is avoided in these SANC algorithms, as well as a fixed filter.

C. Storage requirement

Referring to the storage requirement for a pre-trained library, the library structure for SANC and SANC_DU are identical. The library structure for SANC_EWT, SANC, and SANC_DU are plotted in Fig. 9. As we can see, both libraries include two main parts. The first part consists of the pre-trained optimal control filters, and the second part is composed of the indicators. Since $M = L/K$, the storage consumption of SANC_EWT, SANC, and SANC_DU for the control filter part are the same, $Q \times L$ double-precision floating-point numbers. For the indicator part, the indicator adopted by SANC and SANC_DU is the frequency index vector of the last comb of the noise signal, whereas the indicator in SANC_EWT's library is just a boundary value.

FIG. 9. Structure of pre-trained optimal control filter library: (a) SANC and SANC_{DU} algorithm; (b) SANC_{EWT} algorithm.

Hence, the storage consumption for the indicator part of SANC_{EWT}, $Q \times 1$, is less than that of SANC and SANC_{DU}, $Q \times M$. Therefore, SANC_{EWT} consumes less storage than SANC and SANC_{DU} for the pre-trained optimal control filter library.

IV. SIMULATION RESULTS OF COMPARISONS

In the following simulations, a single channel feedforward ANC system is considered with one reference microphone, one secondary speaker, and one error microphone. The relative positions of primary source, reference microphone, secondary speaker, and error microphone are assumed to be fixed to simplify the verification procedure. The primary path and secondary path are measured in an ANC headphone system. The magnitude and phase response of the primary and secondary paths are plotted in Fig. 10.

In the ANC application scenario, our targeting control frequency range is around 100–1000 Hz. The first IMF extracted by EWT is a low-pass signal. Based on this *a priori* knowledge, a sequence of a bandlimited WGN signal with the same lower frequency boundary, that is 100 Hz, and varying higher boundary varying from 600 to 1550 Hz are used to constitute the pre-training noises library. The interval of the higher frequency boundary is 50 Hz. The total

FIG. 10. (Color online) Magnitude and phase response: (a) Primary path; (b) secondary paths.

number of noises in the pre-trained library is $Q = 20$. These WGN noises are pre-trained to construct the optimal control filter library for the SANC, SANC_{DU}, and SANC_{EWT} algorithms. The step size is set as 0.002 during both the pre-training and online processing stage. The control filter length is set as $L = 512$. For the SANC and SANC_{DU} algorithms, the comb number is $K = 4$, and the length of each comb is $M = 128$. The block size for SANC_{DU} is $B = 3096$, 6 times the filter length. The stationary WGN noises and non-stationary practical noises discussed in Sec. II are considered here.

A. Storage consumption

After substituting the number of pre-trained samples and combs, and the length of the control filter and each comb, the storage consumption for SANC and SANC_{DU} is 12 800 double-precision floating numbers, and 10 260 double-precision floating numbers for SANC_{EWT}. Therefore, the SANC_{EWT} algorithm consumes less storage for the pre-trained library.

B. Stationary noises

The stationary noises, which have been analyzed in Sec. II, are adopted as the primary noise. Fixed filter, conventional FxLMS, SANC, SANC_DU, and SANC_EWT algorithms are adopted to attenuate these noises. The fixed filter algorithm chooses the optimal control filter pre-trained for bandlimited WGN noise with band of 100–800 Hz for all the simulation cases. Simulation results are presented in Fig. 11.

From Fig. 11(a) for a 500 Hz tonal noise, of which the initial SPL level is -20 dB, SANC_EWT achieves an 80 dB reduction immediately without any delay. The selection time for SANC_DU is around double that of SANC. And the noise reduction performance of SANC is slightly better than that of SANC_DU, both around 60 dB. Immediate control is achieved by a fixed filter with around a 70 dB reduction. For this case, if the common step size value 0.002 is adopted, the FxLMS algorithm diverges at the very beginning and fails to control the noise. It diverges very fast, so that the diverging process is not able to be presented in the simulation results. In order to show how FxLMS would control the noise, for this case we reduce the step size of the FxLMS algorithm to 0.0005 and 0.00002. As we can see from Fig. 11(a), FxLMS with a 0.0005 step size still diverges very fast at the beginning of the controlling process. Only if we reduce the step size to 0.00002, 100 times smaller than the common adopted step size 0.002, FxLMS could gradually control the noise, and reach around a 280 dB reduction, which is better than all the rest of the algorithms.

From Fig. 11(b) for WGN noise 200–400 Hz, of which the initial SPL level is -40 dB, SANC_EWT achieves the best noise reduction performance, around 60 dB reduction, immediately. Fixed filter, SANC, and SANC_DU achieves the same noise reduction performance around 50 dB. Fixed filter instantly controls the noise. However, SANC and SANC_DU need a short period of selection. And the selection time for SANC_DU is around double that of SANC. The conventional FxLMS suffers a long-time convergence and reaches around 30 dB reduction.

From Fig. 11(c) for WGN noise 100–700 Hz, of which the initial SPL level is -35 dB, fixed filter get the best noise reduction, around 45 dB, immediately. SANC and SANC_DU achieve a slightly lower noise reduction level, around 43 dB, with a short period of selection at the beginning. The selection time of SANC_DU is longer than SANC as well. An immediate reduction of 25 dB with large variance is gained by SANC_EWT. The conventional FxLMS achieves a 40 dB noise reduction after a long-time convergence.

In summary, SANC and SANC_DU have an effective control over these stationary noises. The short period of selection replaces the long tedious converging time of FxLMS. The computation complexity of SANC is reduced by inserting discontinuous updating of SANC_DU. On the contrary, the selection time at the beginning is increased. Fixed filter could directly reduce the noise to a considerable

(a)

(b)

(c)

FIG. 11. (Color online) Noise reduction performance for stationary noises: (a) 500 Hz tonal noise; (b) 200–400 Hz; (c) 100–700 Hz.

level. For tonal noise with one single frequency point, SANC_EWT achieves the best noise reduction performance without any delay. For broadband noise containing more than one maximum in spectrum content, if the signal energy of the first IMF dominates the rest, the SANC_EWT algorithm outperforms other algorithms on the noise reduction level without any delay. However, if the signal energy

spreads to more than one IMF, the performance of SANC_EWT would degrade rapidly. To sum up, the wider the noise bandwidth over 100–1000 Hz is, the worse the SANC_EWT algorithm performs. The reason behind this phenomenon is that energy of a broader WGN spreads to more IMF, but only the first IMF is controlled.

C. Switching noises

In order to investigate how the newly proposed SANC_EWT would perform on tracking changes of the signal, a switching noise composed of three bandlimited WGN noise is considered here. This switching noise lasts for 15 s. During the first 5 s, the noise is a bandlimited WGN noise varying between 400 and 600 Hz. For the following 5 s, the noise is a bandlimited WGN noise varying between 500 and 800 Hz. During the final 5 s, the noise is a bandlimited WGN noise varying between 200 and 350 Hz. Simulation results are presented in Fig. 12. As we can see, the proposed methods could response to the changes of the input signal very fast, which benefits from its instant feature extraction mechanism. But when the band of the noise is wider, which means the energy of the noise is spreading to more than one IMF, the control result is worse than SANC and SANC_DU.

D. Non-stationary noises

The non-stationary noises, which have been decomposed by EWT in Sec. II, are adopted as primary noise here. Since all these noises are non-stationary, the disturbance at the error microphone is adopted as the datum line in the simulations to present the results more clearly. The simulation result for a chirp signal is presented in Fig. 13. As we can see, SANC_EWT achieves the best noise reduction performance, and its residual error signal keeps low and stable. The fixed filter gets good control performance at first, but gradually no control is gained at all. The conventional FxLMS algorithm fails to control the chirp signal at the very beginning.

Simulation results for the nonstationary practical noises are presented in Fig. 14. For the aircraft A320 pass-by noise,

FIG. 12. (Color online) Noise reduction performance for a switching noise.

FIG. 13. (Color online) Noise reduction performance for 100–500 Hz chirp noise.

at the beginning part, SANC_EWT performs the best, with a 30 dB reduction on average. The noise reduction level of SANC_DU is around 10 dB, almost half of that of SANC. The fixed filter achieves around a 10 dB reduction, the same as SANC_DU. The control performance of the conventional FxLMS is limited and neglectable. When it comes to the middle part, the SPL of primary noise increases to the maximum point and starts to descend. Fixed filter and SANC_DU algorithms have a similar noise reduction performance, less than 10 dB. The power of the residual error for SANC and SANC_EWT totally overlap. The noise reduction level of these two algorithms is around 20 dB. During the increasing stage, FxLMS still has limited noise reduction. However, when it passes over the maximum point of the power of primary noise, the performance of FxLMS starts to dominate other algorithms until the end. In the ending stage, the power of primary noise decreases in a steady pace. The performance of SANC_EWT starts to pick up again and reaches around 30 dB again, better than SANC, fixed filter, and SANC_DU.

For bulldozer noise, SANC_EWT immediately obtains a stable noise reduction level around 30 dB, which is obviously better than all the other algorithms. The noise reduction level of SANC is around 20 dB with a short time period of selection. Fixed filter and SANC_DU achieve around a 10 dB reduction, but the control performance for both of them suffer from a sharp vibration. The conventional FxLMS gradually gains limited control performance.

As for engine noise, instant control is obtained by fixed filter and SANC_EWT. But the noise reduction level of SANC_EWT is around 25 dB, which is 5 dB higher than that of fixed filter. Both SANC and SANC_DU achieve around a 10 dB reduction. The selection time of SANC_DU is double that of SANC. There is almost no reduction gained by the conventional FxLMS.

Therefore, we can conclude that SANC_DU helps to reduce the computational burden of SANC at the expense of not only lengthening the selection time, but also degrading the noise reduction performance when it comes to the non-

(a)

(b)

(c)

FIG. 14. (Color online) Noise reduction performance for nonstationary practical noises: (a) Aircraft A320 pass-by noise; (b) bulldozer noise; (c) engine noise.

stationary practical cases. The newly proposed SANC_EWT achieves a distinctly better noise reduction performance with sustaining stability compared to SANC. We credit this to the more accurate feature extraction by EWT decomposition. For the engine and bulldozer noise case, SANC_EWT performs much better than FxLMS all the time. But for the

FIG. 15. (Color online) EWT decomposition result of aircraft A320 at peak point area.

aircraft A320 noise case, after passing the peak point of the primary noise power, conventional FxLMS could have a notably better noise reduction level. It could keep tracking the noise by slowly adjusting control filter. Concurrently, the performance of SANC_EWT degrades around the peak point area and finally picks up after the SPL as the primary noise decreases. In order to figure out the reason, we analyze the noise data around the peak point through EWT decomposition. The result is presented in Fig. 15. As we can see, the first IMF of the noise signal no longer dominates the rest of the IMFs. The signal energy spreads to over five IMFs, which results in the performance degradation.

E. Stability over output saturation

In order to validate the stability over output saturation of SANC, SANC_DU, and SANC_EWT, we increase the SPL of these primary noises. The simulation results of band-limited WGN noise 200–400 Hz with a -30 dB initial SPL level of primary noise is presented in Fig. 16. The conventional FxLMS algorithm diverges after a short period of

FIG. 16. (Color online) Noise reduction performance for WGN 200–400 Hz noises with increased power.

adaptation. But the three SANC algorithms and fixed filter maintain the same noise reduction performance as the lower power version. The simulation results for aircraft A320 passing-by, bulldozer, and engine noises with increased power are shown in Fig. 17. With around a 20 dB increment

of the SPL of all the non-stationary practical noises, conventional FxLMS diverges after a period of adaptation by adjusting the control filter. Fixed filter, SANC, SANC_DU, and SANC_EWT achieve the same noise reduction level as the previous lower power version. We try to increase the initial SPL of the primary noise even higher, and the performance of these SANC algorithms remain the same. Thus, we can see the instability caused by output saturation is overcome by the three kinds of SANC algorithms, maintaining the good noise reduction performance in the meantime for all the simulated cases.

V. CONCLUSION

System instability for a practical non-stationary signal and a long adaptation procedure are the two main obstacles to the efficient implementation of ANC to a wider range of low-frequency mitigation. Selective ANC is an efficient way to remove the long adaptation and improve system robustness. In addition, the error microphone is no longer needed as a control feedback. However, for non-stationary noise, the short selection time would degrade the noise reduction performance, and high computation complexity is required. The discontinuous updating SANC_DU drastically reduces the computation burden at the expense of a longer selection time and poorer noise reduction performance. In this paper, we introduced EWT to conduct feature extraction. Instant control is gained by this newly proposed SANC_EWT algorithm, which means it is able to track the variability of the noise very quickly. This advantage leads to better noise reduction performance especially for non-stationary practical noise, of which the energy of the first IMF is dominant over the rest of the IMFs. Simulation results showed that immediate convergence and better noise reduction performance is achieved by this newly proposed SANC_EWT algorithm compared to a conventional FxLMS, fixed filter, and SANC and SANC_DU algorithms. The instability caused by output saturation is overcome by SANC_EWT. In addition, as the label used to indicate different kinds of noise in the pre-trained library, the storage required by SANC_EWT is much less than SANC. The performance of the algorithm could be further improved by adaptively choosing the right number of IMFs to be controlled. The high computational burden problem caused by the meaningful boundary search process could be reduced by choosing other searching methods.

ACKNOWLEDGMENTS

This material is based on research support by the Singapore Ministry of National Development and National Research Foundation under the Cities of Tomorrow R&D Programme: COT-V4-2019-1. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Singapore Ministry of National Development and National Research Foundation, Prime Minister's Office, Singapore.

FIG. 17. (Color online) Noise reduction performance for non-stationary practical noises with increased power: (a) Aircraft A320 passing by noise; (b) bulldozer noise; (c) engine noise.

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