An Active Noise Control Algorithm Simulation Results and Discussion without Secondary Path Identification Based on Kalman Filter

Can Chen[1], Ru He[2]
[1] *Computer & Information Science Department, Delaware University , Newark, DE 19716, USA*
[2] *Earth Science College, Northeast Petroleum University, Daqing 163318, China*

Abstract

To illustrate the effectiveness of the proposed MECKF (model error compensatory Kalman filter) algorithm, its higher performance is demonstrated by comparing with DSLMS algorithm, and the feasibility of the model noise determination by comparison with MECKF-S-H method. In the simulation experiments compared with DSLMS algorithm, we employed stationary condition for single-tone and broadband ANC, non-stationary conditions with primary path, secondary path varying and additive noise increasing, the results show that the MECKF algorithm converge fast, has a wide noise reduction band, and performs well in either stationary or non-stationary condition with single-tone and broadband original noise.
Keywords: active noise control (ANC),Kalman filter, secondary path, state-space.

1. Introduction

To illustrate the effectiveness of the MECKF[1] algorithm[2,3], We refer simulation experimental conditions to [4] . The sampling rate of ANC system is 300 Hz. The single-tone original disturbance signal is a 30 Hz sin signal with unit amplitude. For 0~400 Hz broadband original signal, we set a 4 KHz sampling rate. $v(n)$ is a zero-mean white-noise signal with 0.01 variance, -20 dB power. The length of ANC controller is $L=11$. The step size is $\mu=0.01$ for DSLMS[4], factor $\lambda=0.995$ for MECKF and MECKF-S-H(Saga-Husa)[5] method. Simulation results show learn curves of residual noise $e(n)$ and residual noise power ($RNP(dB)=10\log_{10}\mathrm{E}\left[e^2(n)\right]$), data after convergence, all averaged after 200 Monte Carlo experiments. Note that the secondary path knowledge is unknow in iterations of different algorithms.

© 2015. The authors - Published by Atlantis Press

Due to the diversity of the convergence rate, we set different time and iteration coordinate ranges with the same amplitude range for different algorithms, in order to clearly demonstrate convergence process and noise control effect. For non-stationary conditions in primary and secondary path, we set the changing points at 2 s, 1 s, 17 s for MECKF, MECKF-S-H and DSLMS respectively. For the additive noise increasing experiment, the changing points of DSLMS and MECKF remain the same, while MECKF-S-H method changes to 2 s.

2. Single-tone ANC with stationary secondary path

In this simulation, the secondary path is modeled by an IIR filter with transfer function

$$S(z) = (z^{-1} + 0.96z^{-2} + 0.4923z^{-3}) / (1 + 1.06z^{-1} + 0.3352z^{-2})$$

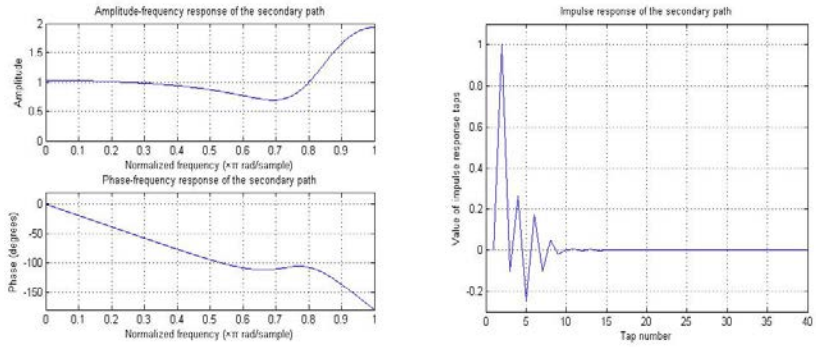
Fig.1 shows its amplitude, phase and impulse responses. Fig.2 and Tab.1 show simulation results for different algorithms.

Fig.2 a), b) and Tab.1 show that both MECKF and MECKF-S-H algorithm converge to the same performance level. However, MECKF-S-H converges fast at the first 50 samples, but its convergence rate slows down more than MECKF between 50 to 100 samples. Compared with Fig.2 c), MECKF converges much faster than DSLMS, its RNP is also 4dB smaller with variance of RNP 0.4 smaller. We found that MECKF performed well between normalized frequency $0 < \Omega < 0.4(\times\pi \,\text{rad/sample})$ while DSLMS between $0 < \Omega < 0.2(\times\pi \,\text{rad/sample})$, for a single tone original noise with frequency f_a, sampling rate F_s and normalized frequency $\Omega = 2f_a/F_s$. We also observe that MECKF converges when phase response of secondary path near ±90°, where DSLMS diverges[4].

Tab.1 RNP of three algorithms with 30 Hz single tone original disturbance

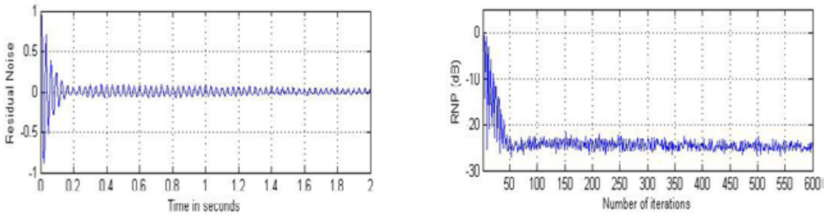
Algorithm	RNP (dB)	Variance of RNP
MECKF	-24.8	0.6
MECKF-S-H	-25.4	0.5
DSLMS	-19.4	1.0

By multiplying computation amount per iteration by iteration number for convergence, we can estimate the convergence time. As can be seen from Fig.2, MECKF converges at 50 iteration, DSLMS at 3900 iteration. We denote T_{mul} as computational time for one multiplication, T_{add} as one addition. Then the convergence time of MECKF is about $2.3235\times10^5 T_{mul} + 2.137\times10^5 T_{add}$, DSLMS about $4.8633\times10^6 T_{mul} + 4.8048\times10^6 T_{add}$. MECKF has an order of magnitude less time than DSLMS, so in this simulation, MECKF performs faster than DSLMS, and can be real-time.

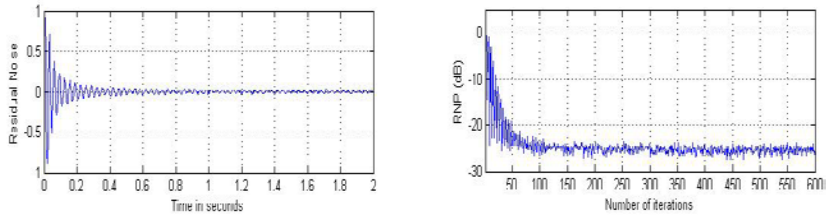


a) Amplitude response and Phase response b) Impulse response

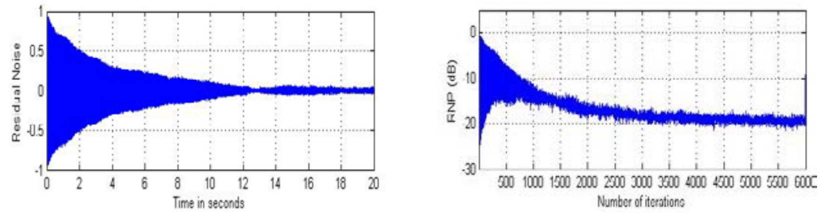
Fig.1 Responses of secondary path



a) Learn curves of MECKF



b) Learn curves of MECKF-S-H method

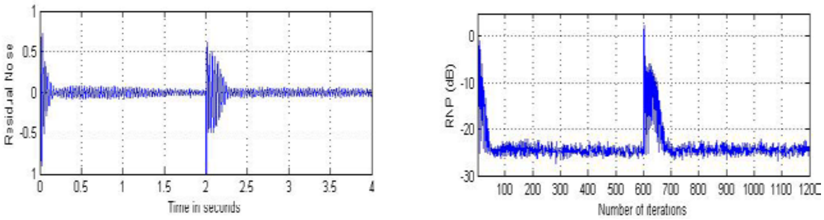


c) Learn curves of DSLMS

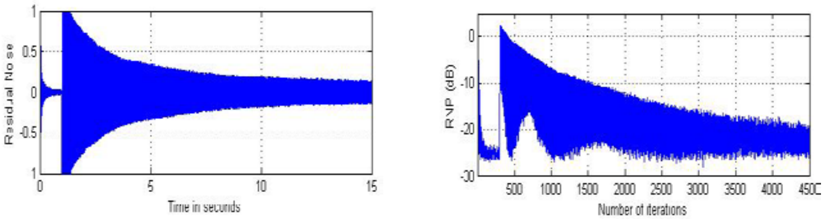
Fig.2 Learn curves of three algorithms with 30 Hz single tone original disturbance

3. Single-tone ANC with sudden change in primary path

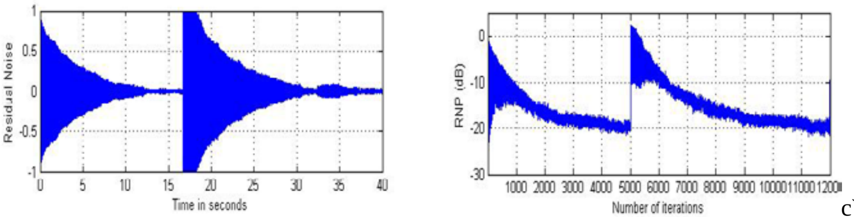
Fig.3 and Tab.2 provide results after primary path $P(n)$ changes to [0, 0, 0, 2, -1.7083, 3.1861, -2.0451, 0, 1.73071]. Fig. 3 a) illustrates the robustness and tracking competent of MECKF when $P(n)$ is unstable, RNP fluctuates little, but the convergence time doubles. The MECKF-S-H converges much more slowly, RNP varies more greatly. DSLMS algorithm shows no apparent change. Thus we conclude that MECKF has a better tracking performance than the other two algorithms.



a) Learn curves of MECKF



b) Learn curves of MECKF-S-H method



c)

Learn curves of DSLMS

Fig.3 Learn curves of three algorithms with sudden change of primary path

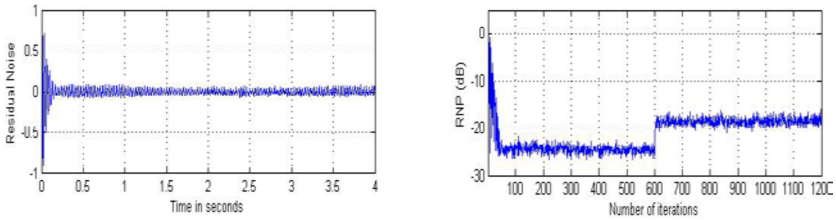
Tab.2 RNP of three algorithms after sudden change of primary path

Algorithms	RNP (dB)		Variance of RNP	
	Before P(n) changes	After P(n) changes	Before P(n) changes	After P(n) changes
MECKF	-24.8	-24.4	0.6	0.5
MECKF-S-H	-25.4	-21.9	0.5	5.8

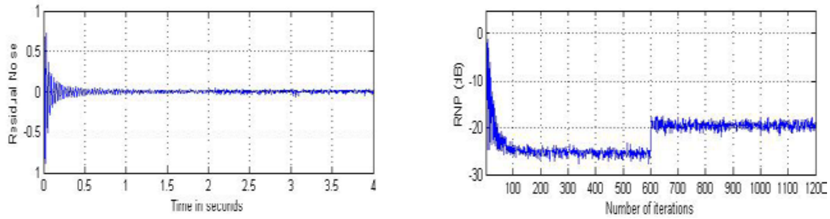
DSLMS	-19.4	-19.4	1.0	0.9

4. Single-tone ANC with sudden increase in additive noise

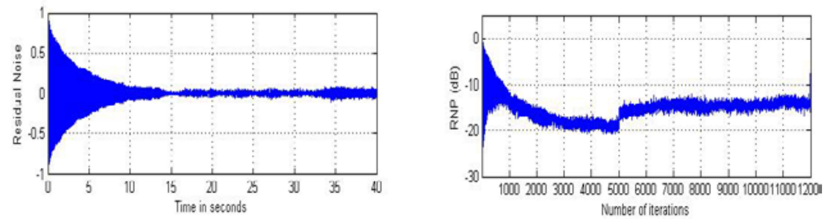
In the condition that additive noise $v(n)$ increases 6 dB, Fig.4 and Tab.3 show the learn curves and RNP data of different algorithm. RNP of MECKF, MECKF-S-H and DSLMS appear a similarly increase, since $v(n)$ is an inherent noise of the system. We observe an immediate RNP increase of MECKF and MECKF-S-H with $v(n)$. However, the learn curve of DSLMS contains a gradually rising transition between 5000 and 7000 samples, due to the fact that DSLMS requires previous $e(n)$ to control updating direction.



a) Learn curves of MECKF



b) Learn curves of MECKF-S-H method



c) Learn curves of DSLMS

Fig.4 Learn curves of three algorithms with 6dB sudden increase in additive noise

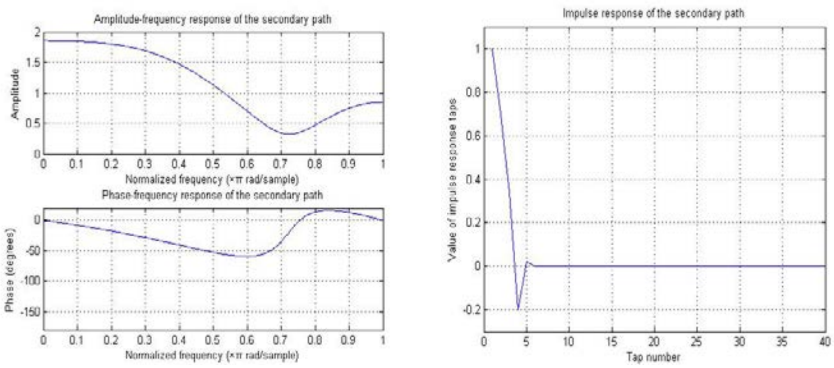
Tab.3 RNP of three algorithms after 6dB sudden increase in additive noise

Algorithms	RNP (dB)	Variance of RNP

	Before v(n) increases	After v(n) increases	Before v(n) increases	After v(n) increases
MECKF	-24.8	-19.1	0.6	0.5
MECKF-S-H	-25.4	-19.5	0.5	0.5
DSLMS	-19.4	-13.8	1.0	0.6

5. Single-tone ANC with sudden change in secondary path

With a sudden change in $S(n)$ to an FIR filter whose coefficients are given by [1, 0.7, 0.3352, -0.2, 0.02], its amplitude, phase and impulse responses are shown in Fig. 5, Fig. 6 and Tab. 4 provide performances of different algorithms. As observed, MECKF has a same RNP both after and before $S(n)$ change, exhibits a robustness property with respect to possible uncertainties in the secondary path model. MECKF-S-H converges very slowly after change. RNP of DSLMS changes little, but its variance reduces a lot, convergence rate also increases greatly. This well confirms that though $S(n)$ effect $e_{MECKF}(n)$ little, it is the main influence to $e_{DSLMS}(n)$.



a) Amplitude response and Phase response

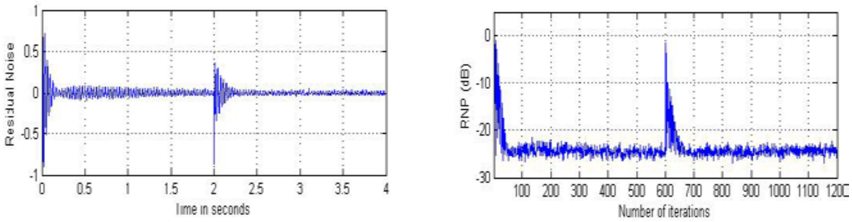
b) Impulse response

Fig.5 Responses of secondary path after change

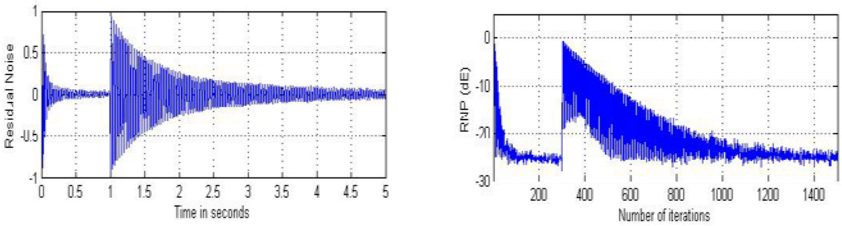
Tab.4 RNP of three algorithms after sudden change of secondary path

Algorithms	RNP (dB)		Variance of RNP	
	Before S(n) changes	After S(n) changes	Before S(n) changes	After S(n) changes
MECKF	-24.8	-24.5	0.6	0.6

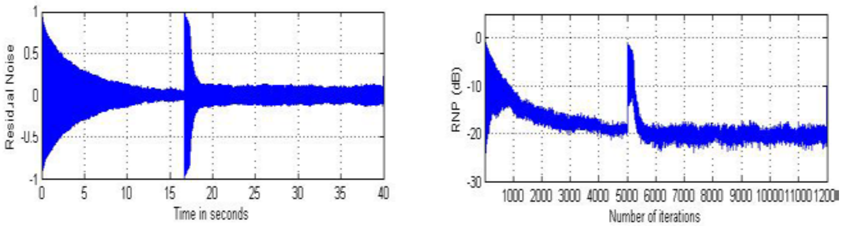
MECKF-S-H	-25.4	-24.7	0.5	0.7
DSLMS	-19.4	-20.1	1.0	1.4



a) Learn curves of MECKF



b) Learn curves of MECKF-S-H method



c) Learn curves of DSLMS

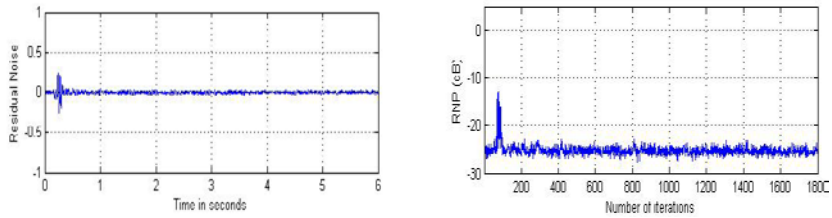
Fig.6 Learn curves of three algorithms with sudden change of secondary pPath

6. Broadband ANC with stationary secondary path

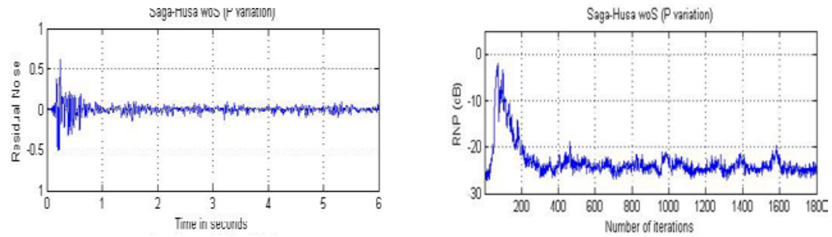
Fig.7 and Tab.5 show results obtained with broadband original noise. It can be seen that the MECKF and MECKF-S-H both have a wider noise reduction band, about $0.3\times\pi\,\mathrm{rad/sample}$ by trial. However, MECKF-S-H shows a significant overshoot and a much slower convergence rate, this can be explained by the iteratively obtained system noise properties. Since DSLMS has a narrow noise reduction band, not only subband structure should be applied but also the order of the adaptive filter should be increased.

To get insight in the robustness in broadband ANC system, the same experiments have been repeated for unstable in $P(n)$, $v(n)$ and $S(n)$ for

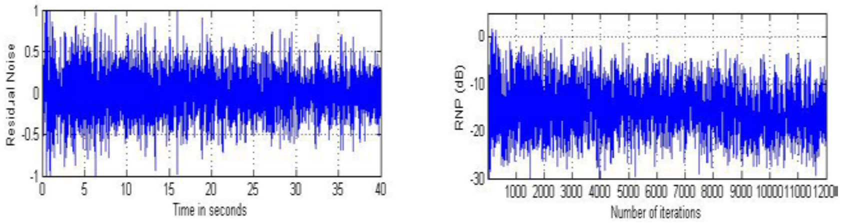
MECKF and MECKF-S-H algorithms. We observe the similar robustness as that of single tone ANC using MECKF, only except for a 3-time increase of convergence time with a sudden change in $P(n)$. But the MECKF-S-H algorithm yields no such robustness in broadband ANC with unstable environment.



a) Learn curves of MECKF



b) Learn curves of MECKF-S-H method



c) Learn curves of DSLMS

Fig.7 Learn curves of three algorithms with 0~400 Hz broadband original disturbance

Tab.5 RNP of three algorithms with 0~400 Hz broadband original disturbance

Algorithm	RNP (dB)	Variance of RNP
MECKF	-25.3	0.4
MECKF-S-H	-24.4	1.3
DSLMS	-16.3	16.7

7. Conclusions

In the simulation experiments compared with DSLMS algorithm, we employed stationary condition for single-tone and broadband ANC, non-stationary conditions with primary path, secondary path varying and additive noise increasing, the results show:

1) The MECKF algorithm converges fast, and has a wide noise reduction band.

2) The MECKF algorithm performs well in either stationary or non-stationary condition with single-tone and broadband original noise.

References

[1] Can Chen, Guo Wei, Ru He, An Active Noise Control Algorithm Principle and Analysis without Secondary Path Identification Based on Kalman Filter, *5th International Symposium on Computers & Informatics (ISCI)*, Beijing, China, Jan, 17-18, 2015.

[2] P.A. Nelson, S.J.Elliott, *Active Control of Sound*. New York: Academic Press, 1992.

[3] S. Haykin, *Adaptive Filter Theory*, Prentice-Hall, Inc., 1991.

[4] D. Zhou and V. DeBrunner, A new active noise control algorithm that requires no secondary path identification based on the SPR property. *IEEE Trans. Signal Processing*, 55(5): pp.1719-1729, 2007.

[5] A. P. Saga, G. W. Husa. Adaptive Filtering with Unknown Prior Statistics， *Proceeding of Joint Automatic Control Conference*, Washington DC, USA, 1969, pp.760-769.