DEVELOPMENT OF AN ADAPTIVE NOISE REDUCTION SYSTEM WITH AUTOMATIC WIND NOISE DETECTION UTILIZING TMS320C6713

Chao-Min Wu, Wei-Lun Lou, and Ting-An Liu

Dept. of Electrical Engineering, National Central University, Chung-Li, Taiwan,
email: wucm@ee.ncu.edu.tw.

The purpose of this study was to develop an adaptive wind noise reduction system. Our system has two parts: firstly we applied the decision tree machine learning algorithm to detect existence of wind noise with the mel frequency cepstrum coefficients (MFCC) used as input features, and parameters of an adaptive filter would be changed to reduce the wind noise. Then we calculated the input short time entropy to detect the voice activity in order to make the output speech signal more comfortable and intelligible. This approach would reduce the wind noise if it detected the input signals with no speech activity. To verify if our system could reduce different wind noise properly, we applied real and simulated wind noise as the noise sources with SNR set from 10 to -10dB, and compared our results with two common noise reduction algorithms: minima controlled recursive averaging (MCRA) and Forward-Backward MCRA (MCRA-FB). Then the objective perceptual evaluation of speech quality (PESQ) approach was used to evaluate the quality of the results. In this study, the MATLAB program was first used to implement the wind noise reduction system. Our results showed that the PESQ score was increased by 0.35 when compared to the original signal with 0dB SNR real wind noise signal while MCRA-FB algorithm could only be increased by 0.05. At the same time, the speech hit rate was 96%, and the accuracy of the wind noise detection rate is 93%. We further implemented the wind noise reduction system on the DSP starter kit (DSK), TMS320C6713 and compared to the results of MCRA. Our results indicated the PESQ score could be increased by 0.3 at high SNR (6dB) signal while the results of MCRA algorithm could not improve the PESQ score. These results show that our wind noise reduction system achieves better performance.

Keywords: wind noise, mel frequency cepstrum coefficients, voice activity detection, short time entropy, TMS320C6713

1. Introduction

As we have known in our daily life, a great noise on the microphone would be produced and signal-to-noise ratio (SNR) of the perceived speech and its quality would be lowered when wind passes through the microphone. If the microphone is part of a hearing aid, the user experiences large noise, distorted sound and masked speech [1]. Study of Chung et al. [2] also indicated that unstable sound was produced due to turbulent effect of wind noise on the microphone of the hearing aid. In addition, wind noise is a non-stationary noise because different noise spectrum would be generated with different velocity of wind noise on the microphone [3]. Due to its non-stationary attribute, few studies of wind noise reduction were found in the literature. In 2008, King and Atlas [4] proposed a method of using the coherent modulation comb filter to reduce wind noise. In their study, the voiced speech was used to derive its formant frequency to design the comb filter. The error of the formant frequency prediction caused problems in wind noise reduction. Another problem was that only the voiced speech would be processed in their study. Other approaches used wind detector to adjust the gain of the filter to reduce the wind noise. These approaches would have the problem of wind noise reduction when the wind and speech exist at the same time [5][6]. To solve this problem, Nelke et al. [7] proposed a method of low frequency speech reconstruction to reduce the low frequency featured wind noise. However, their approach was not successful because of the difficulty in formant frequency estimation. In 2014, Kokkinakis and Cox [1] developed a dual-microphone wind noise suppression strategy to enhance the speech intelligibility of the subjects with cochlear implant, while Chung and Mckibben [8] found a great reduction in wind noise by changing the microphone from directional to omni-directional mode. Previous studies of our laboratory have compared different speech noise reduction algorithms and found that minima-controlled recursive averaging (MCRA) [9] and Forward-Backward MCRA (MCRA-FB) were the two better algorithms for non-stationary noise estimation [10]. Therefore, the purpose of this study was to develop an adaptive wind noise reduction system, evaluate its performance, and compare the result to the aforementioned MCRA and MCRA-FB speech enhancement process to see if it could further improve speech intelligibility and the performance of automatic scene classification and auto-matching noise reduction system after the application of the adaptive directional microphone strategy.

2. Methods

In this study, the MATLAB R2009a (The Math Works, Natick, MA, USA) program was first used to implement the adaptive wind noise reduction system. To verify if our system could reduce different wind noise properly, we applied real and simulated wind noise as the noise sources with SNR set from 10 to -10dB, and compared our results with two common noise reduction algorithms: minima controlled recursive averaging (MCRA) and Forward-Backward MCRA (MCRA-FB). Then the objective perceptual evaluation of speech quality (PESQ) [11] approach was used to evaluate the quality of the results. We further implemented the wind noise reduction system on the DSP starter kit (DSK), TMS320C6713 (Texas Instruments, Dallas, Texas, USA), and compared to the results of MCRA. We further implemented the wind noise reduction system on the DSP starter kit (DSK), TMS320C6713 and compared to the results of MCRA.

2.1 Wind noise reduction system

Figure 1 shows the block diagram of our wind noise reduction system. Our system has two parts: firstly we applied the decision tree machine learning algorithm to detect existence of wind noise (Wind Classifier) with the mel frequency cepstrum coefficients (MFCC) used as input features [12], and parameters of an adaptive filter [13] would be changed to reduce the wind noise. The adaptive filter is responsible for the presence of the wind noise and speech signal at the same time. Then we calculated the input short time entropy to detect the voice activity (VAD) in order to make the output speech signal more comfortable and intelligible [14]. This approach would reduce the wind noise if it detects the input signals with no speech activity. Performance of VAD was evaluated with Receiver Operating Characteristics (ROC) [15].

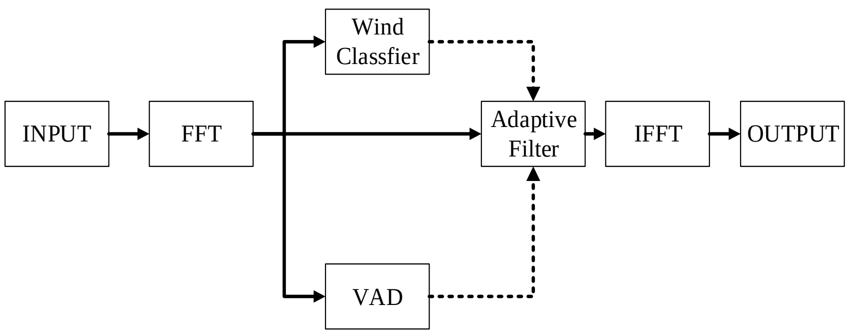


Figure 1: block diagram of our wind noise reduction system.

2.2 Stimuli

For the sentence test material, we used Taiwanese Mandarin HINT developed by Wong et al (2007) [16] for this study. They are 320 equal-difficulty and phonemically-balanced sentences with matched phoneme and tone distributions organized as twelve 20-sentence test lists and four practice lists. Each sentence consists of 10 Chinese characters. They were recorded by a female and male speaker for the tests (16-bits, sampling rate of 44.1kHz).The length of a sentence is 3 seconds. There are three different wind noise stimuli that were used in this study. The first one is the recorded wind noise (16-bits, sampling rate of 44.1kHz) with a mobile phone (HTC Desire 816, High Tech Computer Corp., Taoyuan, Taiwan) while one of the authors was riding a motorcycle at a speed of 50 kilo-meters per hour; the second wind noise (also 16-bits, sampling rate of 44.1kHz) was recorded with a sport camera (Gopro HERO4, GoPro, San Mateo, CA, USA) when the same person was riding a motorcycle at a speed of 105 kilo-meters per hour on a racing field; the last wind noise was a simulated one that was based on the wind speed data from the database of CASES-99 [17] with a stochastic simulation to generate wind noise for a shielded microphone [18]. Figure 2 shows the waveform and spectrogram of a 15 seconds recorded wind noise of the first one noise stimuli.

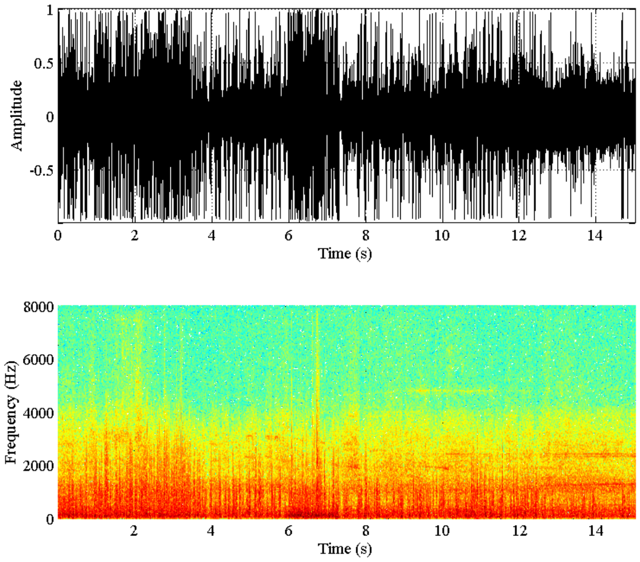


Figure 2: Waveform and spectrogram of a 15 seconds recorded wind noise (the first one).

2.3 Experiments

We further implemented the wind noise reduction system on our speech enhancement dual-microphone noise reduction system. The developed speech enhancement dual-microphone noise reduction system consists of two parts: the microphone preamplifier and TMS320C6713 developer starter kit (DSK) board. The microphones we used are omni-directional electret condenser microphone, LF-M4105B-OWU-25ER2-AC (Ariose Electronics Co. Ltd., Taoyuan, Taiwan). The dual-microphone were in end-fire array with a distance of 2.13 cm; and each received microphone signal was first high-pass filtered with a cut-off frequency of 15.9Hz to remove the low-frequency noise; and then the amplified signal was connected to one channel of LINE IN of the TMS320C6713 DSK board, a new generation of digital signal processing platform from TI. An additional LCD module MzLH04-12864 was added to display root-mean-squared (RMS) amplitudes of the recorded microphone signals [10].

2.3.1 Experiment I: Line-in test

To verify if our system could reduce different wind noise properly, we applied real and simulated wind noise as the noise sources with SNR set from 10 to -10dB, and compared our results with the minima controlled recursive averaging (MCRA) noise reduction algorithm. The noisy speech with various SNR was sent to the TMS320C6713 DSK board via the audio line-in and the processed signals were connected back to the computer via line-out of the DSK board.

2.3.2 Experiment II: Dual-microphone reception test

In this experiment, the dual-microphone system was centered in the hearing test room (ANSI S3.1-1999) and the speakers were 43 cm away from the microphone system, where the speaker A played speech signal and the speaker B played wind noise signal. The received signals were sent to the TMS320C6713 DSK board and then back to the computer to compute the difference between the received and original clean speech signals. The configuration of the experimental setup is shown in Fig. 3.The objective PESQ approach was also used to estimate the quality of speech with the SNR range from 10 and -10dB for this experiment. In this experiment, we compared our wind reduction system with the MCRA noise reduction algorithm with adaptive directional microphone (ADM) and omni directional microphone (Omni) strategies.

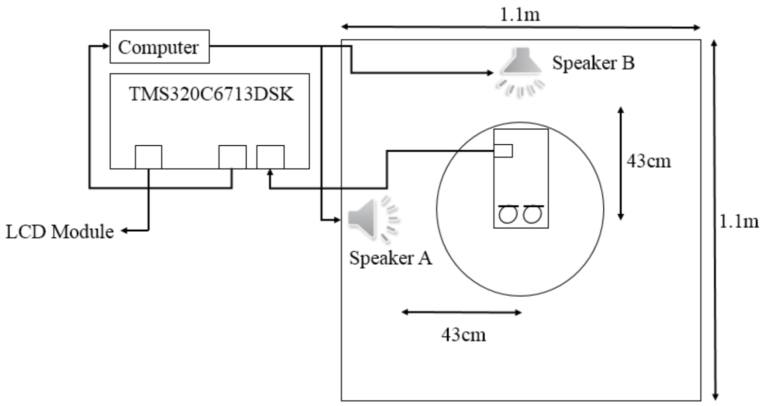


Figure 3: Configuration of the experimental setup for the experiment II.

3. Results and discussion

In this study, the MATLAB program was first used to implement the adaptive wind noise reduction system. To verify if our system could reduce different wind noise properly, we applied real and simulated wind noise as the noise sources with SNR set from 10 to -10dB, and compared our results with two common noise reduction algorithms: minima controlled recursive averaging (MCRA) and Forward-Backward MCRA (MCRA-FB). As shown in Fig. 4, our results showed that the PESQ score was increased by 0.35 when compared to the original signal with 0dB SNR real wind noise signal while MCRA algorithm could only be increased by 0.05. If the result of the simulated wind noise was considered, the PESQ score was increased by 0.22 only when compared to the original signal with 0dB SNR real wind noise signal while MCRA algorithm could only be increased by 0.11. In addition, our proposed wind noise system is better than the MCRA method with SNR between 10 to -6 dB.

Performance of VAD was evaluated with Receiver Operating Characteristics (ROC). Results of evaluation were shown in Fig. 5. When compared to Marzinzik study [15], our overall speech pause hit rate was better than those of [15]. Especially at the threshold frequency was at 1875 Hz, our speech pause hit rate was 70%, but our speech hit rate was 96% (1-0.04 = 0.96). Performance of Wind Classifier was evaluated with random forest method [19]. We applied 180 seconds real and simulated wind noise as the noise sources with SNR set from 5 to -5 dB, and evaluated our wind classifier. The average accuracy of the wind noise detection rate was 93%, as shown in Fig. 6.

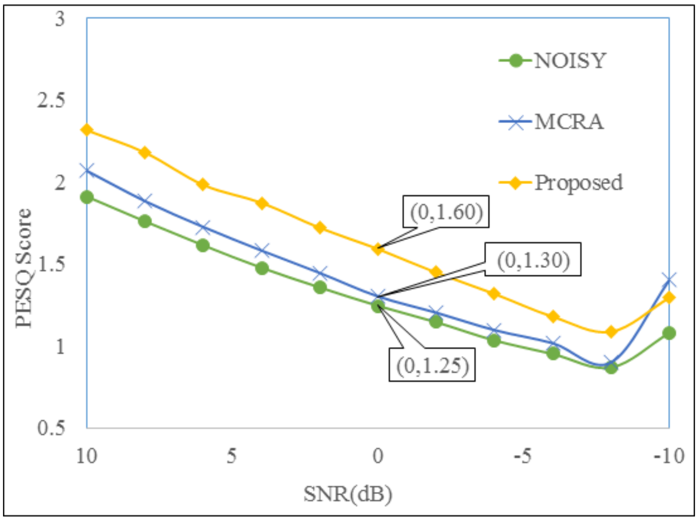


Figure 4: PESQ results of the original noisy speech signal, MCRA, and proposed wind noise reduction system with real recorded wind noise only.

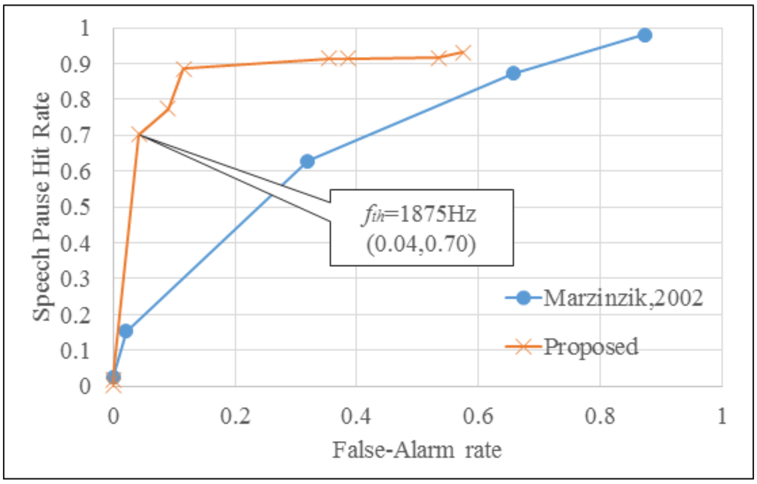
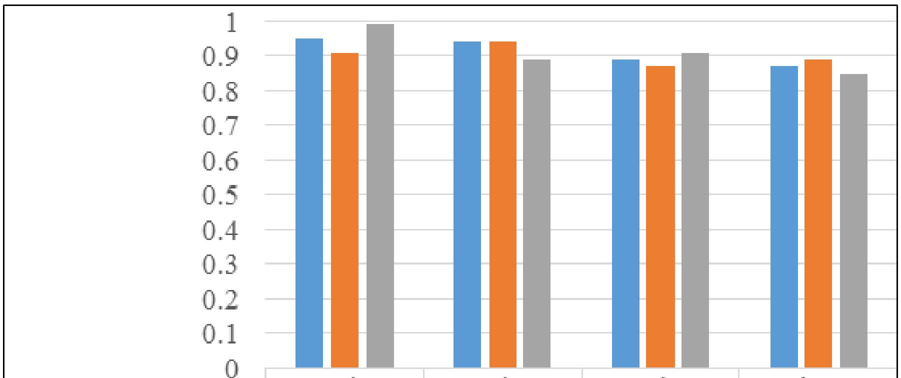


Figure 5: Comparison of speech hit rate between our proposed method and Marzinzik study [15].



	-5dB	0dB	5dB	clean
Average	0.95	0.94	0.89	0.87
Simulated Noise	0.91	0.94	0.87	0.89
Real Noise	0.99	0.89	0.91	0.85

Figure 6: Results of wind detection rate for real recorded and simulated wind noise.

At -5dB SNR the wind detection rate was even up to 99%. These results were better than Jackson et al. study [12], which was about 80%.

We further implemented the wind noise reduction system on our speech enhancement dual-microphone noise reduction system. To verify if our system could reduce different wind noise properly, we applied real and simulated wind noise as the noise sources with SNR set from 10 to -10 dB, and compared our results with the minima controlled recursive averaging (MCRA) noise reduction algorithm conducted in the previous study of our lab. [10] in the experiment I. The results were shown in Fig. 7. As can be seen in Fig. 7, PESQ scores of our proposed approach, MCRA, and the original noisy signal were almost the same when SNR is below 0 dB. However, the PESQ scores between SNR 0 and 10 dB indicated that our proposed method was better than that of MCRA, especially by 0.3 at SNR 6dB.

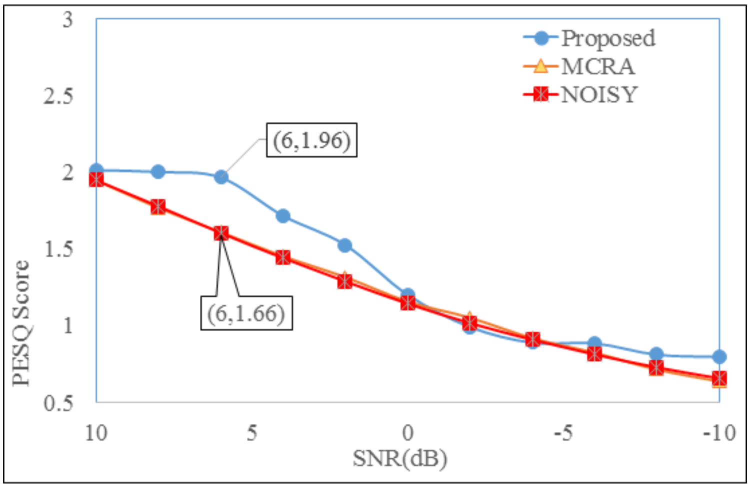


Figure 7: Comparison of wind noise reduction performance with PESQ score between MCRA and our proposed method.

For the experiment II, we compared our wind reduction system with the MCRA noise reduction algorithm with adaptive directional microphone (ADM) and omni directional microphone (Omni) strategies. The objective PESQ approach was also used to estimate the quality of speech with the SNR range from 10 and -10dB. Results of comparison for the MCRA noise reduction algorithm with adaptive directional microphone (ADM) and omni directional microphone (Omni) strategies were shown in Figs. 8 and 9, respectively.

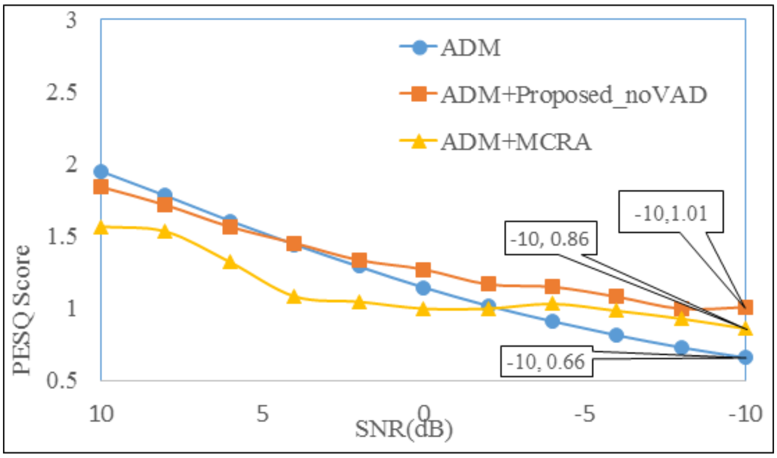


Figure 8: Comparison of MCRA and our proposed method with ADM directional microphone reception.

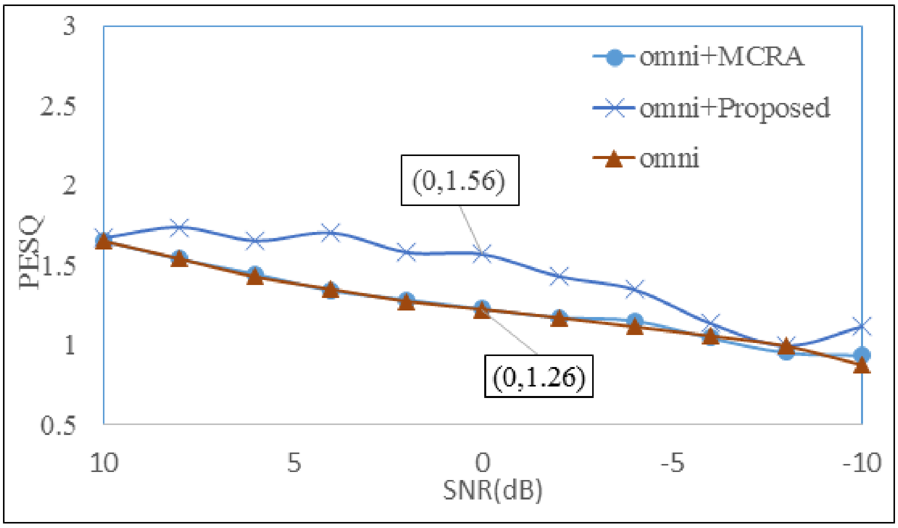


Figure 9: Comparison of MCRA and our proposed method with omni directional microphone reception.

In Fig. 8, when the adaptive directional microphone (ADM) reception was used as the signal input, the PESQ score of our proposed method was 0.35 higher than that of the original (no noise reduction) system at low SNR (-10dB) signal while the result of MCRA algorithm only improved by 0.2. As can be seen in Fig. 8, due to large computation of the ADM reception, the PESQ score of our proposed method with the ADM reception was only improved when the SNR is below 4dB. Also in Fig. 9, the PESQ score of our proposed method was 0.3 higher than that of the original (no noise reduction) system at low SNR (0 dB) signal while the result of MCRA algorithm was not improved.

4. Summary

The purpose of this study was to develop an adaptive wind noise reduction system and compare our results with two common noise reduction algorithms: minima controlled recursive averaging (MCRA) and Forward-Backward MCRA (MCRA-FB). Our results showed that the PESQ score was increased by 0.35 when compared to the original signal with 0dB SNR real wind noise signal while MCRA-FB algorithm could only be increased by 0.05. At the same time, the speech hit rate was 96%, and the accuracy of the wind noise detection rate is 93%. We further implemented the wind noise reduction system on the DSP starter kit (DSK), TMS320C6713 and compared to the results of MCRA. Our results indicated the PESQ score could be increased by 0.25 at high SNR (6dB) signal while the results of MCRA algorithm could not improve the PESQ score. These results show that our wind noise reduction system achieves better performance.

REFERENCES

1 Kokkinakis, K., & Cox, C. Reducing the impact of wind noise on cochlear implant processors with two microphones, *The Journal of the Acoustical Society of America*, **135** (5), EL219-EL225, (2014).

2 Chung, K., Mongeau, L., & McKibben, N. Wind noise in hearing aids with directional and omnidirectional microphones: polar characteristics of behind-the-ear hearing aids, *The Journal of the Acoustical Society of America*, **125** (4), 2243-2259, (2009).

3 Van den Berg, G. Wind-induced noise in a screened microphone, *The Journal of the Acoustical Society of America*, **119** (2), 824-833, (2006).

4 King, B., & Atlas, L. Coherent modulation comb filtering for enhancing speech in wind noise, *International Workshop on Acoustice Echo and Noise Control.*, Seattle, WA, USA, 14-17, (2008).

5 Schmidt, M. N., Larsen, J., & Hsiao, F.-T. Wind noise reduction using non-negative sparse coding, *2007 IEEE Workshop on Machine Learning for Signal Processing.*, Thessaloniki, Greece, 431-436, (2007).

6 Nemer, E., & Leblanc, W. Single-microphone wind noise reduction by adaptive postfiltering, *2009 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, New Paltz, New York, USA, 177-180, (2009).

7 Nelke, C. M., Nawroth, N., Jeub, M., Beaugeant, C., & Vary, P. Single microphone wind noise reduction using techniques of artificial bandwidth extension, *2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO)*, Bucharest, Romania, 2328-2332, (2012).

8 Chung, K. and Mckibben, N. Microphone directionality, pre-emphasis filter, and wind noise in cochlear implants, *Journal of American Academy Audiology*, **22**, 586–600, (2011).

9 Cohen, I., & Berdugo, B. Noise estimation by minima controlled recursive averaging for robust speech enhancement, *IEEE, Signal Processing Letters*, **9**(1), 12-15, (2002).

10 Wu, C.-M., Chen, Z.-F., and Liu, T.-A. Development of a speech enhancement dual-microphone noise reduction system utilizing TMS320C6713, *Proceedings of the 23rd International Congress on Sound and Vibration*, Athens, Greece, 10–14 July, paper 132, 1-8, (2016).

11 ITU-T. Perceptual evaluation of speech quality (PESQ): An objective method for end-to-end speech quality assessment of narrow-band telephone networks and speech codecs. **ITU-T P.862**, (2001).

12 Jackson, I. R., Kendrick, P., Cox, T. J., Fazenda, B. M., & Li, F. F. Perception and automatic detection of wind-induced microphone noise, *The Journal of the Acoustical Society of America*, **136** (3), 1176-1186, (2014).

13 Rangachari, S., & Loizou, P. C. A noise-estimation algorithm for highly non-stationary environments, *Speech communication*, **48** (2), 220-231, (2006).

14 Wu, B.-F., & Wang, K.-C. Robust endpoint detection algorithm based on the adaptive band-partitioning spectral entropy in adverse environments, *IEEE Transactions on Speech and Audio Processing,* **13** (5), 762-775., (2005).

15 Marzinzik, M., & Kollmeier, B. Speech pause detection for noise spectrum estimation by tracking power envelope dynamics, *IEEE Transactions on Speech and Audio Processing*, **10**(2), 109-118, (2002).

16 Wong, L.L.N., Soli S.D., Liu S., Han N., and Huang M.-W., Development of the Mandarin Hearing in Noise Test (MHINT),*Ear Hear*. 28, 70s-74s, (2007).

17 Soler, M. 2006. Tower - 10 Meter 10-second Data (ASCII). Version 1.0. UCAR/NCAR - Earth Observing Laboratory. http://data.eol.ucar.edu/dataset/45.901. Last Accessed 29 Oct 2015.

18 Van den Berg, G. Wind-induced noise in a screened microphone, *The Journal of the Acoustical Society of America*, **119**(2), 824-833, (2006).

19 Liaw, A., & Wiener, M. Classification and regression by randomForest, *R news*, ***2***(3), 18-22, (2002).