A Wavelet Transform-Based Denoising Algorithm for Breathing Sound Detection

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ABSTRACT: Respiratory sound monitoring can be significantly corrupted or degraded by environmental noises. This proposed wavelet-based denoising algorithm was found effective in suppressing environmental noise and preserving the original breathing sound without losing important information contained in the signal. The performance of the developed system for breathing sound detection could be used to provide a better pulmonary disease diagnosis or apnea detection.

Introduction: Breathing sound auscultation has been a valuable part in physical examinations and ventilation monitoring. Sometimes, the auscultation must be done in a noisy environment such as breathing tracheal sound monitoring during a dental procedure with moderate or deep anesthesia involved. The environmental noises would reduce the signal quality and breathing sound detection accuracy, and further influence the accuracy of apnea detection. The main contributions of this work are an algorithm based on wavelet transform to denoise the environmental noise and enhance the performance of breath sound detection.

Materials and Methods: The research obtained experimental equipment from Heroic-Faith Medical Science Co., Ltd. The respiratory sound was collected from the Far East Memorial Hospital, with IRB approval (No. 107052-F). The data was encoded to de-linkage the patient's identity with experienced respiratory therapists and physicians handling the data annotation. The sound was labeled as clean (no obvious noise) and unclean (noisy) breathing sounds. The total data length of clean breath sounds is 435 s, and nonclean breath sounds is 450 s. The sampling interval of clean breath sounds and nonclean breath sounds are all 3 s.

A denoising algorithm was proposed, including a machine learning-based process for determining the sound was clean or nonclean and a wavelet-based process for denoising. In the machine learning process, the clean and unclean signals were transformed to spectrum by fast Fourier transform. The center of gravity of the main feature was used to train a model to differentiate clean signals from unclean signals. In the wavelet-based process, a model learned to remove the noisy components from the wavelet spectrogram. The processing flowchart is illustrated in Fig 1.

Results and Conclusion: Fig 2 displays a clean breath sound signal (Fig 2a), and another unclean signal (Fig 2b) and its denoised results (Fig 2c). In Fig 2, the signals in time domain (top row), frequency domain (middle row), and in time-frequency domain. We can observe that the noisy background in the spectrogram of an unclean signal (bottom row of Fig 2b) was processed and the noise was removed and the breathing patterns were preserved (bottom row of Fig 2c). In the future, more environmental noises must be collected from different clinical settings to train a more robust algorithm. The method might be a useful preprocessing step in automated breath sound analysis, which is required in developing an advanced respiratory sound monitor. A breathing tracheal sound monitor can complement capnography in ventilation monitoring, which is crucial in many anesthesia and analgesia scenarios.

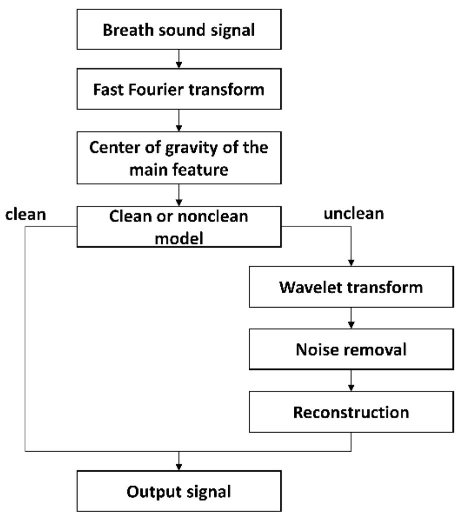

Figure 1. Flowchart of signal processing.

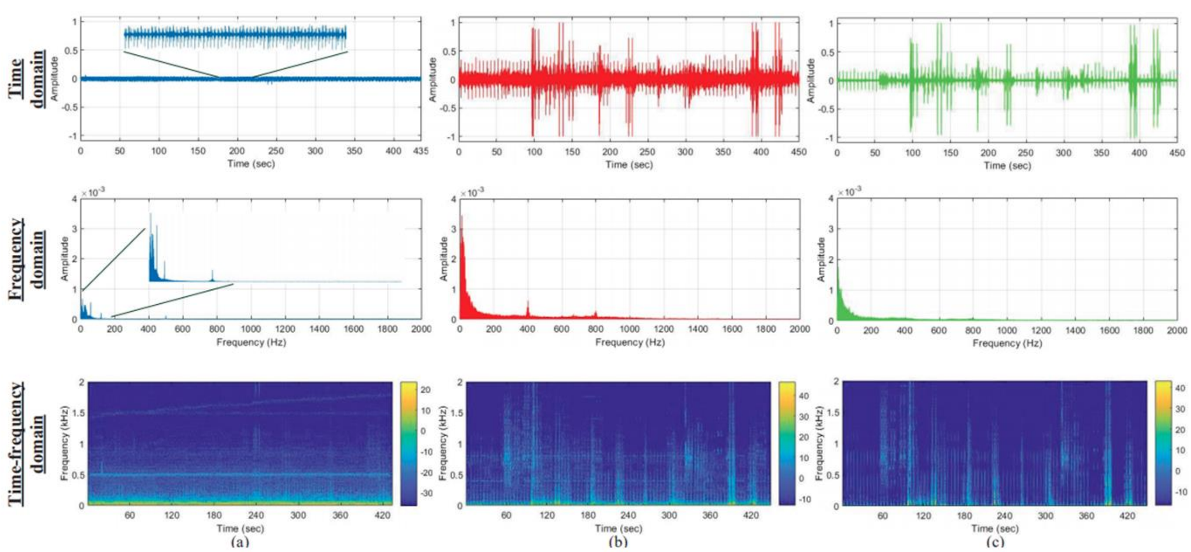

Figure 2. Breathing sounds: (a) clean, (b) nonclean and (c) denoised. Top row: time domain, middle row: frequency domain, and bottom row: time-frequency domain.