On-Line Nonintrusive Detection of Wood Pellets in Pneumatic Conveying Pipelines Using Vibration and Acoustic Sensors

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***Abstract*— This paper presents a novel instrumentation system for on-line nonintrusive detection of wood pellets in pneumatic conveying pipelines using vibration and acoustic sensors. The system captures the vibration and sound generated by the collisions between biomass particles and the pipe wall. Time-frequency analysis technique is used to eliminate environmental noise from the signal, extract information about the collisions, and identify the presence of wood pellets. Experiments were carried out on an industrial pneumatic conveying pipeline to assess effectiveness and operability. The impacts of various factors on the performance of the detection system are compared and discussed, including different sensing (vibration sensor versus acoustic sensor), different time-frequency analysis methods (wavelet-based denoising versus classic filtering), and different system installation locations.**

***Index Terms*— Acoustic sensor, large biomass particle detection, pneumatic conveying, solids handling, time-frequency analysis, vibration sensor, wavelet-based denoising, wood pellets.**

I. INTRODUCTION

BIOMASS has become one of the most commonly used renewable energy sources for power generation due to its CO_2-neutral properties [1]. Unlike pulverized coal, the handling of biomass requires an elutriation process for separating lighter/smaller particles from heavier/larger ones. The small particles (also known as dust) are pneumatically conveyed to temporary storage silos and then to the furnace directly, while the large particles, such as wood pellets are conveyed to grinding mills for further pulverization before combustion. The elutriation process is usually achieved using an air elutriator. However, due to the difficulty in maintaining the optimum control of the elutriator, wood pellets may be present in the dust flow. Direct combustion of wood pellets will give rise to many operational issues, such as low combustion efficiency, high pollution emissions, slagging, and fouling. Currently, the detection of wood pellets in dust flow is realized through regular cumbersome offline manual sampling. It is thus desirable to develop an automated on-line technique for the improved efficiency of solids handling at biomass fired power stations.

Significant research efforts have been devoted in on-line particle size measurement [2], [3]. A wide range of techniques have been developed such as those based on the laser diffraction, digital imaging and piezoelectric sensing. In laser diffraction systems, particle size distribution is determined by applying Mie theory of light scattering [4], [5]. It is a well-established technique which has been used in many commercial products. However, it has the drawbacks of high cost, complexity and requirements for highly skilled personnel to operate. Direct imaging uses a low cost charge-coupled device/CMOS camera to capture 2-D images of particles that are illuminated by external laser beams and then derives the particle size distribution through image processing [6]–[8]. This technique is cost-effective, but suffers from the contamination of optical access windows and requires regular maintenance. Piezoelectric sensing inserts an impact probe into the particle flow and derives the particle size from the piezoelectric signal due to collisions between the probe and the particles [9]. This technique is low in cost and avoids the contamination issue that optical methods generally face. Owing to its intrusive nature, however, it suffers from degradation and wear and hence requires regular replacement, although the problem may be minimized by special coatings on the impact probe.

A problem shared by all these techniques is the requirement for some form of modification to the pipeline. This can be prohibitive in an industrial environment due to cost or safety reasons. The present technique avoids the difficulties of pipe modification at the expense of detailed particle size information. The technique indicates the presence of wood pellets in the wood dust flow, allowing optimization, through monitoring and control, of the elutriation process. This can be achieved due to the natural dynamics of gas–solid flows. Particulate materials, conveyed in a pneumatic pipeline, may collide with the internal wall of the pipeline, particularly at the bends where the flow changes direction. The vibration and sound generated by the collisions between the particles and the pipe wall make it possible to nonintrusively detect the presence of wood pellets.

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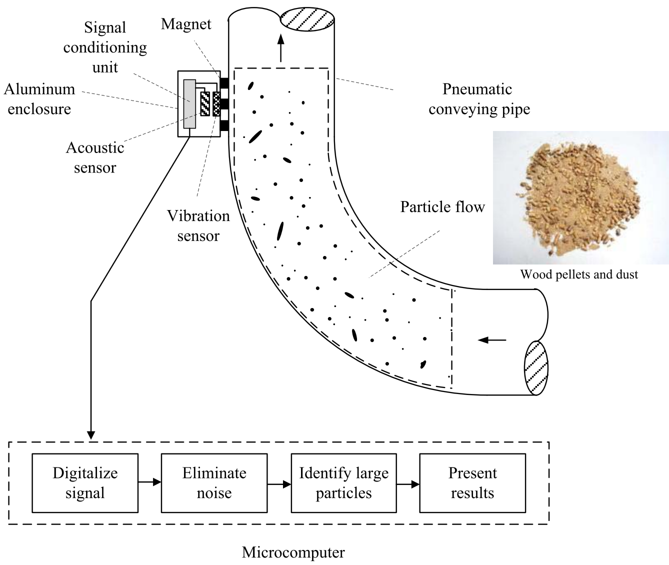

Fig. 1. Schematic diagram of the wood pellet detection system.

An acoustic sensing system for wood pellets detection, together with preliminary results, was reported at 2013 IEEE International Instrumentation and Measurement Technology Conference [10]. The work presented in this paper is the result of a continuing effort following the previous work. The main contribution of this paper lies in that it provides a comparative experimental study on the nonintrusive detection of wood pellets in pneumatically conveyed dust flow. Specifically, this paper compares and discusses the performance of different nonintrusive sensing (vibration sensor versus acoustic sensor) and time–frequency analysis methods (wavelet-based denoising versus classic filtering) in the detection of wood pellets, based on the experimental data obtained on an industrial pneumatic conveyor. The effects of sensing system installation location are also discussed.

II. Methodology

A. System Description

Fig. 1 shows a block diagram of the system developed. The sensing head consists mainly of a vibration sensor, acoustic sensor, and signal conditioning unit. The vibration and acoustic sensors capture the vibration and sound generated by the collisions between the particles and the pipe wall, respectively. The sensors, together with the signal conditioning unit, are integrated into a compact box, which can be attached magnetically to a steel pipeline. The vibration sensor (model: RS724-3162) is of piezoelectric type with a diameter of 27 mm and thickness of 0.52 mm and is mounted on the inner bottom of the box using a thin layer of steel loaded epoxy to maintain high sensitivity. The acoustic sensor (model: RS535-8168) is a typical electret condenser microphone with a sensitivity range of 100 to 16 kHz and is pointed straight at the pipeline, supported on a flexible mounting to afford isolation from vibration. The analog signals from the sensors are first preamplified and filtered by the signal conditioning unit, then digitized with a sampling rate of 44.1 kHz and processed by a microcomputer.

B. Time–Frequency Characteristics of Wood Pellet Signals

Time–frequency characteristics of ideal collision signals, obtained in the laboratory, can be used to devise an appropriate procedure for recovering noise-corrupted signals, obtained in an industrial environment. The presence of wood pellets can then be identified. This was achieved by manually injecting a wood pellet into a pipe that is identical to the one used in industry. The wood pellets tested here (mostly 5–15 mm in length in cylindrical shape) were those commonly used in biomass fired power stations, as shown in Fig. 1. Figs. 2 and 3 show the obtained signals and their corresponding power spectral densities. In the time domain, a sharp transition can be seen clearly in both signals, revealing the transient process of the collision event, the envelope of the particle signal decreasing gradually with time. In the frequency domain, the energy of both particle signals is distributed unevenly over a range of 2–22 kHz.

C. Signal Processing

1) Signal Recovery Through Denoising: Unlike the signal acquired under "quiet" laboratory conditions, the signals in an industrial environment are generally contaminated by various noises, including that from the sensor itself, surrounding sounds, and mechanical vibration of the pipeline. Signal recovery through denoising is necessary before further data analysis. Common choices include classic finite impulse response (FIR) filtering [11] and wavelet-based denoising. The performance of these two denoising methods in the present case will be compared and discussed in Section III. Before that a brief description of wavelet and wavelet-based denoising procedures is given here.

Wavelets [12] are widely used in signal analysis due to their multiresolution characteristics, having short time windows for high frequencies and long time windows for low frequencies. Given a time-varying signal $x(t)$, the continuous wavelet transform (CWT) of the signal is defined as

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{1}$$

where a is the scale parameter, b is the time parameter, and ψ is a mother wavelet. Commonly used mother wavelets include Morlet, Mexican hat, Haar, Daubechies, etc. The inverse CWT is defined as

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \frac{1}{a^2} W(a,b)\psi(a,b,t)\mathrm{d}a\mathrm{d}b \tag{2}$$

where

$$C_\psi = \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{\omega}\mathrm{d}\omega. \tag{3}$$

Since there is an infinite number of scale parameter a and time parameter b, CWT has unnecessary redundancy. Discrete wavelet transform avoids the redundancy by specially choosing an orthogonal wavelet basis, which generally corresponds to

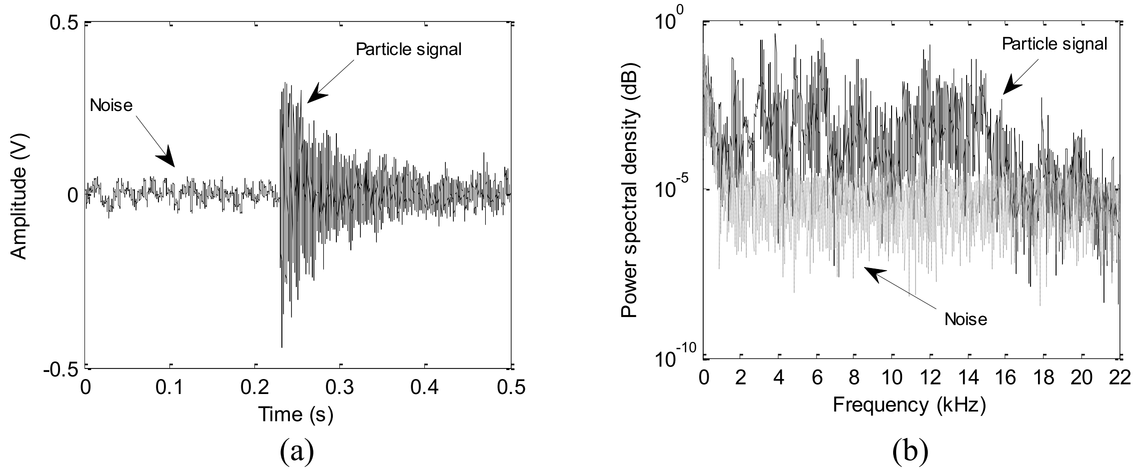

Fig. 2. Typical acoustic signal due to the collision between a wood pellet and pipe wall and its corresponding power spectral density. (a) Time domain. (b) Frequency domain.

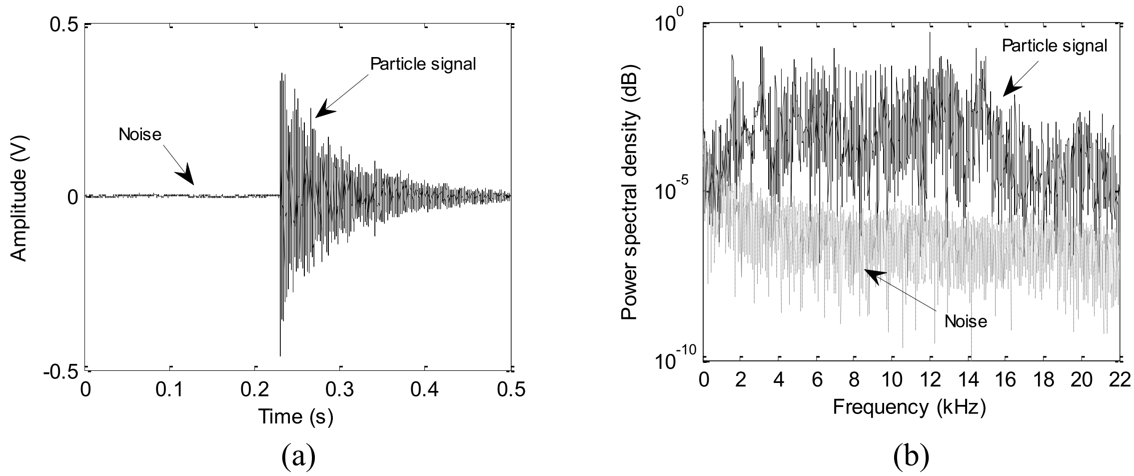

Fig. 3. Typical vibration signal due to the collision between a wood pellet and pipe wall and its corresponding power spectral density. (a) Time domain. (b) Frequency domain.

a dyadic discretization of $a = 2^m$ and $b = n2^m$ for positive integer values of m and n.

The wavelet-based denoising procedure mainly involves three steps. The first step is the forward wavelet transform of the signal. The second step is to process the wavelet coefficients (i.e., wavelet transform of the signal) with soft thresholding operator D_s or hard thresholding operator D_h

$$D_s(W,\lambda) = \begin{cases} \mathrm{sgn}(W)(|W|-\lambda), & \text{if } |W| > \lambda \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$D_h(W,\lambda) = \begin{cases} W, & \text{if } |W| > \lambda \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where W is wavelet coefficients and λ is the threshold. The third step is the inverse wavelet transform. Many different kinds of wavelet-based denoising procedures can be created by combining different choices for mother wavelet and thresholding method. In the present study, a Daubechies 3 (db3) wavelet with hard threshold is used to remove the noise to recover the signals. More detailed information about wavelet-based denoising can be found in [13] and [14].

2) Detection of Wood Pellets: As a less noise-corrupted particle signal is characterized by a sharp transition in the time domain [Figs. 2(a) and 3(a)], we take the amplitude of the sharp transition as a measure to distinguish wood pellets from wood dust. This means that a high amplitude indicates a large particle. Specifically, wood pellets are identified using an amplitude threshold A_{th} and a time sliding window with a width of W_{time}. By sliding the time window W_{time} along the signal, a sharp transition due to a large particle is identified if the amplitude of the middle point of the window exceeds A_{th} and is the maximum of the window. The total number of wood pellets identified within a period (several minutes) can be used as an indication of the proportion of wood pellets in the pipeline. The threshold A_{th} for distinguishing the wood pellets from the smaller particles can be determined through an offline sampling and calibration procedure.

D. System Evaluation

The system was evaluated in the laboratory by pneumatically injecting one hundred wood pellets onto the internal wall of the pipe with an angle of 30°. Figs. 4(a) and 5(a) show

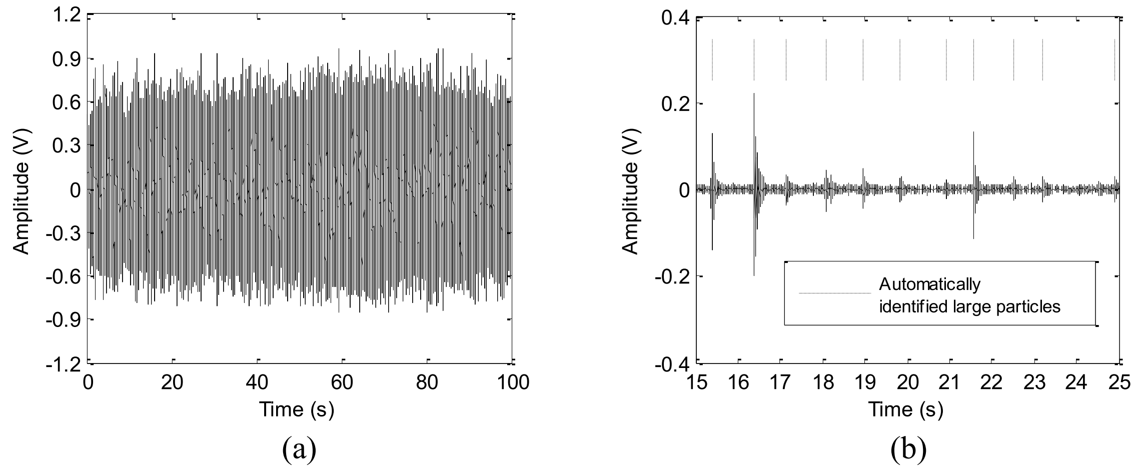

Fig. 4. Acoustic signal before and after being denoised. (a) Original. (b) After wavelet-based denoising.

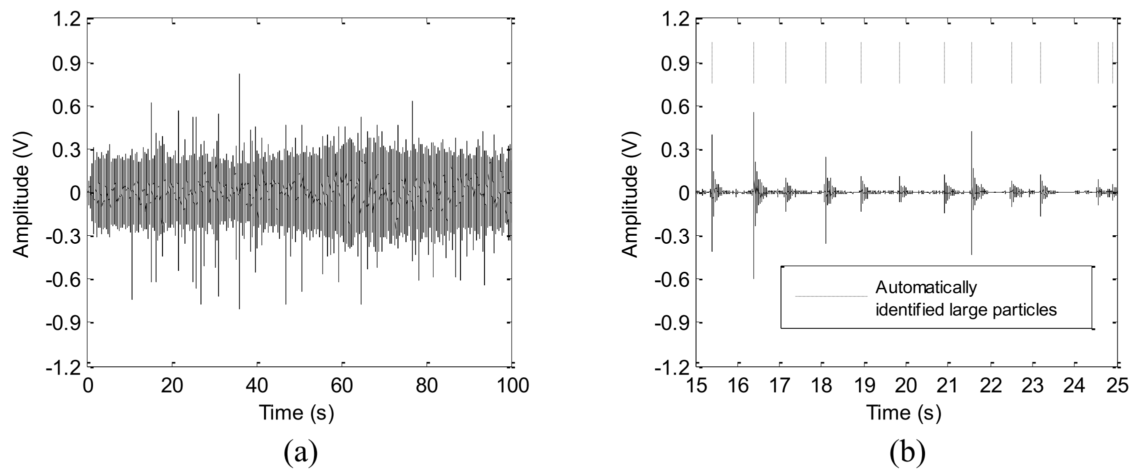

Fig. 5. Vibration signal before and after being denoised. (a) Original. (b) After wavelet-based denoising.

the obtained acoustic and vibration signals, while Figs. 4(b) and 5(b) illustrate typical denoised results, with the automatically detected wood pellets indicated by dash lines. Although the collision signals are buried in the noise produced by the nearby air compressor that is used to generate air flow for pneumatic conveying, the majority of collisions are clearly revealed after wavelet-based denoising. Both the acoustic and the vibration sensors gave satisfactory performance and detected 94 and 96 of the 100 wood pellets, respectively.

The performance of wood pellet detection depends on a number of factors, including particle density, flow velocity, air pressure, sensor sensitivity, sensor installation method, and environmental noise. The first three factors affect significantly the amplitude of the collision signal, which is used to distinguish wood pellets from wood dust and noise. However, these three factors are generally constant during the elutriation process. Apart from the sensor itself (its sensitivity and installation), environmental noise is another important factor directly affecting the detection performance of the two types of sensor. It has been found that in the laboratory environment, after denoising, the vibration sensor yields a higher signal-to-noise ratio (SNR) than the acoustic sensor, as shown in Figs. 4(b) and 5(b). This is mainly due to the fact that the

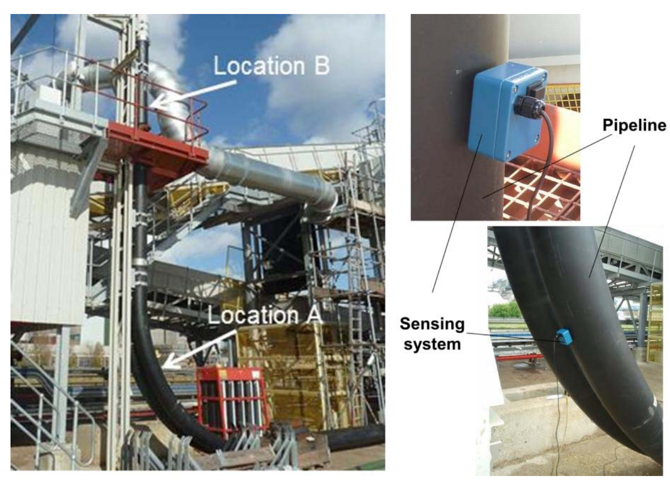

Fig. 6. Installation location of the sensing system (particles moving from A to B).

noise from the air compressor corrupted the acoustic signal much more significantly than it did the vibration signal. The effects of noise in an industrial environment on the detection performance of these two sensors will be compared and discussed in Section III.

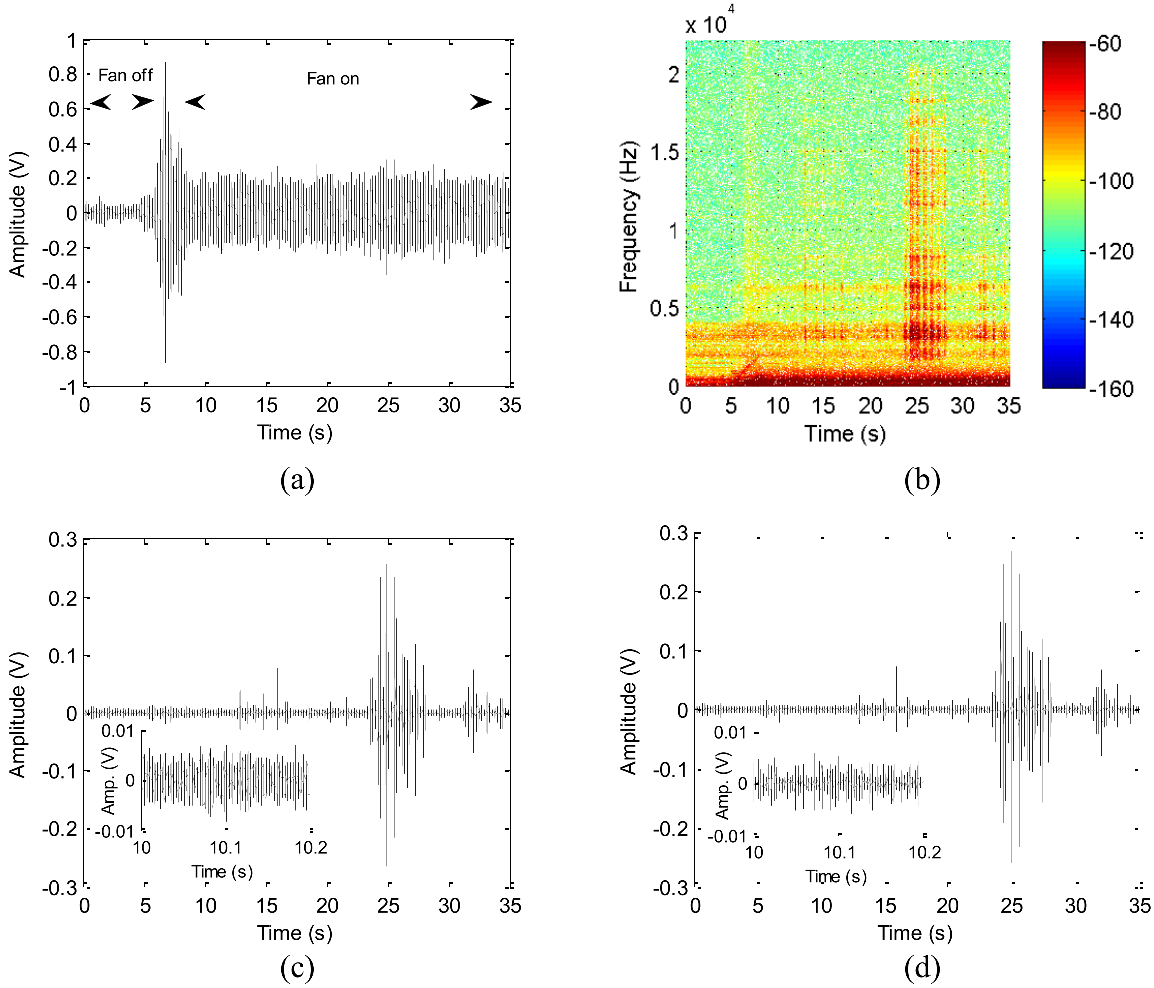

Fig. 7. Acoustic signal and its time–frequency analysis results at location A. (a) Original signal. (b) STFT of (a). (c) After FIR-based denoising. (d) After wavelet-based denoising.

III. Results and Discussion

Experiments were carried out on a pneumatic transport pipeline at a full-scale power plant to investigate the effectiveness of the proposed methodology for nonintrusively detecting the presence of wood pellets. The pipeline is of standard industrial type, which is made of mild steel with an inner diameter of 254 mm and a wall thickness of 14 mm. Two different installation locations were tested, assigned as A and B, respectively, marked in Fig. 6. Location A is at a bend of the pipeline while location B is at the vertical section three meters downstream of the bend. During the tests, the acoustic signal and vibration signal were captured simultaneously.

Figs. 7(a) and 8(a) show a typical sample of the acoustic and vibration signals, respectively, captured at the location A. It was found that the vibration sensor exhibits much better performance than the acoustic sensor in the immunity to environmental noise. When the fan of the elutriator started to run (which means the elutriator started to operate), a sharp pulse was observed in the acoustic signal [Fig. 7(a)]. After the fan started, the background noise of the acoustic signal increased significantly, indicating that the acoustic sensor is sensitive to environmental noise. The particle signals (featured as sharp transitions) contained in the acoustic signal are contaminated and buried in the background noise. On the other hand, the background noise of the vibration signal stayed unchanged before and after the fan ran, indicating its nonsensitivity to environmental noise. The collisions between the particles and the pipe wall are seen by the sharp transitions of the vibration signal in the time domain, even without further processing. The results are supported by the spectrograms of the signals, as shown in pseudo color in Figs. 7(b) and 8(b), which were obtained using a short-time Fourier transform (STFT) technique [15]. STFT is implemented by sliding a Fourier transform window along the time axis, resulting in a 2-D representation of the signal, i.e., the time–frequency distribution of the signal. The number of data points used for each Fourier transform computation was 2048. A Hamming window [16] was used for the STFT to improve the quality of the estimates and ameliorate the problem of spectrum leakage. After the fan started to run, the intensities of low frequency components in the acoustic signal increased considerably while they remained consistent in the vibration signal. The frequency range of the particle signals from both acoustic and vibration sensors is consistent with offline laboratory

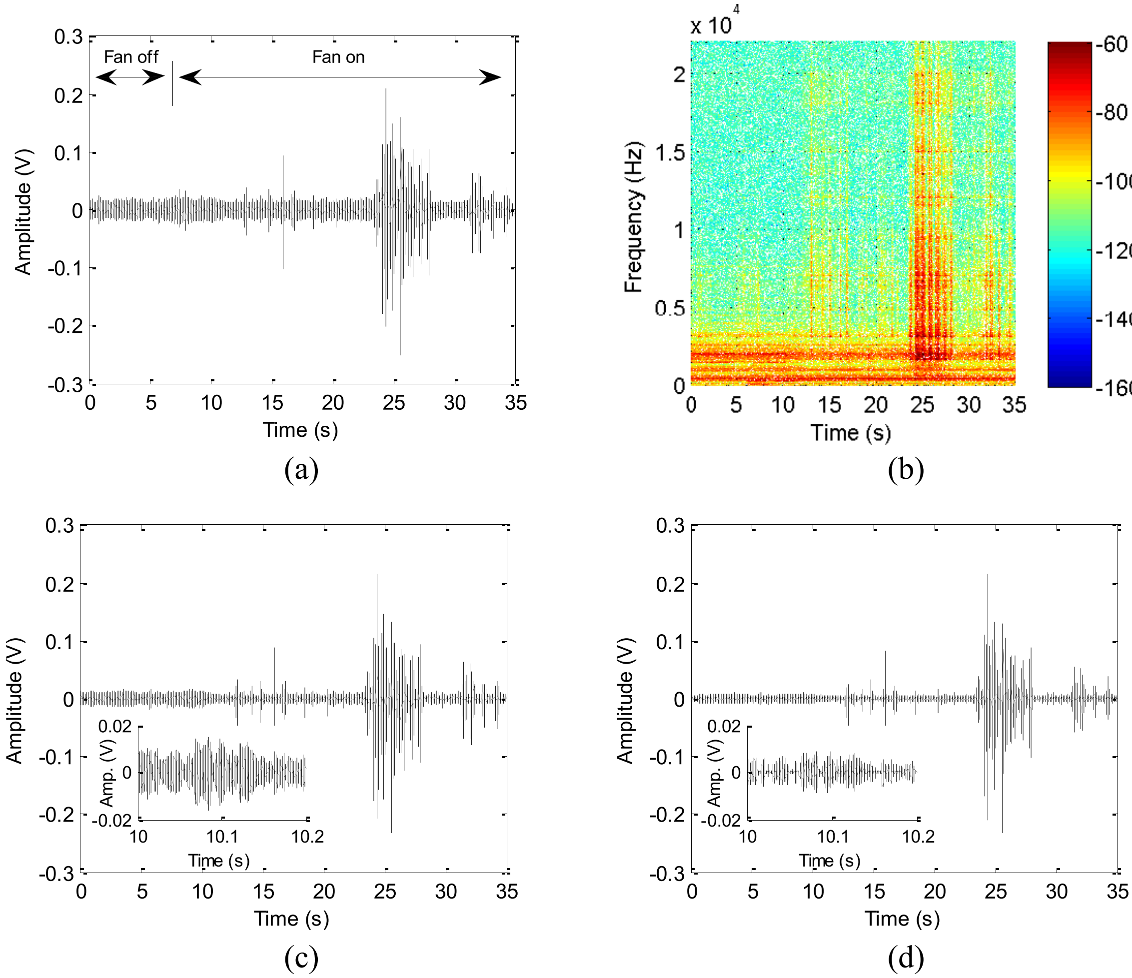

Fig. 8. Vibration signal and its time–frequency analysis results at location A. (a) Original signal. (b) STFT of (a). (c) After FIR-based denoising. (d) After wavelet-based denoising.

tests (Figs. 2 and 3), mainly from 2 to 22k Hz, while the onsite noise was mainly distributed between 0 and 4 kHz. The collision events of the particles against the pipe wall can be clearly observed as individual peaks in both STFTs. The STFTs results suggest that both sensor signals can be used to identify wood pellets if appropriate noise filtering is used.

The performances of a classic FIR filter and wavelets in denoising are compared in Figs. 7(c), (d) and 8(c), (d). Considering the energy distributions of noise and particle signals, a 256th-order FIR high-pass filter with a cutoff frequency of 2 kHz was adopted. A Daubechies 3 (db3) wavelet with hard threshold was used to remove the noise and recover particle signals. Although the resulting amplitudes of the particle signals (peaks) are similar in both methods, the remaining noise after wavelet denoising is much lower than that after classic FIR filtering (as illustrated in the insets), indicating that in the present case wavelet transforms are capable of providing a higher SNR than classic FIR filtering. The superior performance of wavelet transforms over FIR filtering can be explained by the fact that the distribution of noise overlaps with that of particle signals in the frequency domain. Although the classic FIR filter removes only the noise below its cutoff frequency, but not the noise in the frequency range that particle signal also resides in, wavelets are capable of reducing noise across the whole frequency domain.

The selection of wavelet db3 for signal denoising in the present study is based on two criteria: the SNR after denoising and the computation time. As shown in Figs. 9 and 10, three commonly used wavelet families with different thresholding methods were tested on the acoustic signal captured at location A, including Daubechies (dbN), Symlets (symN), and Coiflets (coifN), where N represents the number of vanishing moments [17]. It has been found that hard thresholding and soft thresholding gave similar performance. The "db1"-based denoising performs fastest, but has the lowest SNR among the tested wavelets, due to the simple wavelet form of "db1." The SNRs after other wavelet-based denoising are about 51–55 dB. Within one wavelet family, the SNR improves generally with the increasing number of vanishing moments at the expense of processing time. This can be explained by the fact that wavelet transforms decompose and analyze a signal by projecting the signal on to a set of blocks, generated from a mother wavelet at different scales and positions; on the one hand, the wavelets with an increased number of vanishing moments may be more representative of the collision signals, resulting in improved

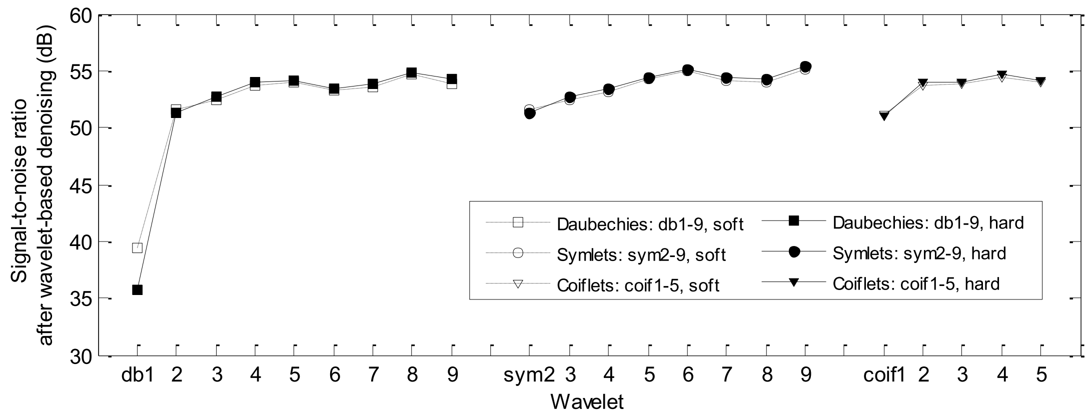

Fig. 9. SNR after denoising using different wavelets.

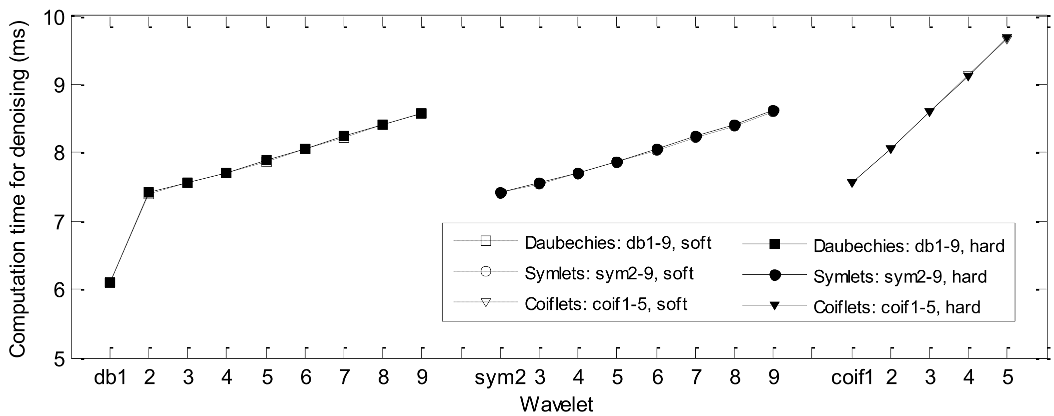

Fig. 10. Computation time for denoising 1 s data using different wavelets.

denoising performance, but on the other hand, the increased number of vanishing moments introduced more computation. The wavelet db3 with a hard threshold is selected here due to its satisfactory denoising performance and comparatively low computation requirement. Other wavelets, such as db4, sym3, and coif 2 could also be used in the present application.

The effects of installation location on system performance were also investigated. Figs. 11(a) and 12(a) show a sample of the two signals captured at location B. Figs. 11(b) and 12(b) depict the corresponding results of the signals filtered by wavelets. For succinctness, STFT and FIR results are excluded here. The noise contained in the vibration signal is little affected by the location, while the noise in the acoustic signal at location B is higher than that at location A. The increased noise in the acoustic signal can be explained by the fact that location B is closer to an exhauster fan which was one of the major noise sources during the onsite test. For both sensors, the amplitudes of particle signals at location B are slightly lower than that at location A. This may be because that location A is further away from the bend of the pipe, and hence the intensity of collisions between the particles and the pipe wall are relatively weaker. However, the sharp transitions, indicating the collision events, are evident in the filtered signals at both locations. The results imply that the installation point of the sensing system is not critical, provided that the system is installed near the bend. This is very useful because not all locations along the pipeline are convenient to be shielded and connected to the control room for practical use.

It should be noted that, in the above-mentioned tests, although the vibration sensor performs much better than the acoustic sensor in terms of immunity to environmental noise, the SNR of the acoustic signal is higher after the denoising, as shown in Figs. 11(b) and 12(b). This suggests that the acoustic sensor may have a higher sensitivity to both collisions and noise than the vibration sensor, and if the environmental noise is preknown, the acoustic sensor may be capable of providing a better detection of wood pellets, assuming a properly designed filter. However, environmental noise may vary considerably with time, a preconfigured filter may not perform satisfactorily. Therefore, a combination of the two sensors may provide a more reliable solution to the detection problem.

Figs. 11(b) and 12(b) also illustrate the automatically detected wood pellets (indicated by the dash lines). The wood pellets are identified using the sliding-window approach (Section II-C). It should be emphasized that the number of peaks identified by the system provides qualitative information about the presence of wood pellets, rather than absolute quantity. This is because only a small fraction of particles in the conveying pipeline collide with the pipe wall. However, statistically, the more wood pellets the dust flow contains, the higher is the likelihood of the occurrence of collisions between the particles and the pipe wall. In addition, as compared to small particles, wood pellets are much more likely to collide

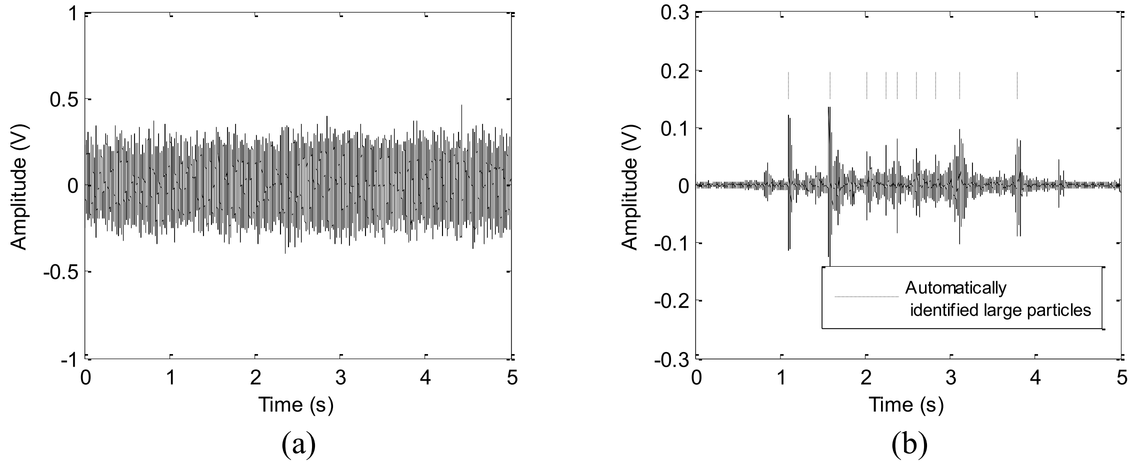

Fig. 11. Acoustic signal and its time-frequency analysis results at location B. (a) Original. (b) After wavelet-based denoising.

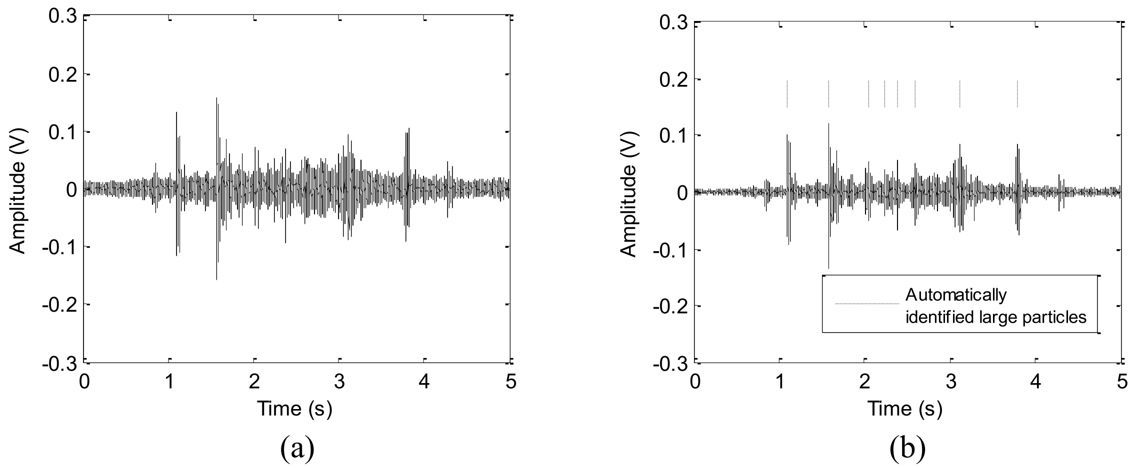

Fig. 12. Vibration signal and its time-frequency analysis results at location B. (a) Original. (b) After wavelet-based denoising.

with pipe wall due to their larger inertia. Therefore, the change in the number of identified wood pellets can be used as an indicator for the improvement or deterioration of the elutriation process.

IV. Conclusion

A methodology has been presented for nonintrusively detecting the presence of wood pellets in pneumatic conveying pipelines. Experimental work has been carried out on an industrial pneumatic conveyor at a biomass fired power station. The results presented have demonstrated the feasibility and effectiveness of the proposed methodology. Several conclusions can be drawn from the results presented. First, both vibration and acoustic sensors can be used to detect collisions between particles and the pipe wall. In the tested industrial environment, the vibration sensor performs better than the acoustic sensor in terms of immunity to the environmental noise, while the acoustic signal has a higher SNR than the vibration signal if appropriate denoising is applied. The two complementary sensors should, therefore, be combined to enhance the performance of the system. Second, wavelet-based denoising provides a higher SNR than a classic FIR high-pass filter in the present application, due to the fact that while a classic FIR high-pass filter removes only the noise below cut-off frequency, wavelet is capable of denoising across the whole of the frequency domain. Third, the approach is insensitive to the installation location, offering further flexibility in practical application. In addition, the sensing system has the advantages of simple system structure, low cost, easy installation, and low maintenance. It is envisaged that such a system could help power plant operators to optimize the elutriation process, leveraging improved overall plant efficiency, and reduced emissions.

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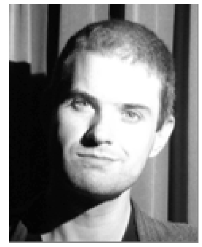

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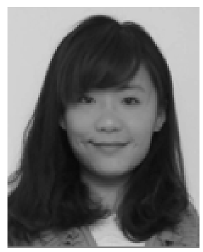

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