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Noise reduction by using wavelet transform in charge signal acquired from an electrostatic inductive sensor

T. Hussain [a,b,*], T. Deng [a], M.S.A. Bradley [a], D. Armour-Chélu [a], J.R. Pillai [b], S. Saadat [b], W. Kaialy [c]

[a] The Wolfson Centre, University of Greenwich at Medway Kent, ME4 4TB, UK
[b] Military Technological College, Al Matar Street, Muscat, Oman
[c] School of Pharmacy, Faculty of Science and Engineering, University of Wolverhampton, UK

1. Introduction

In recent years, the use of the electrostatic inductive sensor is getting more popular, and the inductive sensor has been serving different industries for many years. Charge measurement using the non-contact method, which has been developed based on an electrostatic inductive sensor, offers numerous advantages for the investigation of charge distribution in terms of bipolar charging in a population of particulate materials [1–7]. The pulses present in the charge signal acquired as a result of moving charged particles through the sensor indirectly represent the polarity and magnitude of the charge on moving particles. During signal acquisition, the charge signal shows a mixture of characteristics including signals of interest (transient pulse peaks), noise, drift in the baseline, and the existence of overlapping peaks, making it difficult to extract the distribution of charges in a population of particles. A signal processing method is then required to reduce the level of noise and thus improve the signal-to-noise ratio, detect the peaks (positive and/or negative), and present the charging distribution data required to understand the complex phenomenon of turbocharging.

Vaseghi briefly reviewed several types of noise and signal processing methodologies and their application to reduce the noise level in a range of different types of signals, such as modern telecommunication, information system processing, and adaptive network management [8]. A charge signal is usually time-varying, non-stationary, and contains the transient pulses (peaks) representing the moving charged particles through the sensor [5]. Therefore, for such signals, data analysis and modelling methods in multiple scales (where frequencies change over time) are better suited for noise reduction than methods where frequencies don't change over time. Short-time Fourier transform and wavelet transform are useful methods to determine the frequency content in a signal [9]. However, the Fourier transform provides a less efficient representation for those functions which contain discontinuities in comparison to the short Fourier and Wavelet transform. Short-time Fourier Transform (STFT) is a useful tool for the signal where noise distributes uniformly in the entire frequency domain [8,10]. One of the main limitations of the short-time Fourier transform is that, once the window size is fixed, it remains the same for all frequencies despite some signals requiring a more flexible approach [9]. One of the solutions to this problem is the use of wavelet transform which allows multi-resolution analysis to examine functions at different levels.

Xu et al. used the electrostatic inductive sensor to measure the particle mean velocity during pneumatic conveying [11]. Due to the noise factor in the acquired signal from the electrostatic inductive sensor, the peak frequency f_{max} was submerged in local frequencies which can misinterpret the results to measure the particle mean velocity [11]. Xu et al. adapted the multi-scaling wavelet-based filtration method for the power spectrum, which effectively overcomes the issue of noise factor and improves the particle mean velocity measurement accuracy [11]. in recent years, many researchers have used wavelet transform as a tool for reducing the noise level in raw data. These solutions employ windowing techniques with variable-sized regions matched to the signal scale depending on the chosen mother wavelet transform rather than the size of the window [12–17].

The presence of noise in raw signal causes a continuous background signal which sometimes completely takes over the signal from those particles containing low-level charges and as a result, the ability of the sensor to detect charge distribution gets limited [18]. This paper highlights for the first time the use of wavelet transforms to denoise the charge signal to improve the SNR of a charge signal which contains the transient peaks generated as an abrupt change and contains the information of interest. In comparison to the traditional noise reduction method Wavelet transform successfully isolate and minimize the noisy

* Corresponding author. The Wolfson Centre, University of Greenwich at Medway Kent, ME4 4TB, UK.
E-mail address: go2tariq@gmail.com (T. Hussain).

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and preserves the shape and quality of the signal while achieving improved SNR.

2. Wavelet transform

Wavelet transform is a signal processing technique where the signal is successively decomposed into various resolutions with the help of multiple high and low pass filters. Compared to the Fourier transform, which is also used for signal analysis, the wavelet transform allows for the analysis of non-stationary signals and preserves the temporal characteristics of the raw data [19–21]. Wavelet transform is based on a windowing technique with variable-sized regions matched to the signal scale depending on the selected mother wavelet transform [12]. This work focus on discrete wavelet transforms (DWT), which is a special type of wavelet transform. DWT is ideal for denoising the signal and compressing the signal and images. With DWT, the raw data signal is passed through two complementary filters, low pass filter h(n) and high pass filter g(n). The coefficients of these filters are determined by the mother wavelet. Equations (1) and (2) present the mathematical representation of this process which is a convolution of the signal with the impulse response of the filters to map out the wavelet coefficients [22].

$$Y_{high}(k) = \sum_{n} x(t) * g(2K - t) \tag{1}$$

$$Y_{low}(k) = \sum_{n} x(t) * h(2K - t) \tag{2}$$

3. Experimental tests

3.1. Solids material

Glass beads S-100 (nominal particle size from 45 μm to 60 μm) used as a test material were provided by Silibeads, Germany. The glass beads were charged in a plastic stoppered test tube (9.0 cm high × 2.5 cm in diameter) in whirl mixer (PV-1 vortex mixer, Cambridge) for 5 min at the speed of 1200 (rpm).

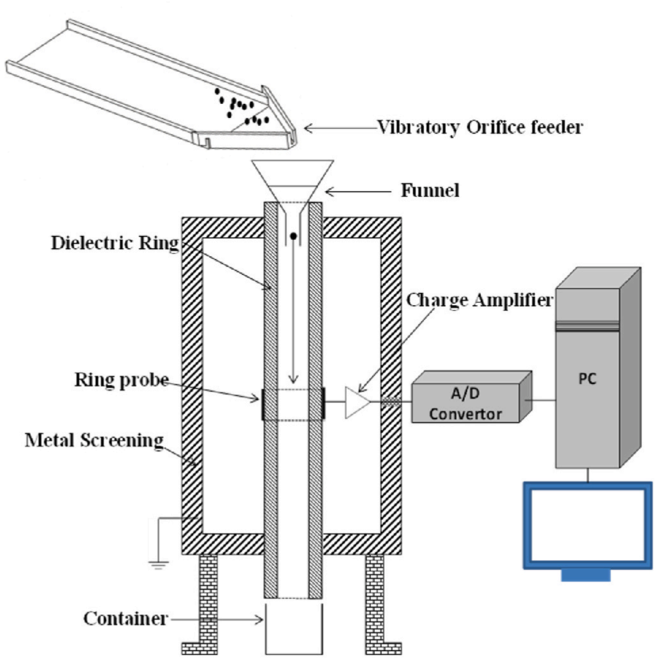

Fig. 1. Schematic diagram of experimental test facility [2,5].

3.2. Experimental setup

Fig. 1 illustrates the experimental setup. A grounded shield around the inductive sensor was installed to resist electromagnetic interference. Charged glass beads were fed into the sensor using vibratory orifice feeder. Experimental work was undertaken at a retention time of 6 s and in temperature and humidity control room (20 °C, 50% RH). The method assumes particles moving under central flow condition.

3.3. Signal acquisition and analysis

The data acquisition system NI 6034E from National Instruments with high performance NI CB-68LPR connector block was used to convert the analogue signal into the digital domain. Fig. 2 shows a typical example of the voltage signal from the inductive charge sensor for glass beads with nominal particle size distribution of 45–60 μm travelling at 1.10 ms^{-1} velocity over a 6s time interval. The charge amplifier configured as a pure integrator with capacitance 10 pF, for a particle carrying charge +2o fC the output expected volt peak will be +2 mV. The voltage signal shows a mixture of numerous characteristic signals of interest (peaks), noise, as well as over lapping peaks which cannot be dismissed. In-situ there may arise many electrical disturbances which contribute to the background noise in the signal.

The noise causes a continuous background signal which sometime covers the amplitude of the signal of interest having positive and/or negative peaks with amplitudes ≤2 mV. The estimated minimum amplitude of the peaks in the signal representing the charged particle moving through the sensor is 2 mV.

4. Results and discussion

MATLAB wavelet toolbox provides a platform to implement the noise reduction steps with the help of wavelet transform. Equation 3 was used to choose the mother wavelet Daubechies wavelet filter of order 6 (db6) as an optimal mother wavelet because it maximizes its cross-correlation coefficient with the signal of interest as compared to others. Level 5 of decomposition was used as the optimal choice for decomposition because other choices can cause transient peaks to disappear. The right thresholding technique is crucial to reducing the level of noise. In both soft thresholding and hard thresholding, coefficients are less than thresholding values set to zero. As shown in Fig. 3, thresholding has a positive effect. MATLAB's Wavelet toolbox includes a universal thresholding method that can be used to apply soft and hard thresholding techniques. The processed signal showed the suitability of the hard thresholding method, as the signal-to-noise ratio (SNR) is improved from 3.52 dB to 10 dB by embracing this technique.

Fig. 4 shows the comparison between the raw data obtained and the signal processing for noise reduction. One of the main advantages of the proposed method is that it preserves the shape and quality of the signal while achieving improved SNR. When compared to the other methods, such as low pass filtering and FFT (presented in Fig. 3), these methods besides removing the noise from the signal, also make the signal smooth and remove the peaks that contain the desired information. In such a case, the signals of interest are compromised as can be seen in Fig. 3.

Fig. 4 also shows the difference between the processed signals by

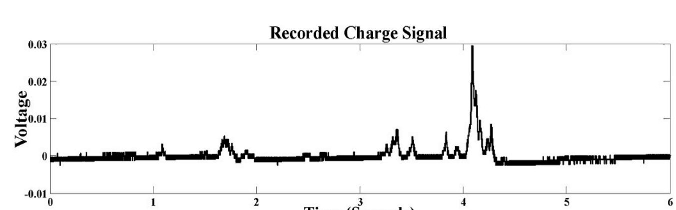

Fig. 2. Raw data for further processing noise reduction.

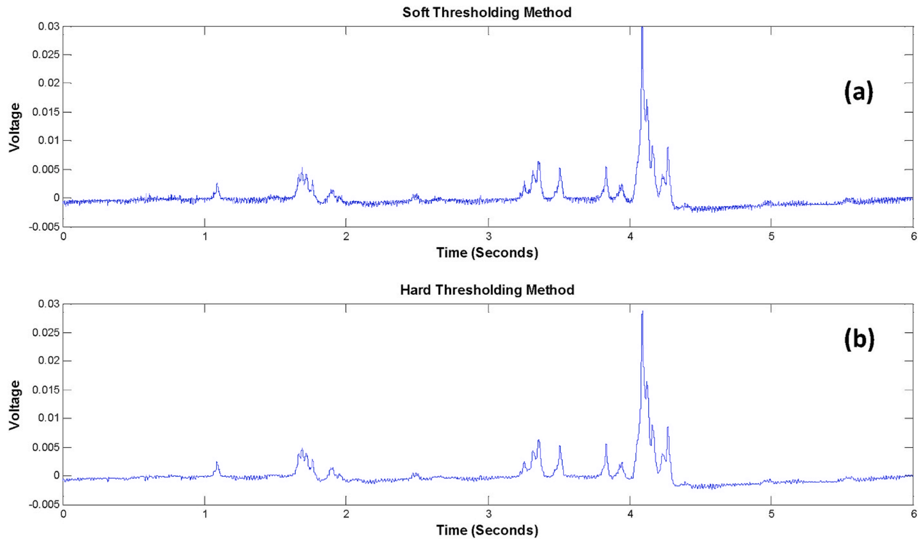

Fig. 3. Implication on selection of thresholding type (a) Thresholding of wavelet coefficients with the help of hard thresholding method, (b) Thresholding of wavelet coefficients with the help of soft thresholding method.

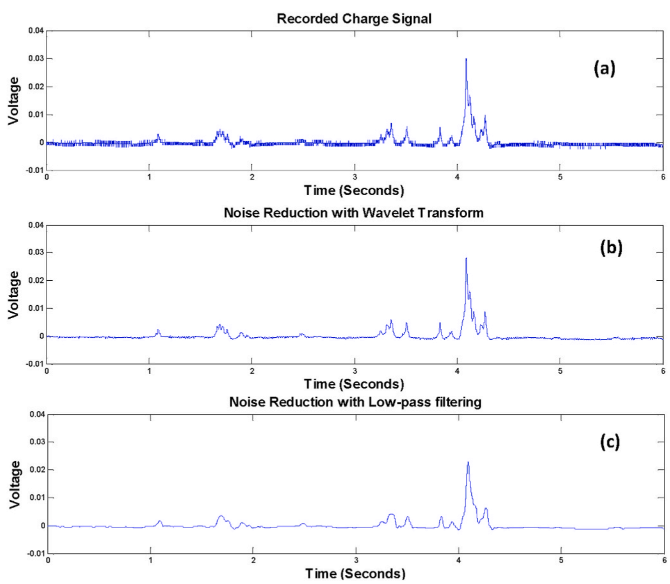

Fig. 4. Recorded charge signal and minimising the noise level (a) Recorded charge signal, (b) Noise reduction with the help of wavelet transform and (c) Noise reduction with the low pass filtering.

using two different methods. Fig. 4 (a) shows the filtration with the help of a low pass filter by using Fourier analysis, whereas Fig. 4 (b) shows the filtration of signal with the help of wavelet transform. The results clearly show that in the case of wavelet transform the number of peaks and quality of the signal compared to the original signal remains the same, only the noisy component in the signal is removed to achieve better SNR. Fig. 5 explains the successful implementation of the noise reduction method and peak detection method on raw charge signal data and presents the result in charge distribution in a population of particulate. The processed signal contains positive and negative peaks and their magnitude which contains information of bipolar charge distribution in the population of particulates passing through the sensor [2 5].

5. Conclusion

This article presented investigations on the signal acquisition, recording, and post-test run processing to denoise the charge signal obtained as a result of charged particles fed into the sensor. Traditional methods used for noise reduction in the signal just remove the noise from the peaks, however, such a solution can also compromise the information of interest. To isolate and minimize the noisy component from the charge signal, the orthogonal wavelet transforms show significant advantages. Results clearly indicated that the wavelet transform used for the signal processing has better efficiency in noise reduction from the raw data than the other noise reduction method while preserving the

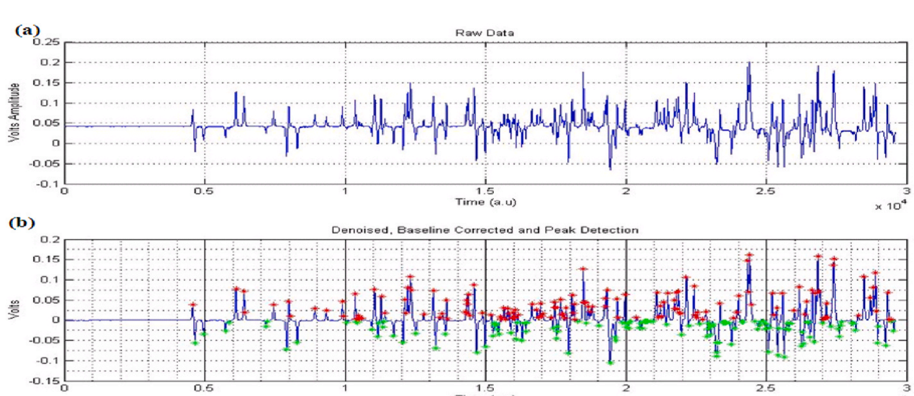

Fig. 5. Method successfully detect the positive and negative peaks in the signal [5].

shape, magnitude, and a number of peaks, which was critical for determining the charge results. This study will be helpful to go to the next level to monitor charging characteristics in real-time monitoring in harsh industrial environments.

Declaration of competing interest

I declare that all information provided is correct according to the best of my knowledge and there is apparently no conflict of interest to show.

Data availability

No data was used for the research described in the article.

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