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RESEARCH PAPER

Analysis of Changes on Mean Particle Size in a Fluidized Bed using Vibration Signature

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Abstract

Vibration signals were measured in a lab-scale fluidized bed to investigate the changes in particle sizes. Experiments were carried out in the bed with a different mass fraction of coarser particles at different superficial gas velocities, and probe heights. The S-statistic test evaluates the dimensionless squared distance between two attractors reconstructed from time series of vibration signals. Values of parameters needed for the attractor reconstruction were derived from time series. These parameters consist of time delay, embedding dimension, bandwidth, and segment length with the values of 1, 35, (0.4-0.8), and (300-400), respectively. To reduce the sensitivity of the S-statistic to small changes in superficial gas velocities, the vibration signals were normalized in order to apply the attractor comparison test. The results showed that the attractor comparison can be a reliable technique for detecting particles size changes in fluidized beds even with small changes in the amount of coarser particles. The sensitivity of the method to particle size changes was decreased with an increase in superficial gas velocity. The results also show that the S-statistic test was almost independent of the measurement position of the vibration signals.

Keywords:
Agglomeration,
Hydrodynamics,
Fluidization,
Particle Size Changes
S-Statistic,
Vibration Signature

Introduction

Gas-solid fluidized beds are widely used in physical and chemical processes, such as agricultural, food, metallurgical, environmental and pharmaceutical. Some advantages of these beds are efficient contact between fluid and particles, thermal uniformity, enhanced mixing and high heat and mass transfer rates as compared to conventional unit operations. In spite of their advantages, fluidized beds have a number of disadvantages limiting their industrial applications. Hydrodynamics of fluidized beds may be altered over time due to either imposed or unwanted changes in superficial gas velocities and mean particle size which may result in partial or complete defluidization of the bed due to the agglomeration or sintering of bed particles. High-temperature conditions [1-3], existence of sticky particles [2-4], and chemical reactions [2,3] have been known to increase particles size in fluidized beds to a high extent. This phenomenon reduces solid mixing and may lead to partial defluidization of the bed,

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distributor blocking, an undesirable distribution of the gas, local hot spots, and finally, an unwanted bed shut down [5]. Therefore, early detection and monitoring of undesirable hydrodynamic changes are important in order to take preventive actions for managing bed failure.

There are several intrusive and nonintrusive measurement techniques for monitoring the hydrodynamics of fluidized beds. The efficient monitoring approach toward the characterizing of bed hydrodynamics requires reliable data, which highly depends on measuring techniques. However, as the hydrodynamics of gas-solid fluidized beds are governed by complex nonlinear dynamics occurring in the bed (such as bubble formation, coalescence eruption, and passage as well as particles behaviors), the hydrodynamic state of the bed at a given conditions could not be determined by linear methods, and many investigators [6,7] showed that fluidized beds exhibit chaotic and nonlinear behavior. For example, the attractor comparison method in the state space [1] has been used for analyzing the nonlinear characteristic of bed. This method is based on attractor reconstruction.

Pressure fluctuations (PFs) signals have been widely used for fluidized bed hydrodynamic characterization. Kai and Furusaki [8] used PFs to evaluate the fluidization quality of the catalytic hydrogenation of carbon dioxide to methane in a fluidized bed. Also, many investigators focused on pressure signals to determine the effects of agglomeration phenomena in fluidized beds at high temperatures [1]. Quality of fluidization using short-term predictability and variance of PFs was monitored by Schouten and van den Bleek [9] and Chong et al. [10]. Furthermore, pressure signals were used to determine gradual particle size changes in fluidized bed combustors and circulating fluidized beds [11,12]. Recently, a nonintrusive method based on the vibration signature of the bed was proposed by Abbasi et al. [13] to investigate the fluidized bed hydrodynamics. Vibration signals have been used to determine minimum fluidization velocity, transition velocities from bubbling to slugging and from bubbling to turbulent regime in gas-solid fluidized beds [13,14]. Measured vibration signals were successfully investigated for monitoring and the on-line detection of bed fluidity changes in a large-scale gas-solid fluidized bed after liquid injection [15]. Staniforth and Quincey [16] have used an intrusive measurement technique for granulation monitoring in a planetary mixer via a swing-arm probe mounted in the mixer. Changes in displacement, velocity, and acceleration were monitored and investigated for detection of the granulation end point. They found that displacement and velocity monitoring have a higher sensitivity to granulation changes than acceleration values.

There are limited studies on changes in particle sizes detection via analysis of vibration signals. The present study focuses on using vibration signatures of a lab-scale fluidized bed for early detection of changes in particle sizes representing agglomeration and analyzing the bed vibration signatures using the S-statistic method as developed by Diks et al. [17]. This method was first introduced by Van Ommen et al. [5] to early detection of agglomeration using pressure fluctuations. Shiea et al. [18] applied the attractor comparison method to vibration signals in a fluidized bed for predicting the onset of the turbulent regime. In this study, the early detection of changes in particle sizes is performed by comparing reconstructed attractors of the bed vibration signatures in the state space domain.

Experimental

Experiments were carried out in a gas-solid fluidized bed made of a Plexiglas of 15 cm inner diameter and 200 cm height. A perforated plate with 435 holes of 7 mm triangle pitch was used as the distributor of air. Air at ambient temperature was supplied by a compressor to the bottom of the column and the flow rate was controlled by a mass flow controller. A cyclone, placed at the top of the bed, was used to separate particles from the air at high superficial gas velocities and returned them back to the bed. The whole system was electrically grounded to minimize electrostatic effects. The performed experiments are simulated by stepwise changes in particles size leading to significant changes in mean particle size.

In these experiments, two types of S_1 and S_2 sands are used. The particle size distribution of both types of sand was determined by sieving analysis method and presented in Table 1. The mean diameter of sands is calculated using the following equation:

$$\overline{d_p} = \frac{1}{\sum_i (\frac{X_i}{d_{p_i}})} \tag{1}$$

where X_i is the fraction of total mass that remained on ith mesh and d_{pi} is the hole mean diameter of ith and (i-1)th mesh. The main properties of two types of sand are given in Table 2. In this table, the minimum fluidization velocities of the sands calculated by the correlation proposed by Wen and Yu [19] and the transition velocities are calculated by Bi and Grace expression [20]. In order to investigate the sensitivity of the method to changes in the particle size, the experiments were first carried out in a bed with S_1 sand type and then substituting 2.5%, 5%, 7.5% and 15%of the bed particles with S_2 sand type. The experiments were carried out at aspect ratio of 2 and superficial gas velocities ranging from 0.2 to 0.8 m/s.

Table 1. Size distribution of sand particles used in this study

d_{pi} (μm)	Weight Fraction	
	S_1	**S_2**
107.5	0.035	0
137.5	0.04	0
165	0.05	0
215	0.325	0
302.5	0.55	0
460	0	0
500	0	0
550	0	0
655	0	0.02
780	0	0.19
925	0	0.615
1090	0	0.16
1180	0	0.015

Two DJB accelerometers with a sensitivity of 305.6 and 307.5 mV/ms^{-2} were used to measure vibrations of the bed. Accelerometers produced analog signals that were converted to digital signals using the B&K PULSE system with 3560 hardware. The output of sensors was based on voltage. Then accelerometers were calibrated based on the gravitational acceleration. Therefore the unit of vibration signatures from microvolt was converted to m/s^2. In order to examine the effect of probe position on the vibration, the accelerometers were mounted on the column at 5, 10, 15 and 20 cm above the distributor plate by means of magnets to reduce the sudden fluctuations. To ensure the reproducibility of the measured signals, the measurements were repeated three times at the same operating conditions.

The sampling frequency and time were set to 65 kHz and 30 s to prevent information loss from signals. These were determined based on two criteria. According to the frequency spectrum of the vibration signals, the main bed frequencies were limited to 10 kHz. On the other hand, according to the Nyquist criterion, the sampling frequency (f_s) should be greater than twice the highest frequency component. Considering that the dominant frequency spectrum of vibration fluctuations in a fluidized bed is less than 10 kHz, a sampling frequency higher than 20 kHz is enough. So the sampling frequency for vibration fluctuation signals was set to about 65 kHz, which is much more than 10 kHz, satisfying the Nyquist criterion. Also, Rulle [21] showed that the correlation dimension (d_c) of the system should be less than $2\log10^N$, where N is the number of data points, thus by measuring the correlation dimension, the number of points which is enough for attractor reconstruction can be determined. For a sample vibration signal of about 65 kHz, the correlation dimension of the system is determined about 12.485 [18]. According to the suggested method by Ruelle [21], the number of required points for vibration time series is 1747800. Thus, in this work, the sampling frequency and sampling time were set at 65 kHz and 30 s.

Method of Analysis

Theory

To characterize the nonlinearity behavior of the measured time series of a fluidized bed, first, it is necessary to reconstruct an attractor of the time series. The simplest method to reconstruct an attractor is the delay vector method applied in fluidized beds by many researchers [5,22,23]. In this method, a single measured variable of a system can be used for reconstructing of attractor [24]. The reconstructed attractor contains all properties of the original signals [24]. A sampled time series (e.g., vibration signal) $x(i)$ with i=1, 2 ,3,… , N can be represented in the state space as a set of s(i) [23]:

$$s(i) = (x(i), x(i+\tau), ..., x(i+(\mathrm{m}-1)\tau)) \tag{2}$$

where τ and m are time delay and embedding dimension, respectively. For the attractor reconstruction with this method, the embedding parameters (τ and m) should be determined carefully. In this method, every m points of $T_w = m\tau\Delta t$ (time window) on time series is converted to one point of the attractor in m-dimensional state space.

To compare two delay vectors (reconstructed attractors), a statistical indicator should be defined. The S-statistic test proposed by Diks et al [17] compares two delay vector distributions in order to describe the behavior of the bed at two different states, known as reference and evaluation time series. When two sets are generated by the same mechanism, the S-statistic value has a mean value of zero and the standard deviation of unity, therefore the null hypothesis is valid [17]. The S-value is calculated using the following equation [17]:

$$S = \frac{\hat{Q}}{\sqrt{V_c(\hat{Q})}} \tag{3}$$

where Q and Vc are the unbiased estimator of the squared distance of two delay vector distributions and variance of Q in the state space, respectively. If the calculated S-value is greater than 3, significant changes have taken place in the hydrodynamics of the bed and the null hypothesis is rejected with a confidence level of more than 95% [17]. The S-test shows changes in the attractor by observing it as a whole identity instead of focusing on just one property. This method can detect any changes that happen in the system.

Input Parameters Settings

For the attractor reconstruction in the state space, followed by the S-statistic calculation, it is required to obtain the input parameters. These parameters, which include the time delay, embedding dimension, bandwidth, and segment length, strongly affect the performance of the method and should be chosen properly. Their identification procedures and the optimum value of these parameters are discussed below.

The reconstructed attractor based on the embedding dimension should have the same geometrical properties as the original phase space attractor of the system. There are various methods for determining this parameter. In this work, the time window method was used. Zarghami et al. [23] showed that after specifying an optimum value for the time window (T_w), the embedding dimension (m) can be calculated by:

$$m = \frac{T_W}{\tau \Delta t} \tag{4}$$

Zarghami et al. [23] also indicated that for attractors with a dominant periodic characteristic, the average cycle time is a good choice for determination of the time window. This is due to the fact that one cycle corresponds to the physical phenomena taking place in the bed such as bubble passage or coalescence [25]. The optimum value for the time window can be chosen one or one-quarter of the average cycle time [5,22,26]. The average cycle time is defined as the length of the time series (in time unit) divided by the number of cycles. It should be noticed that for the calculation of the embedding dimension, τ is usually considered equal to 1 [23].

The segment length (L) is another main parameter of the S-test which is applied to eliminate dynamic correlations between successive points in the state space. As recommended by Theiler [27], the value of time delay can be assumed as an appropriate segment length. Thus, the method for determination of the time delay parameter can be used for the segment length calculation.

In this work, the autocorrelation function (ACF) [6,26,28,29] and mutual information function (I) [6,26,30] were used for selection of the segment length. Addison [26] and Kantz, and Schreiber [28] recommended that the first value of τ in which ACF is equal to one-half or zero or the first inflection point of ACF can be selected as the segment length. In principle, the autocorrelation function should be zero at all lags equal to or larger than τ [28]. The first value of τ which corresponds to the first minimum of the mutual information is an appropriate value for the time delay [28]. Also, van Ommen et al. [5] have introduced a method for estimation of the segment length which the effect of this parameter on S-statistical outcome was investigated and then the optimum delay was selected. In this work, these three methods were investigated and finally, the method of van Ommen et al. [5] was used.

Bandwidth (d) is the last key parameter to be determined. The investigation of Diks et al. [17] showed that the proper choice of the bandwidth (d) had a great effect on the accuracy of their test. If the small bandwidth value is selected, the test picks up local differences between the two distributions and poor statistics will be obtained. The large value of the bandwidth parameter may lead to very smooth delay vector distributions. Selection of the optimal bandwidth will be possible by considering both effects and it is highly affected by the number of observations [17]. The observations used in this work are based on calculating the S-value for different combinations of time series at various bandwidth values. Then the bandwidth which gives a maximal value of S-value will be chosen as the optimal value of d [18,29,31].

Results and Discussions

Typical raw vibration signals for pure S_1 sand in the bed and bed with 92.5 % wt S_1 sand and 7.5 % wt S_2 sand, recorded by the accelerometer are shown in Fig. 1. As shown in this figure, it is impossible to extract reliable information from such raw signals. Therefore, in order to investigate the hydrodynamic changes of the system from vibration signals, first, the effect of changes in the mass fraction of coarser particles on the average cycle frequency (f_c) of the bed is analyzed. The f_c at its minimum value approaches to the main frequency of the bed [32] which is related to larger structures of the bed (such as bubbles) [6]. Therefore, whenever the f_c becomes closer to the main frequency, the bed behaves more periodic.

Fig. 2 shows the $f_c/f_{c,S1}$ ratio of the signals obtained from the bed against a mass fraction of S_2 sand at different gas velocities and measurement position 5 cm above distributor. $f_{c,S1}$ relates to average cycle frequency recorded vibration signal of the bed filled with pure S_1. In general, it can be seen that the $f_c/f_{c,S1}$ ratio decreases with an increase in the mass fraction of coarser particles equivalent to the average particle size increase. This makes the bed behave periodic and more regular. On the other hand, as larger particles are added to the bed, minimum fluidization velocity and transition velocities are increased as shown in Table 2. The presence of larger particles in the bed retards the onset of fluidization and the bed behaves more regular.

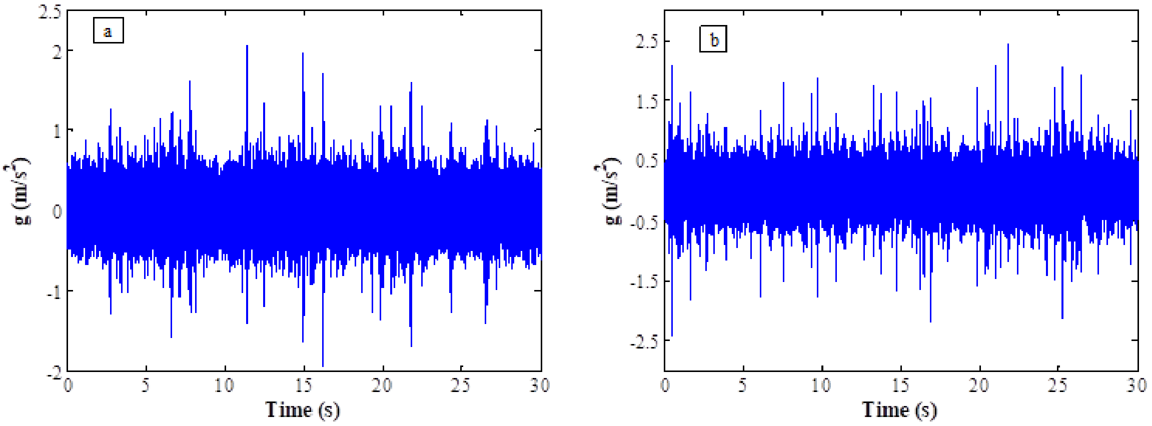

Fig. 1. Raw vibration signal recorded from the bed (sampling frequency 65 kHz, initial bed height of 30 cm, superficial gas velocity of 0.2 m/s, with a) pure S_1 sand in the bed and b) 92.5 % wt S_1 sand and 7.5 % wt S_2 sand in the bed)

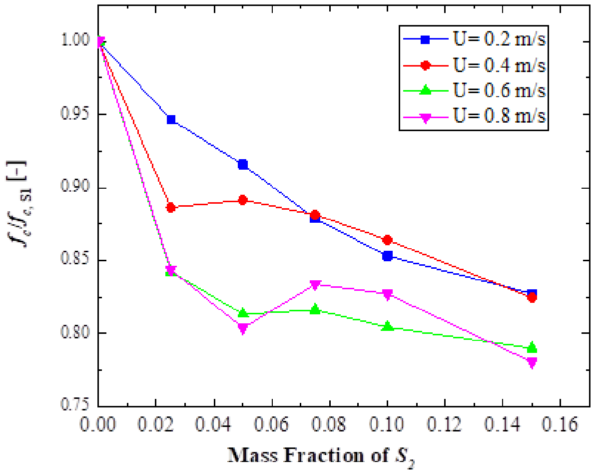

Fig. 2. Ratio of average cycle frequency for vibration signatures obtained from the bed of S_1 sand particles balanced with S_2 sand at different gas velocities

Table 2. Properties of sand particles

Sand Type	d_p(μm)	ρ_p(kg m^{-3})	U_{mf}(m.s^{-1})	U_c(m.s^{-1})
S_1	235	2310	0.0417	0.917
S_2	911	2310	0.452	1.53

On the other hand, Fig. 3 shows the impact of fluidization velocity on the f_c for original and normalized data. As can be seen, f_c is very sensitive to changes (e.g. 10 % around reference velocity of 0.4 m/s) in the superficial gas velocity. Thus it is not clear that changes in f_c of the bed are related to the change in particle size or gas velocity fluctuations. Thus, this cannot be a good index for particle size changes, when gas velocity changes. In fact, any proposed size monitoring index should not be sensitive to the small gas velocity changes in industrial fluidized beds where small variations (typically around 10 %) in the gas velocity occur frequently. So, a statistical index is needed in order to exactly detect changes in particle sizes in the bed. In addition, a disadvantage of the average cycle frequency is that it cannot easily be extended to a multiple-signal method, which is required for large industrial applications [5]. Therefore the S-statistical test was chosen for this purpose. In this work, the vibration signals obtained from the bed, operating at a particle size of 235 µm and the bed aspect ratio of L/D= 2, is considered as the reference state. For each superficial gas velocity and measurement positions, one reference state is chosen. Table 3 shows these references.

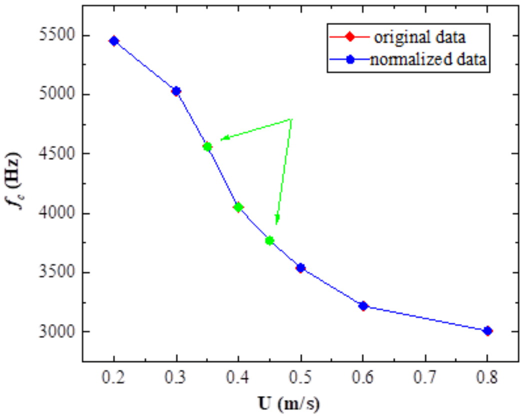

Fig. 3. Average cycle frequency of vibration signatures obtained from the bed of S_1 sand against gas velocity for original and normalized data

Table 3. Reference states for the attractor comparison in the state space

Parameters	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8
U (m/s)	0.2	0.4	0.6	0.8	0.2	0.6	0.2	0.2
Probe height (cm)	5	5	5	5	10	15	15	20

Parameters Selection

Performance of the S-statistic algorithm requires the optimization of its input parameters. The first parameter is the embedding dimension. As mentioned earlier, the time window method was used to find an appropriate value for the embedding dimension based on average cycle time. The average cycle time was calculated for time series at different operating conditions and its average was found to be 0.000538 s. Therefore, according to the time window method, by considering τ equal to 1, the proper embedding dimension of the reconstructed attractor would be 35. The next important parameter is the segment length. In time series with high sampling frequency, some close points in the state space are obtained. The segment length is used to exclude pairs of close points, those unrelated to the attractor geometry. It is important to consider the segment length large enough to remove a dynamic correlations between successive points in the state space. As recommended by Theiler [27], the value of time delay can be assumed as an appropriate segment length. Thus, this parameter can be determined through the autocorrelation and mutual information functions and van Ommen et al. [5] method. The optimal parameter values are given in Table 4.

Table 4. Optimal parameter settings for applying the attractor comparison test to the fluidized bed signals

Time Window (s)	Embedding dimension	Bandwidth	Segment Length
0.000538	35	0.4 – 0.8	300 - 400

Fig. 4 shows two examples of the functions described above at various time delay and superficial gas velocity of 0.2 m/s based on information generated from vibration signatures. According to Fig. 4a, the first value of τ in which ACF is equal to zero was considered as the appropriate delay which is equal to about 22. According to Fig. 4b, the first minimum of the mutual information approximately occurs at a delay time of 20. The time delays provided by the autocorrelation function and mutual information function are close to each other.

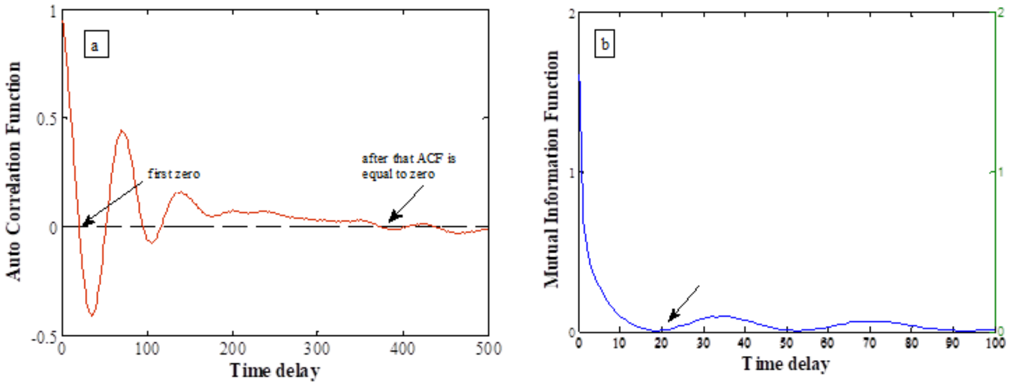

Fig. 4. a) autocorrelation function and b) mutual information function of a sample vibration signatures (at gas velocity of 0.2 m/s and measurement position 5 cm above distributor for bed containing 85 % wt S_1 sand and 15 % wt S_2 sand), against time delay

The third method introduced by van Ommen et al. [5,11] was used to obtain the best choice for the segment length. The S-value was calculated for different combinations of time series at various segment lengths including 20 in which a limited change around them has not sensible influence on S-values. In this case, the standard deviations of S-values, which are not very large, was chosen as the optimal value of segment length. According to this note and Fig. 5, a segment length in the range of 300 to 400 yields good test results. In this figure, the reference time series has been measured in a bed with 0 wt. % S_2 sand. As could be seen in this figure, the standard deviation of S-value for the segment length equal to 20 obtained from mutual information and ACF method is very large, while as shown in Fig. 4a estimated value of segment length by the prescribed method of van Ommen et al. [5,11] is closer to the selected τ (where ACF for all time lag ≥ τ is equal to zero). It can be concluded that for systems which their ACF does not decay with increasing time lag, it is better to use τ as segment length where ACF for all time lag ≥ τ is equal to zero.

Fig. 6 indicates the behavior of S-value versus bandwidth for two different sets of vibration signatures. The lower curve corresponds to the signatures obtained at operating conditions similar to the reference signature (in the bed with 0 wt. % S_2 particles and R_1 condition in Table 3). As expected, this curve is below the value of 3 for all values of bandwidth. This behavior indicates that the null hypothesis is valid. The upper curve is related to S-value obtained from two different operating conditions (same reference signature and evaluation signature which measured at the bed with 15 wt. % of S_2 particles). To increase the sensitivity of this method to even smaller changes in the hydrodynamics of the fluidized bed, the bandwidth at which the maximum S-value is observed was selected as the optimum value [18,29,31]. The maximum S-value is observed at bandwidth equal to 0.6. By studying a large number of vibration signals, it was found that for fluidized bed vibrations, the optimal bandwidth should be selected from 0.4 to 0.8. This figure also shows that limited deviations in this range only have a small influence on the outcome of the test. Therefore, this range can be extended to all vibration signals.

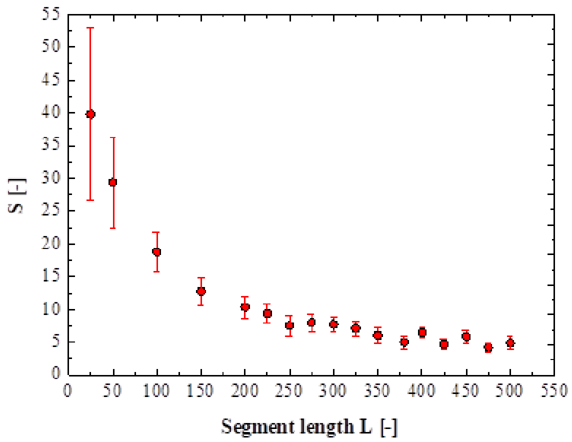

Fig. 5. Behavior of *S*-values versus segment length; gas velocity 0.2 m/s and measurement position 15 cm above distributor for bed containing 92.5 % wt S_1 sand and 7.5 % wt S_2 sand (the reference time series has been measured in a bed with 0 % wt S_2 sand)

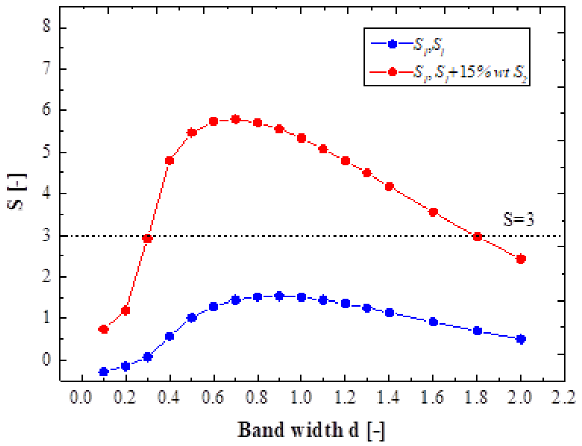

Fig. 6. Behavior of *S*-values versus bandwidth; gas velocity 0.2 m/s and measurement position 5 cm above distributor

Sensitivity of S-Test to Changes in Superficial Gas velocity

To make the test less sensitive to small changes in superficial gas velocity, the time series were normalized with respect to the standard deviation before applying the attractor comparison test as [5]:

$$x_i = \frac{a_i - \bar{a}}{\sigma} \tag{5}$$

S-values showed in Fig. 7 is obtained by comparing time series of U= 0.4 m/s (as a reference state) with the time series of various superficial gas velocities near that velocity, before and after data normalization for the filled with pure S_1 sand. This figure also shows that after data normalizing, the S-values for up to 10% velocity changes around the reference velocity stayed below 3. This means that the test was not sensitive to small unwanted changes in superficial gas velocities. It should be mentioned that the sensitivity reduction of the method to the superficial gas velocity is important in the case of particles size changes detection purposes. It can be concluded that transitions of S-values are related to the changes in parameters rather than superficial gas velocity fluctuations.

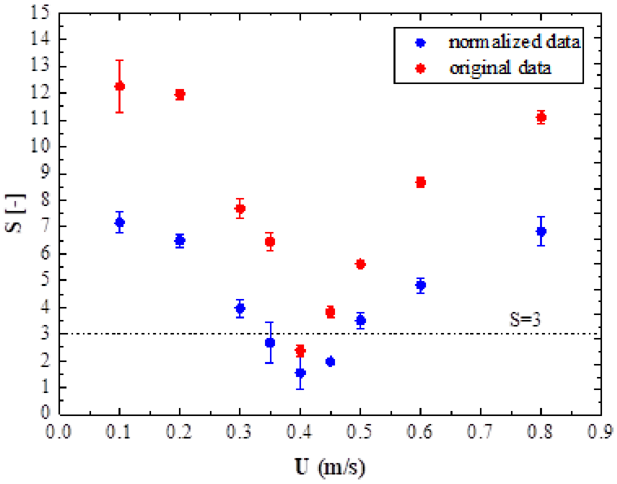

Fig. 7. Influence of the superficial gas velocity changes on the S-value with original and normalized data (the bed filled with pure S_1 sand)

Investigation of Particles Size Changes in the Bed

The sensitivity of S-test to the coarser particles existence in the bed will now be illustrated by the experiment with the stepwise changing of the particle size distribution. Vibration time series have been calculated in the bed of finer (S_1) and coarser sands (S_2) at three superficial gas velocities. Fig. 8 shows the S-value as a function of the S_2 fraction for three superficial gas velocities. In this figure, each test is repeated three times and average values are reported. The vibration signatures with a specified superficial gas velocity were chosen as a reference state (R_1, R_3, and R_4 in Table 3). In all cases, when the same time series are compared, the S-value is less than 3, which indicates that both signals are from the same origin. Except for the mass fraction of S_2, all operating conditions are kept constant in experiments, therefore the transition of S-values from the critical value (3) is related to mean particles size changes. In each curve, S-value is increased with increasing mass fraction of S_2 sand. This represents a relationship between the percentage of coarser particles in the bed and S-values. The similar trend is also observed for the superficial gas velocity of 0.6 m/s. Therefore S-statistical method is capable of detecting the smallest changes of the particles size at lower superficial gas velocities in the bubbling regime. However, as shown in Fig. 8, the S-value is less than 3 for 2.5% wt of S_2 sand and superficial gas velocity of 0.8 m/s. This indicates that at higher superficial gas velocities (>0.8 m/s), this method is able to detect hydrodynamic change at a sufficiently high S_2 fraction.

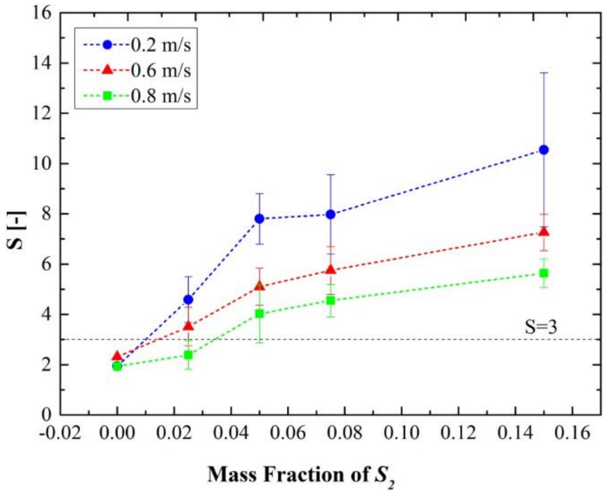

Fig. 8. Influence of coarser particles (S_2 sand) on S-values

Change in Measurement Position

The influence of the measurement position on S-value is illustrated in Fig. 9 for U=0.2 m/s. The vibration signatures with a specified probe height were chosen as a reference state (R_1, R_5, R_7, and R_8 in Table 3). These curves demonstrate that S-values are approximately the same at all measurement positions, at lower mass fractions of S_2 particles. Therefore, the S-test for vibration signatures is almost independent of the vertical position. This can be explained with the fact that the vibration signatures shows global phenomena occurred in the bed. Therefore, the measurement position does not alter the vibration signature.

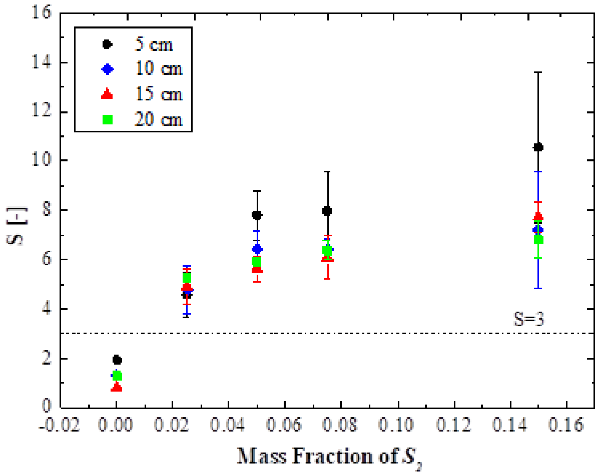

Fig. 9. Influence of the measurement position on the S-value

Conclusions

A method has been developed for the early detection of the changes in particle sizes in fluidized beds based on attractor reconstruction from a vibration signal using S-statics. The method compares the attractor of a reference vibration time series reflecting a certain desired state of fluidization with the attractor of evaluation time series acquired during bed operation. The input parameter settings for the method have been optimized to maximize the power of the method. In this study, it was shown that the S-test is sensitive to particle size changes in the bed. The sensitivity of the method to this phenomenon is significant at low gas velocity. The results show that the measurement of bed vibrations is a nonintrusive technique that provides more reliable information on global phenomena occurring inside the bed.

Acknowledgments

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Nomenclature

a	vibration signal (m/s^2)
$\bar{a}$	mean vibration signal (m/s^2)
ACF	autocorrelation function
D	bed diameter
d	Bandwidth

d_p	sand diameter (μm)
d_{pi}	holes mean diameter in i^{th} mesh
f_s	sampling frequency (Hz)
f_c	Average Cycle Frequency (Hz)
i	Counter
I	mutual information function
L	segment length, bed height
m	state space dimension, embedding dimension
N	total number of samples
Q	unbiased estimator
s	state vector, point on state space attractor
S	S-statistic value
t	time (s)
T_w	time window (s)
U	superficial gas velocity
U_c	transition velocity from bubbling to turbulent (m/s)
U_{mf}	minimum fluidization velocity (m/s)
V_c	conditional variance of delay vector
X	time series

Greek letter

ρ_p	sand particles density (Kg/m^3)
σ	standard deviation
τ	embedding time delay
Δt	time resolution (s)

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