Chinese Journal of Chemical Engineering 23 (2015) 1017–1026

Contents lists available at ScienceDirect

Chinese Journal of Chemical Engineering

journal homepage: www.elsevier.com/locate/CJChE

Energy, Resources and Environmental Technology

Analysis of dynamic of two-phase flow in small channel based on phase space reconstruction combined with data reduction sub-frequency band wavelet☆

Hongwei Li *, Junpeng Liu, Tao Li, Yunlong Zhou, Bin Sun

School of Energy and Power Engineering, Northeast Dianli University, Jilin 132012, China

ARTICLE INFO

Article history:
Received 30 May 2014
Received in revised form 14 September 2014
Accepted 8 November 2014
Available online 26 March 2015

Keywords:
Small channel two-phase flow
Flow pattern dynamics
Phase space reconstruction
Data reduction sub-frequency band wavelet

ABSTRACT

A new method of nonlinear analysis is established by combining phase space reconstruction and data reduction sub-frequency band wavelet. This method is applied to two types of chaotic dynamic systems (Lorenz and Rössler) to examine the anti-noise ability for complex systems. Results show that the nonlinear dynamic system analysis method resists noise and reveals the internal dynamics of a weak signal from noise pollution. On this basis, the vertical upward gas–liquid two-phase flow in a 2 mm × 0.81 mm small rectangular channel is investigated. The frequency and energy distributions of the main oscillation mode are revealed by analyzing the time–frequency spectra of the pressure signals of different flow patterns. The positive power spectral density of singular-value frequency entropy and the damping ratio are extracted to characterize the evolution of flow patterns and achieve accurate recognition of different vertical upward gas–liquid flow patterns (bubbly flow: 100%, slug flow: 92%, churn flow: 96%, annular flow: 100%). The proposed analysis method will enrich the dynamics theory of multi-phase flow in small channel.

1. Introduction

With the development of the micro electro-mechanical system, micro-chemical technology has become one of the development trends in the field of chemical engineering since 1990s [1]. The tiny channels caused by scale miniaturization, the specific surface area, and the heat and mass transfer efficiencies relative to the conventional channel have been improved by two to three orders of magnitude. Special experimental research on the characteristics of two-phase flow in a non-circular small channel is necessary to improve the efficiencies of mass and heat transfer. Flow pattern is one of the most important parameters of two-phase flow; it not only affects the performance of the mixed-fluid flow characteristics and heat transfer but also is an important parameter of the two-phase flow control and forecast system. Therefore, the accurate identification of two-phase flow patterns, the understanding of its internal flow characteristics for two-phase flow industrial system optimization design, and the dynamic monitoring of working conditions are of practical significance [2].

The two-phase flow model is a complex nonlinear dynamical system. Since 1990s, a trend has been growing in the study of flow pattern identification based on the method of chaos, fractal, complex networks, time and frequency domain analysis, *etc.* [3]. Jin *et al.* [4–7] performed dynamics analysis on oil and gas–liquid two-phase flow conductance signal by using the multiple chaotic parameter index; this analysis was limited by the center of multiple gravity trajectory in phase space. Progress has been made in revealing the mechanism of two-phase flow patterns. Gao *et al.* [8,9] applied the complex network on the mechanical characteristics of two-phase flow to evolution analysis, and revealed the detailed mechanism of interaction between gas and liquid. Sun *et al.* [10,11] provided the identification and analysis for the gas–liquid two-phase flow pattern and flow characteristics of a horizontal Venturi tube by adapting the optimal kernel time-frequency analysis method. Du *et al.* [12] analyzed the conductance signals of the gas–liquid two-phase flow by using the optimal kernel time-frequency characterization method. They accurately distinguished the different flow patterns by extracting the two time-frequency characteristic values (total energy and entropy). Manfredo [13] characterized flow properties by the phase density time-frequency distribution characteristics of gas–liquid two-phase flow image signal. Ommen *et al.* [14] reviewed two-phase time-frequency domain analysis methods and analyzed their advantages/disadvantages in the characterization of two-phase flow dynamics characteristics.

Compared with that from regular channels, the information collected from tiny channels is sensitive to the change in experimental environment; and noise reduces more severely the amount of effective information. Therefore, revealing the inherent nonlinear dynamic characteristics of a tiny channel as easily as that in a regular channel seems difficult. In this case, an effective algorithm is required to prevent noise and acquire the essentials from signal. A sub-frequency band wavelet is selected in this study. The use of wavelet transform to analyze and identify model parameters is currently a popular research tool. Ruzzene *et al.* [15] utilized a band wavelet to analyze the free attenuation vibration response of

☆ Supported by the National Natural Science Foundation of China (51406031).
* Corresponding author.
E-mail address: lihongweihw@163.com (H. Li).

http://dx.doi.org/10.1016/j.cjche.2014.11.031

structures and identify their natural frequency and damping ratio. Sun and Chang [16] proposed a wavelet model parameter identification method based on signal covariance to identify the modal parameters of a system with multi degrees of freedom under environmental excitation; they verified the effectiveness of the method experimentally. Min *et al.* [17,18] combined wavelet transform and singular-value decomposition model identification to effectively increase modal identification precision. Zhang *et al.* [19] proposed a recognition algorithm that combines data reduction and a sub-frequency band wavelet. The identification of structural model parameters with a wavelet analysis requires considerable computation time to ensure high accuracy. Phase space reconstruction must be applied to any component in the system to enable equivalent state space transformation as well as to apply a weak information sequence and obtain the intrinsic dynamic mechanisms. The system dynamic model can then be reconstructed. To this end, high-dimensional space can be utilized to obtain additional information. However, high-dimensional space entails a large amount of subsequent calculations. Data reduction and sub-frequency band wavelet are combined in this study to reduce this burden. The high-dimensional matrix obtained after phase space reconstruction is regarded as input. The dynamic characteristics of the gas–liquid two-phase flow pattern in a vertical, upward, tiny, rectangular pipe are analyzed.

2. Theoretical Basis

2.1. The phase space reconstruction

Phase space reconstruction was based on limited data to reconstruct an attractor and study the dynamic behavior of a system. The basic idea behind this process is as follows. The evolution of any component in the system is determined by its interaction with other components; therefore, the related component information is implicit in the development of the component of interest. A component must be analyzed to reconstruct an equivalent state space, and the data measured at some fixed point of time delay must be regarded as a new dimension, which is identified as a point in multidimensional state space. This process is repeated, and the data at different values of the delay time are measured to produce many of these points, which can preserve many properties of attractors. The observation component of the system can be utilized to reconstruct the system dynamics model.

For any time series signal $z(it)$, $i = 1,2\ldots,M$ (where t is the sampling interval and M is the total number of points). After selecting appropriate embedding dimension m and delay time t, phase space reconstruction can be immediately conducted. The vector points of the reconstructed phase space can be expressed as

$$\begin{aligned}\overline{X}_k &= \{x_k(1), x_k(2), \ldots, x_k(m)\} \\ &= \{z(kt), z(kt+\pi), \ldots, z(kt+(m-1)\pi)\}\end{aligned} \tag{1}$$

where $k = 1,2,\ldots,N$, $N = M - (m-1) \times \tau/t$ is the total number of points in the phase space, τ being the delay time. If embedding dimension m is extremely small, a point cannot be fully developed in the phase space; if m is too large, the kinetics of the phase space will be polluted by noise. If delay time τ is extremely small, the phase space attractor will be compressed in line, not fully developed; if delay time τ is too large, the attractor dynamics will be split and no longer be continuous in the phase space. Therefore, embedding dimension m and time delay τ must be selected properly with a proper algorithm. The embedding dimension can be obtained with the FNN algorithm, whose advantage was discussed in Ref. [20]. The C–C algorithm is commonly utilized to obtain delay time τ (refer to [21] for details). Compared with other delay time calculation methods (such as mutual information method-I, mutual information method-II, and autocorrelation function method), the C–C algorithm has a better capability to resist noise. Therefore, the C–C algorithm was employed in this study to compute delay time τ. Embedding dimension m was obtained with the FNN algorithm.

2.2. Determination of order time and frequency band

The SFBW method can determine the modal order N_m of the system and the approximate frequency range of each mode by decomposing the positive power spectrum density (PPSD) matrix. The lr covariance signal is reduced to an N_m signal by the singular value decomposition (SVD) of the matrix. Finally, signal reduced by the wavelet analysis was used for the by-band modal parameter identification. The foremost advantage of the method is the ability to integrate multi-channel information for accurate positioning frequencies, damping ratios and major modes. The SFBW is very effective in signal identification. In this work, this method is adopted to analyze and recognize the differential pressure fluctuation signal of the two-phase flow.

Bart *et al.* [22] defined the positive cross-power spectral density $\boldsymbol{G}_{ij}^{+}$ as follows:

$$\boldsymbol{G}_{ij}^{+}(j\omega) = R_{ij}(0)/2 + \sum_{k=1}^{N} R_{ij}(k)\exp(-j\omega k\Delta t). \tag{2}$$

Positive power spectral density matrix is constituted as follows:

$$\boldsymbol{G}_{ij}^{+}(j\omega) = \begin{bmatrix} G_{11}^{+}(j\omega) & G_{12}^{+}(j\omega) & \cdots & G_{1r}^{+}(j\omega) \\ G_{21}^{+}(j\omega) & G_{22}^{+}(j\omega) & \cdots & G_{2r}^{+}(j\omega) \\ \cdots & \cdots & \cdots & \cdots \\ G_{l1}^{+}(j\omega) & G_{l2}^{+}(j\omega) & \cdots & G_{lr}^{+}(j\omega) \end{bmatrix}_{l\times r} \tag{3}$$

where l is the number of measuring points, and r is the number of reference points.

By using SVD for the PPSD singular value in each discrete frequency ω, the correlation can be obtained:

$$\boldsymbol{G}^{+}(j\omega) = \boldsymbol{U}_i\boldsymbol{S}_i\boldsymbol{V}_i^{\mathrm{T}}, \tag{4}$$

with

$$\boldsymbol{U}_i = [u_{i1} \quad u_{i2} \quad \cdots \quad u_{il}],\quad \boldsymbol{S}_i = \begin{pmatrix} \sum_i \\ 0 \end{pmatrix},\quad \textstyle\sum_i = \mathrm{diag}(\sigma_{i1} \quad \sigma_{i2} \quad \cdots \quad \sigma_{ir}),$$
$$\boldsymbol{V}_i = [v_{i1} \quad v_{i2} \quad \cdots \quad v_{ir}].$$

The vector $\boldsymbol{B}$ is constituted by the first singular value of each discrete frequency point as follows:

$$\boldsymbol{B} = [\sigma_{11} \quad \sigma_{21} \quad \cdots \quad \sigma_{N_\omega 1}] \tag{5}$$

where N_ω is number of frequency domain points.

The vector $\boldsymbol{B}$ exist a local peak in each order modal frequency point of the system. However, because of the existing problem of frequency resolution, the frequency range can only be determined approximately in each mode as follows:

$$[\omega_{li} \quad \omega_{ri}],\quad i = 1, 2, \cdots, N_\mathrm{m}.$$

2.3. Use of SVD to reduce covariance data

The covariance and cross covariance was calculated for l response signal. The r reference channel is selected, and the lr covariance signal is obtained. The covariance matrix is defined as follows:

$$\begin{gathered}\boldsymbol{R} \in R^{lr\times N}(lr < N) \\ \boldsymbol{R} = \begin{bmatrix} R_{11}(1) & R_{11}(2) & \cdots & R_{11}(N) \\ R_{12}(1) & R_{12}(2) & \cdots & R_{12}(N) \\ \cdots & \cdots & \cdots & \cdots \\ R_{lr}(1) & R_{lr}(2) & \cdots & R_{lr}(N) \end{bmatrix}_{lr\times N}\end{gathered} \tag{6}$$