Physica A 469 (2017) 136–147

Contents lists available at ScienceDirect

Physica A

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

Characterization of flow pattern transitions for horizontal liquid–liquid pipe flows by using multi-scale distribution entropy in coupled 3D phase space

Lu-Sheng Zhai [a], Yan-Bo Zong [b], Hong-Mei Wang [a], Cong Yan [a], Zhong-Ke Gao [a], Ning-De Jin [a,*]

[a] School of Electrical Engineering and Automation, Tianjin University, Tianjin 300072, China

[b] Sinopec Research Institute of Petroleum Engineering, Beijing 100101, China

HIGHLIGHTS

- A method of multi-scale distribution entropy (MSDE) in a coupled 3D phase space is proposed to uncover dynamics underlying complex systems.
- The performance of the MSDE is validated with Lorenz system and ARFIMA processes.
- The MSDE is dramatically associated with the cross-correlations of coupled time series.
- The MSDE is an effective tool uncovering the complex dynamic behaviors of oil–water flow pattern transitions in a horizontal pipe.

ARTICLE INFO

Article history:
Received 27 July 2016
Received in revised form 20 October 2016
Available online 16 November 2016

Keywords:
Horizontal oil–water two-phase flow
Flow pattern transition
Coupled phase space
Distribution entropy

ABSTRACT

Horizontal oil–water two-phase flows often exist in many industrial processes. Uncovering the dynamic mechanism of the flow pattern transition is of great significance for modeling the flow parameters. In this study we propose a method called multi-scale distribution entropy (MSDE) in a coupled 3D phase space, and use it to characterize the flow pattern transitions in horizontal oil–water two-phase flows. Firstly, the proposed MSDE is validated with Lorenz system and ARFIMA processes. Interestingly, it is found that the MSDE is dramatically associated with the cross-correlations of the coupled time series. Then, through conducting the experiment of horizontal oil–water two-phase flows, the upstream and downstream flow information is collected using a conductance cross-correlation velocity probe. The coupled cross-correlated signals are investigated using the MSDE method, and the results indicate that the MSDE is an effective tool uncovering the complex dynamic behaviors of flow pattern transitions.

1. Introduction

Horizontal oil–water two-phase flows are widely encountered in oil industries. The flow pattern transition in the horizontal pipe is of great significance for understanding the flow dynamics and modeling the flow parameters. Note that horizontal oil–water flow patterns greatly depend on many factors, such as the flow rate, fluid properties, pipe diameter

* Corresponding author. Fax: +86 22 27407641.
E-mail address: ndjin@tju.edu.cn (N.-D. Jin).

http://dx.doi.org/10.1016/j.physa.2016.11.020

and pipe material, and thus substantial challenges remain in regard to uncovering the hydrodynamic mechanism of the flow pattern transitions.

Progress has been achieved in studying the horizontal oil–water flow patterns during the past decades [1]. Notably, Zhai et al. [2] presented a new experimental flow pattern map of oil–water flows using a technology of mini conductance probe, and divided the ST&MI flow into four types. De et al. [3] observed an interesting rivulet pattern during oil–water flow through a 12 mm horizontal acrylic pipe. Recently, more and more attention was paid to the geometry and instability of oil–water interfacial waves [4–8]. Meanwhile, a model based on minimum energy concept was developed to predict flow behaviors including flow pattern, pressure gradient and holdup for horizontal oil–water two-phase flows [9]. Despite the previous research efforts, the characterization of flow pattern transition in a horizontal pipe is still a great challenge due to the complex flow structures and slippage behaviors [10].

Nonlinear analysis methods based on observed time series have a great development in recent years. Notably, since complex systems always consist of interacting constituents with a coupled relationship, cross-correlation and causality analyses based on coupled time series have been very popular topics and present potential utilities in uncovering the dynamics of complex nonlinear systems. For example, as a bivariate extension of recurrence plot, cross recurrence plot was introduced to analyze the dependencies between two different systems by comparing their states and attracted substantial attention of scholars [11,12]. More recently, Podobnik et al. [13,14] proposed a method of detrended cross-correlation analysis (DCCA) to investigate the power-law cross-correlations between different simultaneously recorded time series. Based on the DCCA, Zebende [15] proposed a DCCA cross-correlation coefficient to quantify the level of cross-correlation between nonstationary time series. Kristoufek [16] investigated the ability of the DCCA coefficient to measure correlation level between non-stationary series and introduced a correlation measure based on a detrending moving-average cross-correlation analysis (DMCA) [17]. Interestingly, a multifractal detrended cross-correlation analysis (MFDCCA) is generalized by Zhou [18] to investigate the multifractal behaviors in power-law cross-correlations between two time series. Jiang and Zhou [19] developed a multifractal detrending moving-average cross-correlation analysis (MFXMDA) based on the detrending moving average (DMA) algorithm [20] and the multifractal detrending moving average (MFDMA) algorithm [21]. Besides, selected new multifractal analysis based on long-range cross-correlations are developed by scholars recently [22–25]. Notably, a method of detrended partial-cross-correlation analysis (DPCCA) [26,27] was proposed to quantify the intrinsic relations of two non-stationary signals with influences of other signals removed. Qian et al. [28] developed a multifractal DPCCA method and found it beneficial to reveal the hidden multifractal nature of time series. In addition, measuring causal influence in multivariate time series based on information-theoretic approaches is favorable to uncover the dynamic behaviors underlying complex systems. The information-theoretic measures are essential for the analysis of information flow between two systems or between constituent subsystems [29]. Schreiber [30] proposed transfer entropy to distinguish driving and responding elements in interaction of subsystems. The transfer entropy has been widely used in society system [31], financial system [32], neuroscience [33,34] and others. Notably, we used the transfer entropy to study the information transferring of gas–liquid two-phase flows in an annular space [35].

Coupling property analysis of system constituents shows great advantages in diagnosing and understanding the whole system. However, very few efforts were made to investigate multi-phase flow systems using coupled observed data, especially for the flow pattern transitions [36]. In this current study we conducted an experiment of horizontal oil–water flows in a small diameter pipe, and collected coupled upstream and downstream conductance signals for different flow interfacial structures. A multi-scale distribution entropy analysis in a 3D phase space is proposed to study the coupling properties of the flow structures and uncover the complex dynamic behaviors of oil–water flow pattern transition in the horizontal pipe.

This paper is structured as follows: Section 2 presents the algorithm of the proposed MSDE and its performance evaluation; Section 3 shows the experiment of horizontal oil–water two-phase flows; Section 4 presents the dynamics of flow pattern transition in the horizontal pipe using MSDE analysis.

2. Multi-scale distribution entropy in 3D coupled phase space

2.1. Algorithm of MSDE

The algorithm of MSDE in a coupled phase space can be briefly introduced as follows.

(1) For given original time series $\{u_i\}$ and $\{v_i\}$, $i = 1, 2, \ldots, n$ (see Fig. 1(a)), we first construct a set of coarse-grained time series of the original series. The coarse-grained time series $\{x_j^s\}$ and $\{y_j^s\}$, as shown in Fig. 1(b), for a time scale s can be expressed as:

$$x_j^s = \frac{1}{s}\sum_{i=(j-1)s+1}^{js} u_i, \qquad y_j^s = \frac{1}{s}\sum_{i=(j-1)s+1}^{js} v_i \quad 1 \le j \le N,\ N = \left[\frac{n}{s}\right] \tag{1}$$

where $\left[\frac{n}{s}\right]$ represents the greatest integer less than or equal to $\frac{n}{s}$.

(2) Next, taking into account abundant dynamic information contained in increment series [37,38], the first-order differential sequence of $\{x_j^s\}$ and $\{y_j^s\}$ are calculated and defined as $\{dx_j^s\}$ and $\{dy_j^s\}$, respectively.