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Multi-scale cross entropy analysis for inclined oil–water two-phase countercurrent flow patterns

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ABSTRACT

The flow of an oil–water two-phase fluid in an inclined pipe exhibits fundamentally different behaviors to that of a vertical two-phase flow, especially the flow commonly presents complex countercurrent flow structure due to the influence of gravity. The understanding of inclined oil–water flow is of important significance for flow measurement and production optimization. We using multi-scale cross entropy (MSCE) analysis investigate the nonlinear dynamics of inclined water-dominated oil–water two-phase flow patterns which are Dispersion oil-in-water-Pseudoslugs (D O/W PS), Dispersion oil-in-water-Countercurrent (D O/W CT) and Transitional Flow (TF). We find that the rate of low-scale cross entropy can effectively identify flow patterns, and the high-scale cross entropy can represent their long-range dynamics. The research results show that the multi-scale cross entropy analysis can be a helpful tool for revealing nonlinear dynamics of inclined oil–water two-phase flow in terms of microscopic and macroscopic views.

1. Introduction

Inclined oil–water two-phase flow is commonly encountered in wellbores; however, its hydrodynamics behavior under a wide range of flow conditions is still relevant unsolved problem. It is crucial to understand the flow pattern dynamics for production-engineering applications and predictions of liquid holdup and pressure drop.

In early studies, semi-empirical and semi-theoretical methods were often employed in the study of inclined oil–water two-phase flow. Mukherjee et al. (1981) studied the effect of input liquid fraction and inclination angles on water holdup and friction pressure gradient, and found that the maximum friction pressure gradient at phase inversion point and oil–water slippage were both functions of inclination angles. Hill and Oolman (1982) found that the most troublesome effect of well deviation on production logging tool response is the non-uniform phase distribution across the pipe and observed a kind of segregated flow pattern with water phase occupying most of the pipe and steady reverse flow of water along the bottom pipe. Davarzani et al. (1985) observed stratified flow and stratified wavy flow in a 160 mm ID pipe at inclined 30°. Zavareh et al. (1988) concluded that countercurrent bubble flow pattern exists in the inclined pipe. Vigneaux et al. (1988) reported the experimental measurements of inclined oil–water flow in a 20 cm ID pipe, and presented the distribution of the local water volume fraction across a pipe section using local high-frequency probes. Tabeling et al. (1991) found that the main factors of controlling flow structure are the mean liquid holdup and deviation angle, and they proposed a phenomenological model for local holdup prediction. Mobbs and Lucas (1993) presented a turbulence model for inclined liquid–liquid flows and predicted the qualitative features of large amplitude unsteady eddy motions in inclined two-phase flows. Lucas (1995) described a mathematical model which provides an initial estimate of the velocity profile of an inclined multiphase flow. It is worth to point out that Flores et al. (1999) made a comprehensive experimental study in vertical and inclined oil–water flows with 50.8 mm ID pipe. They summarized seven flow patterns in inclined oil–water flows with four water-dominated, two oil-dominated and a transitional flow pattern (TF). The water-dominated flow patterns include Dispersion of oil-in-water-Pseudoslugs (D O/W PS), Dispersion of oil-in-water Countercurrent (D O/W CT), Dispersion of oil-in-water Cocurrent (CC) and Very fine dispersion of oil-in-water (VFD O/W). The oil-dominated flow patterns are Dispersion of water-in oil (D W/O) and Very fine dispersion of water-in-oil (VFD W/O). Oddie et al. (2003) investigated gas–water, oil–water and oil–gas–water multiphase flows in 150 mm ID inclinable pipe by using several water holdup measurement techniques. Lum et al. (2006) found that oil plug flow pattern existed at inclined 80° and 85°, and the stratified wavy flow pattern would disappear at inclined 95° in 38 mm ID. Gao and Jin (2009) and Gao et al. (2010) developed

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a complex network-based method to uncover the nonlinear dynamics leading to the formation of different patterns in multiphase flow systems and achieved interesting and significant results. Kumara et al. (2010) utilized particle image velocimetry (PIV) to study the flow structure of oil–water flow in horizontal and slightly inclined pipes in the range from 5° upward to 5° downward, and they found the velocity and turbulence profiles were strongly depended on the pipe inclination. Strazza et al. (2011) focused on the core-annular flow pattern boundary pressure drops, and oil hold-up measurements in horizontal and slightly inclined pipes and showed the experimental data had a good agreement with the classical models.

Since the multiphase flow is a typical nonlinear system, characterizing inclined oil–water two-phase flow from measured signals has attracted many attentions and some progresses have been made in applying the nonlinear analysis method (Oddie, 1991; Daw et al., 1995; Wu et al., 2001). In our previous study, we using the chaotic attractor geometry morphology characterized the inclined oil–water two-phase flow, but the proposed method can only identify D O/W PS and D O/W CT, cannot reveal dynamic characteristics of flow patterns (Zong et al., 2010).

Entropy, which is the useful complexity measure for dynamic systems, plays a significant role in studying dynamic characteristics. The concept of Shannon entropy (Shannon, 1948) is defined as the probability distribution of a random variable and can be shown to be a good measure of uncertainty. Pincus (1991) devised a theory for measuring regularity, named approximate entropy, which has been widely applied to the physiological and other time series analysis. Then based on approximate entropy, Richman and Moorman (2000) developed a new and related complexity measure, i.e., sample entropy, and compared both approaches by using them to analyze sets of random numbers with known probabilistic character. Zhuang et al. (2008) indicated that sample entropy method was more appropriate than approximate entropy in quantifying the short-term heart rate variability signals. Costa et al. (2002a, b) introduced multi-scale entropy (MSE) for complex time series analysis and found that MSE robustly separated and well interpreted healthy and pathologic groups. Recently, MSE can not only well analyze physiologic time series (Thuraisingham and Gottwald, 2006; Bornas et al., 2006) but also can be widely applied to other fields, such as environment (Li and Zhang, 2008), metal materials (He et al., 2008).

Pincus and Singer (1996) and Pincus et al. (1996) proposed cross-approximate entropy to measure the degree of dissimilarity of two concurrent, non-stationary biological signals. Then Richman and Moorman (2000) provdied an indication between two time series, by a correlation of their sample entropy, to give a statistic termed cross-sample entropy, which provided an indication of the degree of synchronizing between the signals. A significant drawback of cross-sample entropy is the estimation of the embedding dimension. Based on MSE and cross-sample entropy, Yan et al.(2009) developed a novel algorithm, named multi-scale cross entropy (MSCE), to assess the dynamical characteristics of coupling behavior between two sequences on multiple scales. They showed that the analysis of MSCE can be used to measure cross-correlation and coupling behavior between two time series in either physical systems or physiological systems.

In multiphase flow field, entropy is sensitive to the flow pattern characteristics and can act as an efficient diagnostic tool for revealing the flow pattern transition mechanism. Zhang and Shi (1999) calculated Shannon entropy of two-phase flow systems from the power spectral density and showed Shannon entropy could be a factor to measure the system stability. Zhong and Zhang (2005) found that Shannon entropy could be used to identify the flow regimes and helped to grasp the complex characteristics of dynamic behavior in spout-fluid beds. And the multi-scale entropy is helpful to understand the nonlinear dynamic characteristics of gas–water flows (Zheng and Jin, 2009). Although the rate of MSE at low scales sensitively indicates the variation of flow patterns, it cannot identify the flow patterns at high scales. Aiming at this problem, we introduce MSCE expecting to well identify the flow patterns at all scales and further understand dynamics of inclined oil–water two-phase flow in microscopic and macroscopic views.

2. Multi-scale sample entropy and multi-scale cross entropy

2.1. Multi-scale sample entropy

The algorithm of multi-scale sample entropy is shown as follows:

1. Given a one-dimensional discrete time series $\{u(i)$: $i=1, 2, \ldots, n\}$, we construct consecutive coarse-grained time series:

$$x^{(\tau)}(j)=\frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau}u(i),\quad 1\le j\le n/\tau, \tag{1}$$

2. Then we define m-dimensional sequence vectors: $X_m^{(\tau)}(i)=[x_m^{(\tau)}(i),x_m^{(\tau)}(i+1),\ldots,x_m^{(\tau)}(i+m-1)]$
3. The distance between two vectors is defined as

$$d[X_m^{(\tau)}(i),X_m^{(\tau)}(j)]=\max\{|x_m^{(\tau)}(i+k)-x_m^{(\tau)}(j+k)|:0\le k\le m-1\} \tag{2}$$

For each $1\le i\le n-m$, let $B_i^m(r,n)$ be the relative frequency to find a vector $X_m^{(\tau)}(j)$ whose distance to $X_m^{(\tau)}(i)$ is in a tolerance level r and $j\ne i$.
4. The average of $B_i^m(r,n)$ can be calculated:

$$B^m(r,n)=(n-m)^{-1}\sum_{i=1}^{n-m}B_i^m(r,n) \tag{3}$$

5. Then we increase over one step from m to $m+1$ and repeat the steps 2–4 to get $B^{m+1}(r, n)$.
6. Consequently sample entropy can be calculated

$$SampEn(m,r,n)=\lim_{n\to\infty}\{-\ln[B^{m+1}(r,n)/B^m(r,n)]\} \tag{4}$$

7. We then calculate the sample entropy measure for each coarse-grained time series plotted as a function of the scale factor τ and call this procedure multi-scale entropy. In our analysis we use $m=2$ and $r=0.1$–0.25σ where σ is the standard deviation of the original time series. For a discussion on optimal choices for m and r, see the literature (Lake et al., 2002).

2.2. Multi-scale cross entropy algorithm

The algorithm of multi-scale cross entropy is shown as follows:

1. Given two one-dimensional discrete time series with equal length: $\{u(i)$: $i=1, 2, \ldots, n\}$ and $\{v(i)$: $i=1, 2, \ldots, n\}$, we normalize both discrete time series:

$$u_{norm}(i)=\{[u(i)-mean(u)]\}/[std(u)] \tag{5}$$

$$v_{norm}(i)=\{[v(i)-mean(v)]\}/[std(v)] \tag{6}$$

2. We construct consecutive coarse-grained time series:

$$x^{(\tau)}(j)=\tau^{-1}\sum_{i=(j-1)\tau+1}^{j\tau}u_{norm}(i) \tag{7}$$

$$y^{(\tau)}(j)=\tau^{-1}\sum_{i=(j-1)\tau+1}^{j\tau}v_{norm}(i) \tag{8}$$

where $1\le j\le \tau$.