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# The experimental signals analysis for bubbly oil-in-water flow using multi-scale weighted-permutation entropy

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## HIGHLIGHTS

- We test MSWPE and MSPE on typical nonlinear dynamic systems.
- MSWPE shows good anti-noise ability and enables to distinguish different nonlinear time series.
- We apply both algorithms to study oil-in-water two-phase flow system.
- MSWPE can indicate the discrepancy of complexity of two-phase flow system.

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## ABSTRACT

We firstly combine multi-scale method (MS) and weighted-permutation entropy (WPE) to analyze chaotic, noisy, and fractal time series, and find that MSWPE can distinguish different nonlinear time series and exhibit a better robustness in the presence of higher levels of noise, a task that multi-scale permutation entropy (MSPE) fails to work. We then apply MSWPE to analyze the signals from vertical upward oil-in-water two-phase flow experiments. Our results suggest that the change rate of MSWPE enables to characterize the transition of flow patterns and multi-scale weighted-permutation entropy allows indicating the discrepancy of complexity of oil-in-water two-phase flow.



## 1. Introduction

The vertical upward oil-in-water two-phase flow widely exists in the oil production and transportation. A flow pattern is the shape and spatial distribution of two-phase flow within a pipe. The pressure drop and heat transfer rate strongly depend on the flow patterns. Research interests in flow pattern lie on the fact that in each pattern the flow has certain hydrodynamic characteristics [1–3]. Therefore, characterizing the dynamical behavior of vertical upward oil-in-water flow patterns is a significant problem of continuous interests.

Recently, characterizing two-phase flow from the experimental data has attracted much attention. Different methods have been proposed to explore the dynamical behavior of two-phase flow. Ding et al. [4] applied time–frequency transfer analysis and Hilbert–Huang Transform to study signals measured from gas–liquid two-phase flow experiments. The results demonstrated that the energy characteristic is an indication of the gas–liquid two-phase flow patterns. Nguyen et al. [5] analyzed signals obtained from vertical upward air–water flow experiments by using wavelet transform and indicated that the method can characterize different two-phase flow patterns. More recently, Gao et al. [6] inferred and analyzed complex

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networks from signals measured from vertical upward oil-in-water two-phase flow experiments and demonstrated that the local clustering coefficient of complex network allows characterizing dynamic flow behaviors underlying different flow patterns. Moreover, the power spectral density [7–11], probability density function [12–15], neural network [16–19] and digital image analysis [20,21] also have been applied to the identification of two-phase flow patterns.

Entropy, as a measure of complexity and regularity, has been successfully employed to characterize the dynamic behaviors of two-phase flow. Zhang et al. [22] used Shannon entropy to study two-phase flow and found that the Shannon entropy is a useful measure for characterizing the system stability. Zhong et al. [23] utilized Shannon entropy to identify the flow patterns and figured out that it can grasp the complex characteristics of gas–solid two-phase flow. By using multi-scale sample entropy (MSE) [24], Zheng et al. [25] analyzed data from gas–liquid two-phase flow experiments, and indicated that the change rate of MSE can distinguish gas–liquid two-phase flow patterns.

However, the entropy has limitations from the perspective of stability and robustness in the sense that real data are often disturbed by noise. In order to overcome this problem, Bandt and Pompe [26] proposed permutation entropy (PE) to characterize the complexity of nonlinear system. The proposed method has advantages of simpleness and robustness for analyzing different kinds of signals, including chaotic time series and random signals [27,28]. Furthermore, permutation entropy has been applied to many research fields, such as stock market time series [29,30], physiological signals [31–33], mechanical equipment condition assessment [34,35] and climate system [36]. In particular, Fan et al. [37] combined multi-scale method and permutation entropy to develop a novel multi-scale permutation entropy (MSPE) for exploring the dynamical characteristics of gas–liquid flow patterns. The results suggested that MSPE enables to distinguish the flow patterns and characterize the complexity of gas–liquid two-phase flow.

Although permutation entropy has many advantages in distinguishing dynamical behaviors of nonlinear time series, it ignores the amplitude information of nonlinear time series. Hence, Bilal et al. [38] proposed weighted-permutation entropy (WPE) which retains the amplitude information of time series. WPE permutes a vector in a time phase space and calculates the variance of the vector as a weight to compute the Shannon entropy, which can significantly improve the robustness and stability of WPE, especially for the signals containing considerable amplitude information. This method allows detecting sudden changes of signals and has been applied to the analysis of EEG [38].

Currently, in spite of the existing results in characterizing and identifying vertical upward oil-in-water flow patterns, problems still exist, for example, how to characterize the evolution of vertical upward oil-in-water flow patterns when the water cut is very high. In this paper, considering that the WPE has a prominent ability to extract complexity information of nonlinear system, we firstly combine multi-scale method (MS) and weighted-permutation entropy (WPE) to analyze the signals from vertical upward oil-in-water two-phase flow experiments. Then we investigate the relationship between the change rate of MSWPE (multi-scale weighted-permutation entropy) and the evolution of oil-in-water flow patterns under different flow conditions, especially for the situations when the maximum water cut is 98%. The results suggest that the change rate of MSWPE is sensitive to the transition of oil-in-water two-phase flow patterns.

## 2. Methodology

### 2.1. Multi-scale weighted-permutation entropy

Given a one-dimensional discrete time series, $\{u(i) : i = 1, 2, \ldots, N\}$, we construct consecutive coarse-grained time series [26], $\{y^s(j) : j = 1, 2, \ldots, N/s\}$, determined by the factor, $s$, according to the equation:

$$y^s(j) = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} u(i), \quad 1 \le j \le N/s. \tag{1}$$

For scale one, the time series $\{y^{(1)}\}$ is the original time series.

For $\{y^{(s)}\}$ [26,37], given an embedding dimension $m$ and a time delay $\tau$, we embed $\{y^{(s)}\}$ to a $m$ dimensional space:

$$Y^s(t) = [y^s(t),\ y^s(t+\tau),\ \cdots y^s(t+(m-1)\tau)] \quad t \in [1,\ N/s - m + 1]. \tag{2}$$

Then, we arrange the components of $Y^s(t)$ in an increasing order:

$$[y^s(t + (k_1 - 1)\tau) \le y^s(t + (k_2 - 1)\tau) \le \cdots \le^s (t + (k_m - 1)\tau)]. \tag{3}$$

When encountering an equality, e.g., $y^s(t + (k_{i1} - 1)\tau) = y^s(t + (k_{i2} - 1)\tau)$, we consider the quantities $y$ by the $k$ values, namely if $k_{i1} \le k_{i2}$, we set $y^s(t + (k_{i1} - 1)\tau) \le y^s(t + (k_{i2} - 1)\tau)$.

Therefore, any vector $Y^s(t)$ has a permutation:

$$\pi_t = [k_1, k_2, \ldots, k_m] \tag{4}$$

which is one of the $m!$ permutations of $m$ distinct symbols $(1, 2, \ldots, m)$.

We calculate the appearing number of every permutation, $N_l,\ 1 \le l \le m!$. The weighted relative frequency for each permutation is

$$p_w^s(l) = \frac{w(t)N_l}{\sum_{t=1}^{n/s-(m-1)\tau} w(t)} \tag{5}$$