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Cross-correlation analysis of interfacial wave and droplet entrainment in horizontal liquid-liquid two-phase flows

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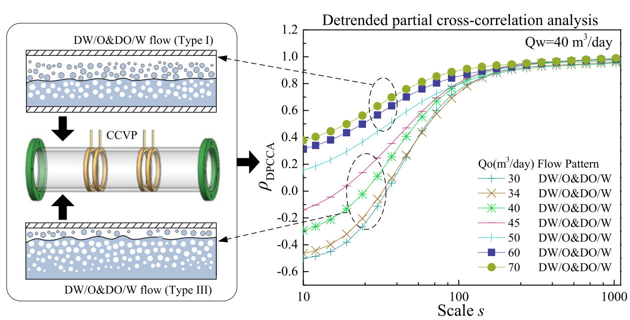
HIGHLIGHTS

- DPCCA quantifying cross-correlations of non-stationary signals is evaluated.
- Conductance signals are collected from horizontal oil-water two-phase flows.
- Multi-scale cross-correlations of flow structures are investigated using DPCCA.
- Interfacial wave and droplet entrainment in flows are uncovered by DPCCA.

GRAPHICAL ABSTRACT



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ABSTRACT

Horizontal oil-water two-phase flows present complex temporal and spatial structures. The cross-correlation analysis of the flow structures is of significance for uncovering the nonlinear dynamics of the oil-water flows. In this study, we first employ a detrended cross-correlation analysis (DCCA) method to investigate the cross-correlation characteristics of two series generated by two-component ARFIMA processes with an adjustable coupling strength. On this basis, to avoid spuriously high cross-correlations caused by noises, we conduct an anti-noise study applying a detrended partial cross-correlation analysis (DPCCA) to ARFIMA processes mixed with periodic signal, stochastic signal and chaotic signal, respectively. It's found that the DPCCA can effectively reveal the intrinsic cross-correlations of coupled series. Through carrying out an experiment of horizontal oil-water two-phase flows, the upstream and downstream flow information is collected by a conductance cross-correlation velocity probe. The DPCCA algorithm is used to calculate the multi-scale cross-correlation coefficient of the upstream and downstream flow structures. The results indicate that the DPCCA cross-correlation coefficient is very sensitive to the dynamics of the oil-water interfacial wave and the entrained droplets, and can serve as an effective indicator of horizontal oil-water two-phase flow structures.

1. Introduction

Horizontal oil-water two-phase flows are widely encountered in petroleum industries. The measurement of oil-water flow parameters is of great importance for the optimization of the oil production process. However, the complex dynamics of interfacial wave and droplet entrainment in the horizontal pipe put forward challenges for the monitoring of the flow parameters, such as total flow rate and phase volume fraction. Uncovering the dynamics of the wavy oil-water interface and the entrained droplets is of significance for improving the measurement accuracy of flow parameters.

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Notation

Q_w	flow rate of the water phase (m^3/day)
Q_o	flow rate of the oil phase (m^3/day)
U_{sw}	superficial velocity of the water phase (m/s)
U_{so}	superficial velocity of the oil phase (m/s)
T	period of sine series
U_i	sinusoidal voltage exciting signal (V)
$U_{o,up}$	upstream response signal of CCVP (V)
$U_{o,down}$	downstream response signal of CCVP (V)
s	time scale
s_{max}	time scale corresponding to the maximum cross-correlation coefficient
$\{x(i)\}$,$\{y(i)\}$	non-stationary time series for the validity of cross-correlation analysis
$\{z(i)\}$	noisy signals

Greek letters

ρ_{DCCA}	cross-correlation coefficient calculated by DCCA method
ρ_{DPCCA}	cross-correlation coefficient calculated by DPCCA method

Nonlinear analysis methods based on observed time series are beneficial to reveal the dynamics of complex systems [1–6]. Multi-phase flow is a typical multi-scale nonlinear dynamic system. Zhao et al. [7] presented the multi-fractal characteristic of bubbling fluidized bed in micro-scale, meso-scale and macro-scale by wavelet method. Zheng et al. [8] used orthogonal wavelet multi-resolution analysis and power spectrum to reveal the multi-scale characteristics of particle fluctuation velocity in a horizontal self-excited gas-solid two-phase flow. Based on differential pressure signals, Wu et al. [9] extracted the multi-fractal characteristics of oil-gas-water flow patterns and realized the intelligent identification of flow regimes by a neural network method. Wu et al. [10] used chaos analysis to study the nonlinear and multi-scale flow behaviors in gas-solids two-phase flow systems. Notably, the internal variables or subsystem variables of a complex system usually present coupling characteristics, so the nonlinear analysis based on the causality, information transferring and cross-correlations of system internal variable have became a popular topic [11–14]. Thomas [15] proposed transfer entropy to quantify the information flow between two systems or between constituent subsystems of a complex system. Then, the transfer entropy was widely used to reveal the dynamics of complex nonlinear subsystems and uncover the causal relationship in the information transferring [16–21]. Zhai et al. [22] employed the transfer entropy theory to investigate the information transferring characteristics of local gas-liquid flow structures in an annular space.

Podobnik and Stanley [23] proposed a detrended cross-correlation analysis (DCCA) method to investigate long-range cross-correlations between two non-stationary time series. Horvatic et al. [24] applied the DCCA method with varying order of the polynomial to meteorological data and demonstrate its ability in subtracting periodic trends. Based on the DCCA, Zebende et al. [25] introduced a DCCA cross-correlation coefficient quantifying the cross-correlation level of two non-stationary series on different scales. The ability of the DCCA coefficient to measure correlation level between non-stationary series was validated by Podobnik et al. [26] and Ladislav [27]. The DCCA cross-correlation coefficient has been widely used in finance, meteorology and economy fields [28–30]. Zhou et al. [31] introduced the MF-DFA [32] and the DCCA into a multi-fractal detrended cross-correlation analysis (MF-DCCA), which can be used to reveal the multi-fractal features of two cross-correlated non-stationary signals. Ruan et al. [33] investigated the cross-correlations between price and volume in Chinese gold spot and futures markets using the MF-DCCA method. Oswiecimka et al. [34] proposed a multifractal cross-correlation analysis (MFCCA), which is a consistent extension of the detrended cross-correlation analysis and free of the limitations of MFDCCA. Jiang and Zhou [35] proposed another class of MF-DCCA algorithms termed multi-fractal detrending moving average (MFXDMA), which based on detrending moving average analysis (DMA) [36–37] and multi-fractal detrending moving average analysis (MF-DMA) algorithms [38]. There are a variety of other methods have been developed to investigate the cross-correlation characteristics of two time series, such as multifractal height cross-correlation analysis (MF-HXA) [39], joint multifractal analysis based on the partition function approach (MF-X-PF) [40–42], multifractal cross wavelet analysis (MF-X-WT) [43] and joint multifractal analysis based on wavelet leaders (MF-X-WL) [44].

Recently, a method of detrended partial cross-correlation analysis (DPCCA) [45–46] was proposed to remove the influences of shared noises and quantify the intrinsic relations of two non-stationary signals. Shen et al. [47] employed the DPCCA method to investigate the intrinsic cross-correlation characteristics of air pollution index (API) records and synchronously meteorological elements data. Lin et al. [48] used DPCCA method to analyze the intrinsic correlations between PNA/EPW and drought in the west United States.

Coherent structures abundantly occur in multiphase flows [49], and have attracted great attention because of their complex self-similar, organized and multi-scale dynamic behavior [50–52]. The organized motion of coherent structures arising from the interfacial wave and droplet entrainment is a predominant feature of horizontal oil-water two-phase flows, and commonly present remarkable multi-scale cross-correlations characteristics. Since the multi-scale coherent structures in two-phase flows can be identified by cross-correlation probe technologies [53–54], in this study we conduct an experiment of horizontal oil-water two-phase flows to collect the upstream and downstream flow information using a conductance cross-correlation velocity probe, and utilize the DPCCA algorithm to calculate multi-scale cross-correlation coefficient of coupled cross-correlated signals. The results indicate that the DPCCA cross-correlation coefficient can effectively indicate the coherent motion characteristics of the oil-water interface and the entrained droplets.

2. Multi-scale detrended cross-correlation analysis (DCCA) algorithms

2.1. Multi-scale DCCA algorithm and numerical experiment

Consider two time series $\{x(i)\}$ and $\{y(i)\}$, $i = 1, 2, \ldots, N$, N is length of series. The DCCA method can be introduced as follows [23]:

(1) Firstly, two integrated signals can be calculated by $R_x(k) = \sum_{i=1}^{k} x_i$ and $R_y(k) = \sum_{i=1}^{k} y_i$, $k = 1, 2, \ldots, N$, and then they are divided into $N - s$ overlapping boxes. Thus, there are $s + 1$ values in each box $R_{x,i}(k)$ and $R_{y,i}(k)$, $i \leqslant k \leqslant i + s$.

(2) Next, we define the local trend of each box as $\tilde{R}_{x,i}(k)$ and $\tilde{R}_{y,i}(k)$. The trend functions could be polynomials in the DCCA method, and the polynomial order is change-