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# Phase characterization of experimental gas–liquid two-phase flows

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ABSTRACT

We propose a method to characterize and distinguish flow patterns in experimental two-phase (e.g., gas–liquid) flows. The basic idea is to calculate the instantaneous phase from the signal and to extract scaling behaviors associated with the phase fluctuations. The effectiveness of the method is demonstrated and its applicability is articulated.



Gas–liquid two-phase flows arise commonly in a variety of physical, engineering, and industrial applications such as filtration, lubrication, spray processes, natural gas networks, and nuclear reactor cooling, etc. Understanding the nonlinear and complex dynamics underlying gas–liquid flows is a significant but challenging problem. In this regard, a primary task is to characterize and quantify the various flow patterns that often appear complex. Generally, the patterns arising from two-phase flows depend on a number of factors including the type of gas–liquid combination, the flow rate and direction, the shape, size, and inclination of the conduit. A common practice in the field is to examine the fluctuating properties associated with two-phase flows, which can be experimentally assessed from measurements such as the local pressure and the instantaneous two-phase mixture ratio [1,2]. Existing methods aiming at characterizing the fluctuations include those based on the power-spectral density (PSD) for pressure drop [3] and transient x-ray attenuation techniques [4,5]. Standard time-series analysis methods from nonlinear dynamics and chaos [6] have also been exploited [7–10].

At the present, the dynamical mechanisms generating various patterns in gas–liquid two-phase flows are elusive, due to the complex and nonlinear interplay among many factors such as fluid turbulence, phase interfacial interaction, and local relative movement between phases, etc. To our knowledge, a systematic theoretical framework to predict the flow patterns is non-existent. The purpose of this Letter is to introduce a instantaneous-phase based method to characterize typical patterns from experimental gas–liquid flows. Our idea is that the phase fluctuations associated with time series are caused by the intrinsic dynamics and can therefore yield important information about the underlying flow that existing, non-phase based methods are incapable of revealing. In particular, given a set of experimentally measured conductance-fluctuating signals, we first use the empirical-mode decomposition (EMD) method pioneered by Huang et al. [11] to extract the phase fluctuations. To uncover any robust scaling behavior hidden in the phase fluctuations, we use detrended fluctuation analysis (DFA) [12]. Our main finding is that, for each of the three distinct patterns arising typically in experimental two-phase flows, a scaling exponent can be extrapolated from the phase fluctuations. For different flow patterns, the values of the exponent are statistically distinct, indicating the effectiveness of the combined EMD/DFA method to characterize and distinguish complex two-phase flow patterns.

Our data are conductance signals from vertically upward pipe of inner diameter 125 mm in multi-phase flow-loop experiments at Tianjin University. The experimental mediums are air and tap water. The experimental system consists of the pipe, a vertical multi-electrode array (VMEA) of conductance sensors [13], high-speed video camera recorder (VCR), exciting-signal generating circuit, signal modulating module, data-acquisition device (PXI 4472, National Instruments), and software for preliminary signal processing. The VMEA component is shown in Fig. 1. The measurement system

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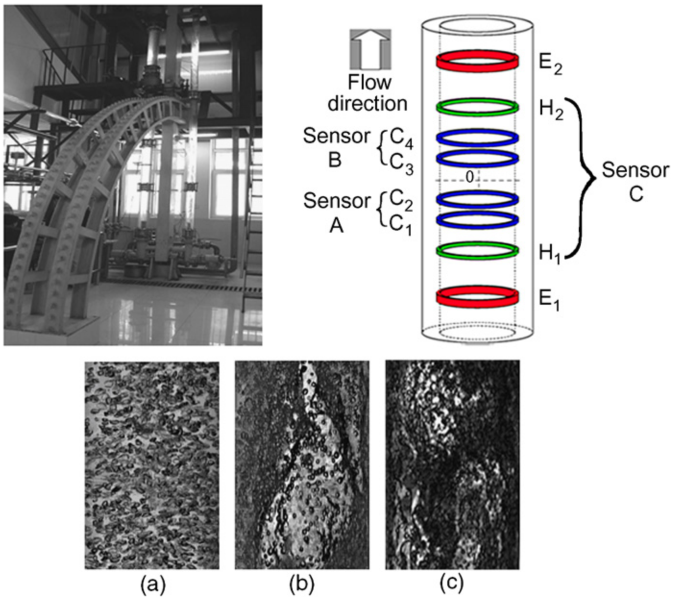


**Fig. 1.** (Color online.) VEMA sensor and three typical patterns experimentally recorded from vertically upward gas–liquid two-phase flows: (a) bubble flow ($U_{sw} = 0.18$ m/s, $U_{sg} = 0.01$ m/s), (b) slug flow ($U_{sw} = 0.18$ m/s, $U_{sg} = 0.12$ m/s), and (c) churn flow ($U_{sw} = 0.18$ m/s, $U_{sg} = 0.61$ m/s). The VEMA consists of eight alloy titanium ring electrodes axially separated and flush mounted on the inside wall of the flowing pipe. E1 and E2 are exciting electrodes. C1–C2 and C3–C4 are two pairs of upstream and downstream correlation electrodes denoted as sensor A and sensor B, respectively. Based on the cross-correlation technique, we can extract the axial velocity of the two-phase flow from fluctuating signals from sensors A and B. H1–H2 is the volume-fraction electrodes denoted as sensor C. The measurement circuit is embedded inside the instrument.

uses a 20 kHz sinusoidal voltage signal of amplitude 1.4 V to excite the flow. The signal-modulating module consists of three submodules: differential amplifier, sensitive demodulation and low-pass filter.

A typical experimental run starts by generating water flow at a fixed rate in the pipe and then gradually increasing the gas-flow rate. When the gas and water flow rates reaches a pre-defined ratio, a conductance signal is collected from VMEA and the flow pattern is visualized by the high-speed VCR. Fig. 1 shows three typical patterns from the water–gas flows. The water- and gas-flow rates are between 0.02 m/s and 0.27 m/s and from 0.0045 m/s to 2.94 m/s, respectively. The sampling frequency is 400 Hz, and the data recording time for one measurement point is 60 s.

Let $b(t)$ be a measured conductance-fluctuating signal. To see the need for the EMD method, we first perform the Hilbert transform:

$$b'(t) = P.V.\left[1/\pi \int_{-\infty}^{+\infty} b(t')/(t-t')\,dt'\right] \tag{1}$$

where $P.V.$ stands for the Cauchy principal value for integral. We then construct the corresponding analytic signal as

$$\psi(t) = b(t) + ib'(t) \tag{2}$$

Fig. 2(a) shows, for a signal from the bubble flow, a trajectory of the analytic signal in its complex plane. We observe that there exist multiple centers of rotation, so a properly defined phase variable cannot be obtained from the analytic signal. It is thus necessary to decompose the original signal $b(t)$ into a number of modes whose analytic signals correspond to proper rotations. Similar behaviors have been observed for slug and churn flows.

The EMD method was invented [11] to address this decomposition problem. The method has been applied to different problems

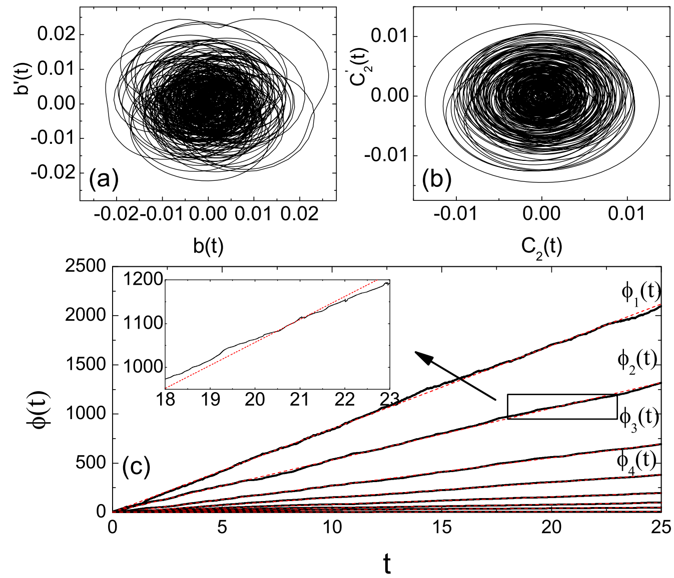


**Fig. 2.** (Color online.) Trajectory in the complex plane of the analytic signal from a bubble flow ($U_{sw} = 0.18$ m/s, $U_{sg} = 0.01$ m/s): (a) for the original signal and (b) for the second intrinsic mode. (c) Phase function $\phi_k(t)$ corresponding to eight different intrinsic modes from the bubble flow. The red dashed lines are the linear fitting of phase functions. The extracted frequencies of these modes are $w_1 \approx 84.66$, $w_2 \approx 52.54$, $w_3 \approx 28.26$, $w_4 \approx 15.47$, $w_5 \approx 7.6$, $w_6 \approx 3.5$, $w_7 \approx 1.7$, and $w_8 \approx 0.29$.

such as phase characterization of chaos [14] and laser signals [15]. The basic steps of the EMD method are: (1) construction of two smooth splines connecting all the maxima and minima, respectively, to get $b_{max}(t)$ and $b_{min}(t)$; (2) computation of

$$\Delta b(t) \equiv b(t) - \left[b_{max}(t) + b_{min}(t)\right]/2 \tag{3}$$

and (3) repetitions of steps (1) and (2) for $\Delta b(t)$ until the resulting signal corresponds to a proper rotation. Denote the resulting signal by $C_1(t)$, which is the first intrinsic mode. We then take the difference

$$b_1(t) \equiv b(t) - C_1(t) \tag{4}$$

and repeat steps (1)–(3) to obtain the second intrinsic mode $C_2(t)$. The procedure continues until the mode $C_M(t)$ shows no apparent variation (i.e., it has fewer than two local extrema). Result from the decomposition procedure can thus be represented by

$$b(t) = \sum_{k=1}^{M} C_k(t) \tag{5}$$

where the intrinsic modes $C_k(t)$ are nearly orthogonal to each other [11]. By construction, each mode $C_k(t)$ generates a proper rotation in the complex plane of its own analytic signal

$$\psi_k(t) = A_k(t)e^{i\phi_k(t)} \tag{6}$$

and the average rotation frequencies

$$w_k = \langle d\phi_k(t)/dt \rangle \tag{7}$$

obey the following order $w_1 > w_2 > w_3 > \cdots > w_M$ [11], where the amplitude function $A_k(t)$ and the phase function $\phi_k(t)$ can be obtained from the analytic signal of $k$th intrinsic mode:

$$\psi_k(t) = C_k(t) + iC_k'(t) = A_k(t)e^{i\phi_k(t)} \tag{8}$$

for $k = 1, 2, \ldots, M$, where $M$ is the number of intrinsic modes. Correspondingly, a proper rotation for $k$th intrinsic mode can be