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Detection of two-phase flow patterns using the recurrence network analysis of pressure drop fluctuations☆

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ABSTRACT

The two-phase flow (water–air) occurring in the square minichannel (3 × 3 mm) has been analysed. In the minichannel it has been observed: flow of grouped isolated bubbles, flow of confined bubbles, flow of elongated bubbles, slugs flow and semi-annular flow. The time series of pressure drop fluctuations was analysed using the analyses of traditional recurrence quantification and recurrence network. The two coefficients: recurrence period density entropy and transitivity have been used for identification of differences between the dynamics of two-phase flow patterns. The algorithm which has been used normalizes the analysed time series before calculating the recurrence plots. Despite the neglect of quantitative signal characteristics the analysis of its dynamics allows us to identify the two-phase flow patterns. This confirms that this type of analysis can be used to identify the two-phase flow patterns in minichannels.

1. Introduction

The identification of flow patterns in minichannels often depends on the subjective evaluation of the observer and used experimental technique [1–3]. Many researchers make efforts to use the non-linear methods of data analysis to identify the two-phase flow patterns based on the analysis of single signal recorded during the experiment [4–9].

The subject of the research is the development of method for identifying the two-phase flow patterns in the rectangular minichannel using the time series of pressure drop fluctuations. Usually the non-linear methods of data analysis require the long time series for calculation of different coefficients, which characterise the system dynamics. In the present paper the proposed method is based on the recurrence quantification analysis. Such method does not require the analysis of long time series. Therefore, it can be useful for implementation in the sensors, which automatically can identify the flow patterns.

2. Experimental setup

The different flow patterns (water–air at 21 °C) in a square channel 3 × 3 mm have been analysed. In Fig. 1 the schema of experimental stand is presented. Due to the size of the minichannel the obtaining of the bubbly flow inside it requires the usage of a special generator of mini bubbles (8 — Fig. 1). The proportional pressure regulator (Metal Work Regtronic with an accuracy of 1 kPa) was used to maintain the constant overpressure in the supply tank (10 — Fig. 1) — the overpressure was 50 kPa. Flow patterns were recorded with using the Casio EX-F1 digital camera at 1200 fps (336 × 96 pixels). Pressure

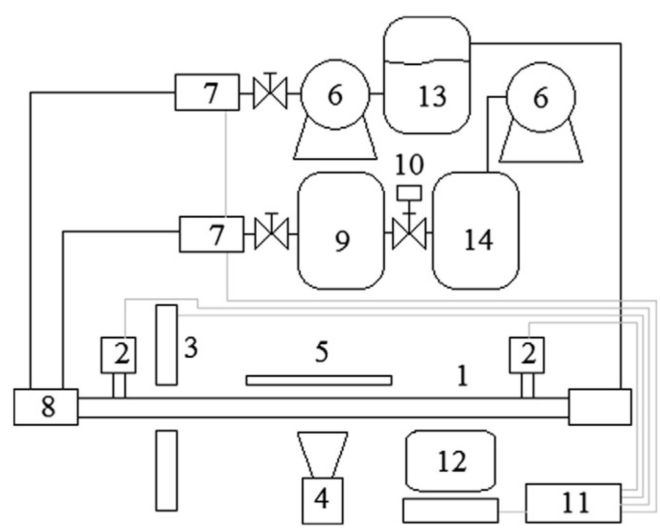

Fig. 1. Schema of experimental stand. 1. minichannel, 2. pressure sensors (MPX12DP), 3. laser–phototransistor sensor, 4. Casio EX-FX1 camera, 5. lighting, 6. pumps (air or water), 7. flow metres, 8. mini bubbles generator, 9. air tank, 10. automatic valve to maintain a constant pressure in the tank 9, 11. data acquisition station (DT9800), 12. computer, 13. water tank, and 14. air tank.

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Nomenclature

A	adjacency matrix
C_T	transitivity
H	normalized entropy of recurrence period density
I	mutual information
N	number of considered states
p	probability distribution function
q	volume flow rate
R	recurrence plot (RP)
RR	Recurrence rate
T	recurrence time
x	measurement
t	time

Greek letter

τ	time delay
δ	main diagonal
ε	threshold distance
Θ	Heaviside function

Indexes

a	air
i, j, k, m	index
w	water

difference between the inlet and outlet of minichannel was measured using the silicon pressure sensor MPX12DP (range 0–10 kPa, sensitivity 5.5 mV/kPa, response time 1 ms, accuracy ±0.05 kPa). The length of minichannel was equal to 300 mm. Sampling frequency was equal to 1 kHz.

3. Data characteristic

In Fig. 2 it has been shown the map of two phase flow patterns observed during the experiment for different air and water volume flow rates. The grouped isolated bubbles have been observed for all q_w and q_a in the range from 0.001 l/min to 0.0424 l/min (Fig. 2). For $q_a =$ 0.1 l/min the confined bubbles appear in the minichannel. The flow of elongated bubbles appears for $q_a = 0.2$ l/min. Slug flow appears for $q_a = 0.3$ l/min and $q_a = 0.4$ l/min and semi-annular flow appears for $q_a = 0.5$ l/min.

In Fig. 3 it has been shown the examples of pressure drop fluctuations for $q_w = 0.057$ l/min and different air volume flow rates. Both amplitude and frequency of pressure drop fluctuations change together with flow pattern modifications. Fig. 4 presents the mean values of pressure drop fluctuations for different air and water flow rates. The non-linear character of function of mean pressure drop vs. air volume flow rate makes impossible the identification of the two-phase flow pattern in minichannel based on the mean pressure drop measurement — the same values of mean pressure drop characterise the different flow patterns.

Pressure drop fluctuations describe the two-phase flow conditions in the whole minichannel. The frequency of pressure fluctuations is much larger than frequency of signal recorded by laser–phototransistor sensor. We can expect that pressure drop fluctuations contain much more information about flow conditions in comparison with data recorded by single laser–phototransistor sensor. Retrieving this information requires the calculation of coefficients, which characterise the dynamics of pressure fluctuations. For this purpose, the non-linear methods of experimental data analysis have been applied in the paper.

4. Recurrence quantification analysis

In the paper the non-linear analysis was carried out using the Matlab Toolbox [10]. The analysis started from the attractor reconstructed from experimental data. The analysis of attractor data gives us information about the system complexity and its stability. The reconstruction of attractor in a certain embedding dimension is carried out using the stroboscope coordination [11]. The subsequent co-ordinates of attractor points are calculated basing on the subsequent samples, between which the distance is equal to time delay, τ. The time delay is a multiplication of time between the samples. The quality of attractor reconstruction is a function of time delay. In the paper the mutual information between time series: $x(t)$ and $x(t+\tau)$ was used to determine proper time delay for attractors reconstruction [10,11]. The mutual information is defined as [11]:

$$I(x(t), x(t+\tau)) = \sum\nolimits_{x(t+\tau)} \sum\nolimits_{x(t)} p[x(t), x(t+\tau)] log_2 \left\{ \frac{p[x(t), x(t+\tau)]}{p[x(t)]p[x(t+\tau)]} \right\}, \quad (1)$$

where $p[x(t),x(t+\tau)]$ is the joint probability distribution function of $x(t)$ and $x(t+\tau)$, and $p[x(t)]$ and $p[x(t+\tau)]$ are the marginal probability distribution functions of x and $x(t+\tau)$.

The mutual information is equal to zero if $x(t)$ and $x(t+\tau)$ are independent. Usually, as τ is increased, the mutual information decreases,

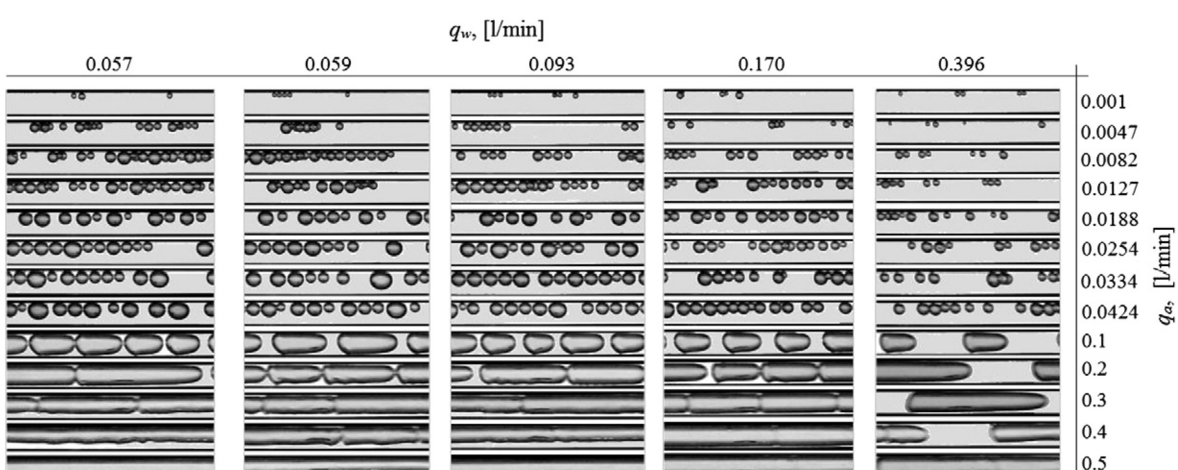

Fig. 2. The map of two phase flow patterns recorded during the experiment for different air and water flow rates.