Identification of two-phase flow patterns in minichannel based on RQA and PCA analysis

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A B S T R A C T

In the paper it has been shown that the analysis of dynamics of void fraction changes in time can be used for identification of two-phase flow patterns. The two-phase flow (air–water) in horizontal square minichannel (3 × 3 mm) has been analysed. The laser–phototransistor sensor signal was used for qualitative assessment of void fraction in minichannel. For data analysis there has been used the recurrence quantification analysis and the principal component analysis. The method of selection of coefficients resulted of recurrence quantification analysis has been proposed. Those coefficients describe the different aspects of two-phase flow patterns, but they are not independent variables describing the dynamics of two-phase flow. To obtain the set of independent variables characterising the dynamics of two-phase flow patterns the principal component method has been used. The proposed method allows us for the identification of following two-phase flow patterns: flow of micro-bubbles, flow of micro- and mini-bubbles, flow of micro- and mini-bubbles with confined bubbles, slug flow, stratified flow. The obtained results confirm that this type of analysis can be considered as an alternative way of identification of two-phase flow patterns in the minichannel.

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1. Introduction

Usually, the two-phase flow patterns are identified based on results of visual observations of gas and liquid arrangement inside the minichannel or on the average values of parameters characterising the two-phase flow such as: mass or volume flux of phases, void fraction, phase momentum flux, dimensionless flow rate, superficial velocity and others. The alternative way of flow pattern identification is based on the analysis of dynamics of changes of parameters characterising the two-phase flow. Such analyses have been proposed by many scientists. Wang et al. in the paper [1] show that the non-linear analysis (Lempel–Ziv complexity and approximate entropy) of data from mini-conductance probe array and vertical multielectrode array conductance sensor enables the identification of flow patterns of the oil–gas–water mixture. The non-linear analyses of temperature and pressure fluctuations in boiling in microchannels are discussed by Mosdorf et al. in the paper [2]. Wang et al. in the paper [3], used the non-linear analysis of the pressure fluctuations to identify the flow patterns. Hurst exponent, largest Lyapunov exponent and correlation dimensions have been used. In the paper [4] it has been shown that the non-linear analysis of the flow of oil–water is useful for identification of the flow patterns and for assessment of the complexity of those patterns. The recurrence quantification analysis (RQA) has been used for investigation of signal from vertical multi-electrode array. The results show that the proposed method of data analysis describes the flow structure complexity. Jin et al. in the paper [5] showed that the correlation dimension and Kolmogorov entropy were sufficient to identify the oil–water flow patterns. Faszczechowski et al. in the paper [6] used the recurrence plot method to analyse the flow patterns in a vertical minichannel. It has been shown that this method allows us to determine the parameters, which define the borders between flow patterns. In the paper [7] the pressure drop fluctuations in two-phase flow (water–air) in square minichannel (3 × 3 mm) have been analysed. The two coefficients of RQA: recurrence period density entropy and transitivity have been used for identification of differences between the dynamics of two-phase flow patterns. It has been shown that the recurrence network analysis of dynamics of pressure drop fluctuations can be used to identify the two-phase flow patterns in minichannels. The method of using the RQA coefficients to analyse the system dynamics has been proposed in the papers [8,9]. The Support Vector Machine has been used as a classifier of recorded data. The idea of using the principal component analysis (PCA) for the RQA has been presented in the paper [20].

The application of RQA and PCA for identification of two-phase flow pattern has been presented in the papers [21,22]. The two-phase flow (air–water) in square minichannel (3 × 3 mm) with using the signal from the laser–phototransistor sensor has been
analysed. In these papers the RQA was prepared for constant embedding dimension, time delay and threshold distance for recurrence identification. In practice, these values vary together with changes of the air and water flow rates. In papers [21,22] the PCA was applied for all (11) calculated RQA coefficients.

In the present paper the method of identification of two-phase flow patterns has been developed: embedding dimension, time delay and threshold were calculated separately for different air and water flow rates. The method of selection of RQA coefficients has been proposed. Finally, the PCA was used only for selected RQA coefficients.

2. Experimental setup and measurement techniques

In the paper it was analysed the flow patterns (water–air at 21 °C) in a horizontal square channel, 3 × 3 mm. In Fig. 1a the schema of experimental stand is presented. Due to the size of the minichannel the obtaining the bubbly flow inside it requires the usage of a special generator of mini-bubbles (8 – Fig. 1a–c). The generator was made of 7 sheets of stainless steel (thickness of 0.5 mm). In the sheets the slots were cut out. The slots were used for supplying the water and air to the minichannel. The outlet of generator is presented in Fig. 1c. The bubbles have been generated in the central channel (0.5 × 0.5 mm – Fig. 1c). The air was supplied by orifice with dimension of 0.25 × 0.5 mm (Fig. 1b). Two outer channels (Fig. 1c) were used to supplying the additional water to the minichannel. 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. 1a) – the overpressure was 50 kPa. Flow patterns were recorded with using the Casio EX-F1 digital camera at 1200 fps (336 × 96 pixels). Pressure difference between the inlet and outlet of the minichannel was measured using the silicon pressure sensor MPX12DP. The content of the minichannel was measured using the laser–phototransistor sensor (Metal Work Regtronic with an accuracy of 1 kPa) was used to record with using the Casio EX-F1 digital camera at 1200 fps (11 – Fig. 1a) at a sampling rate of 1 kHz.

In Fig. 2 it has been shown the examples of signal recorded from the laser–phototransistor sensor for different air volume flow rates. In all charts the examples of flow pattern occurring in the minichannel have been presented. When the channel is filled with water, the sensor generates a high voltage signal (~3.4 V). When the front of the slug or bubble is passing through the laser beam, then the sensor voltage level drops to ~1.8 V. The value of voltage drop below the 3.4 V is a measure of the size of small bubbles appearing inside the minichannel (Fig. 2a). Large bubbles may refract the light in such a way, that the light intensity measured by the phototransistor may be greater than in case when the channel is filled with water. In particular, this phenomenon occurs at the end of long bubbles (rys.2.d). In this case, the signal recorded with the phototransistor reaches a value greater than 4 V. For the slug flow the signal also reaches the value greater than 4 V. When the channel is filled by long slug, then the voltage very often reaches the value over 2 V (Fig. 2e).

In Fig. 3a it has been shown the example of video frames obtained for different air and water flow rates. The following flow patterns have been observed: flow of micro-bubbles, flow of micro- and mini-bubbles, flow of micro- and mini-bubbles with confined bubbles, slug flow, stratified flow. In Fig. 3b it has been shown the points of experimental measurements on the Mandhane et al. map [23].

The identification of borders between flow patterns usually is based on the recorded videos, therefore, it is difficult of estimate the error of border identifications. In the next section it will be proposed the method of identification of borders between two phase flow patterns based on the analysis of dynamics of signal from the laser–phototransistor sensor.

3. Recurrence quantification analysis

Recurrence plot (RP) is a technique of visualisation of the recurrence of states $x_i$ in $m$-dimensional phase space. The recurrence of states at time $i$ and at a different time $j$ is marked with black dot in the 2D plot, where both axes are time axes. The recurrence plot is defined as [10]:

$$R_{ij} = \Theta(\varepsilon - ||x_i - x_j||), \quad x_i \in \mathbb{R}^m, \quad i,j = 1 \ldots N$$

where $N$ is the number of considered states $x_i$, $\varepsilon$ is a threshold distance in $m$ dimensional space, $|| \cdot ||$ is a norm and $\Theta(\cdot)$ is the Heaviside function.

The preparation of the RP starts from the attractor reconstruction from time series $x_i$. The reconstruction of attractor in a certain embedding dimension is carried out using the stroboscope.
In this method the subsequent co-ordinates of attractor points are calculated basing on the subsequent samples, between which the distance is equal to time delay \( \tau \). The time delay is a multiplication of time between the samples. The subsequent co-ordinates of attractor points are as follows \([11]\):

\[
\{x_i, x_{i+\tau}, x_{i+2\tau}, \ldots, x_{i+(m-1)\tau}\}
\]

where \( x_i \) is a measured quantity.

The image of the attractor in \( m \)-dimensional space depends on the time delay \( \tau \). When the time delay is too small, the attractor gets flattened, that makes further analysis of its structure impossible \([11]\). The mutual information, \( I \), between time series: \( \{x_i\} \) and \( \{x_{i+\tau}\} \) can be used to determine the proper time delay for reconstruction of attractors. The mutual information is equal to zero if \( \{x_i\} \) and \( \{x_{i+\tau}\} \) are independent random variables. When \( \tau \) increases, the mutual information decreases and then usually it rises again \([12]\). The time delay for which the mutual information obtains the first minimum is a proper value of \( \tau \). The mutual information of \( \{x_i\} \) and \( \{x_{i+\tau}\} \) can be defined as \([12,13]\):

\[
I(x_i, x_{i+\tau}) = \sum_{x_i, x_{i+\tau}} p[x_i, x_{i+\tau}] \log \left( \frac{p[x_i, x_{i+\tau}]}{p[x_i]p[x_{i+\tau}]} \right)
\]

where \( p[x_i, x_{i+\tau}] \) is the joint probability distribution function of \( \{x_i\} \) and \( \{x_{i+\tau}\} \) and \( p[x_i] \) and \( p[x_{i+\tau}] \) are the marginal probability distribution functions of \( \{x_i\} \) and \( \{x_{i+\tau}\} \).

The false nearest neighbour algorithm \([14]\) has been used for estimation of the proper embedding dimension of attractors. In this method the changes of number of neighbouring points in embedding space with increasing embedding dimension is examined. For each point \( x_i \) the distances to its nearest neighbour \( x_0 \) are calculated in \( m \) and \( m + 1 \) dimensional space. The point is treated as a false neighbour, when the distance between points \( (i,j) \) increases together with increasing the embedding dimension. The number of false neighbours is calculated for the whole time series and for several dimensions until the fraction of false points reaches zero. Such dimension is treated as a proper embedding dimension for the attractor reconstruction.

In (Fig. 4a) the example of data recorded for horizontal position of minichannel, mutual information (Fig. 4b), fraction of false nearest neighbours (Fig. 4c) and RP (Fig. 4d) are presented. RP has been created for \( \{q_w = 0.057 \text{ l/min}, q_a = 0.2 \text{ l/min}\} \) embedding dimension equal to 6 (Fig. 4c) and time delay equal to 10 (Fig. 4b). The circles in Fig. 4b and c mark the proper values of time delay and embedding dimension. In Fig. 4b the circle indicates the first minimum of mutual information and in Fig. 4c the circle indicates the embedding dimension, for which the fraction of false nearest neighbours decreases to zero. In Fig. 4e the RP obtained from signal recorded for \( \{q_w = 0.094 \text{ l/min}, q_a = 0.019 \text{ l/min}\} \) is presented. In this case the embedding dimension is equal to 8 and time delay is equal to 37. The RP depends on the value of \( \epsilon \). When the \( \epsilon \) increases, the number of points on the RP also increases. In this case \( \epsilon \) was equal 20% of attractor diameter in the \( m \) dimensional space. When value of \( \epsilon \) defined this way decreases, then the number of the points in RP shown in Fig. 4e decreases and becomes too small.

A line parallel to main diagonal line occurs when a segment of the trajectory runs parallel to another segment and the distance between trajectories is less than \( \epsilon \). The length of this diagonal line is determined by the duration of this phenomenon. A vertical (horizontal) line indicates a time in which a state does not change or changes very slowly. The diagonal lines (structures) which occur periodically in the recurrence plot are characteristic for the periodic system \([14]\).

The quantitative recurrence analysis \([10,14]\) generates the coefficients which describe the dynamics of two-phase flow patterns. The 11 coefficients have been considered as a set of variables describing the dynamics of two phase flow patterns.

The following properties of the recurrence plot have been considered:
Fig. 2. Examples of time series recorded from laser–phototransistor sensor for $q_w = 0.094$ l/min, (a) $q_a = 0.001$ l/min, (b) $q_a = 0.033$ l/min, (c) $q_a = 0.42$ l/min, (d) $q_a = 0.1$ l/min, (e) $q_a = 0.3$ l/min.
1. The overall quantity characteristic of the recurrence plot which is described by the recurrence rate. Recurrence rate is a measure of the percentage of recurrence points in the recurrence plot and corresponds to the correlation sum. It is defined as follows [14]:

$$RR = \frac{1}{N^2} \sum_{i,j=0}^{N} R_{i,j}$$

(4)

2. The characteristics of diagonal lines which are described by:

Determinism is a measure of fraction of recurrence points which form diagonal lines. Determinism is defined as [10]:

$$DET = \frac{\sum_{l=\text{min}}^{N} P(l)}{\sum_{l=\text{min}}^{N} R_{i,j}^{l}}$$

(5)

where $P(l)$ – denotes the distribution of the lengths of diagonal lines and $N$ is the absolute number of diagonal lines;

Length of the longest diagonal line. The (length of the longest diagonal line)$^{-1}$ is related with the KS entropy of the system, i.e. with the sum of the positive Lyapunov exponents [10].

Entropy of occurrence of the diagonal line lengths defined as [10]:

$$\text{ENTR} = \sum_{l=\text{min}}^{N} p(l) \ln p(l)$$

(6)

where $p(l)$ – probability of finding the diagonal line length of $l$: $p(l) = \frac{P(l)}{\sum_{l=\text{min}}^{N} P(l)}$.

3. The characteristics of vertical lines which are described by:

Laminarity, which describes the percentage of recurrent points belonging to the vertical lines, is defined as [10]:

$$\text{LAM} = \frac{\sum_{v=\text{min}}^{N} v P(v)}{\sum_{v=1}^{N} v P(v)}$$

(7)

where $P(v)$ denotes the distribution of the lengths of vertical lines;

Length of the longest vertical line defines a time in which a state does not change or it changes very slowly [10].

Trapping time describes the average length of vertical line structures [10]:

$$\text{TT} = \frac{\sum_{v=\text{min}}^{N} v P(v)}{\sum_{v=1}^{N} v P(v)}$$

(8)

In case of recurrence time of the first type $T^1$, all points of RP are considered. Such value of $T^1$ depends on the trajectory density and value of $\varepsilon$ [15,16]. From the formal point of view the $T^1$ can be defined as:

$$T^1 = \{ (i,j : x_i, x_j \in R^l) \}$$

(9)

where $R^l$ is a neighbourhood of point $x_i$. 

Fig. 3. Maps of experimental results. (a) The example of video frames obtained for different air and water flow rates. (b) The points of experimental measurements on the Mandhone et al. map [23].
In case of recurrence time of the second type $T^2$ the vertical distances between the pairs “white” pixel/“black” pixel in the columns are measured. Then, in this case for the periodic motion, the $T^2$ accurately estimates the period of the motion. This type of recurrence time is related to entropy and to the information dimension of an attractor [15,16]. From the formal point of view the $T^2$ can be defined as:

$$T^2 = \{(i,j) : (i,j) \in R^2, x_{i,j} \neq x_{i-1,j} \}$$  \hspace{1cm} (10)

Little et al. [17] developed a recurrence period density entropy method. In this method the recurrences into the neighbourhood, $i$, of each points are tracked, and such obtained time intervals are used for construction of the histogram of recurrence times. This histogram is used for the calculation of the recurrence period density function. The normalised entropy of this density has a form [17].

$$H_{\text{norm}} = -\left(\ln T_{\text{max}}\right) - \sum_{i=3}^{T_{\text{max}}} p(t) \ln p(t)$$  \hspace{1cm} (11)

where $p(t)$ is the recurrence period density function.

The value of $H_{\text{norm}}$ changes in the range from zero to one. For the periodic signals, $H_{\text{norm}} = 0$, whereas for the uniform white noise, $H_{\text{norm}} = 1$.

Alternative method of recurrence plot analysis has been presented in paper [18]. In this approach the recurrence plot is treated as the adjacency matrix of a complex network.

4. Results and discussion

In Fig. 5 it has been shown the time delay (lag) and embedding dimension for different air and water volume flow rates.

The value of time delay is related to the rate of decreasing the autocorrelation function. The greater time delay appears in time series with a low rate of decreasing the autocorrelation function. The high rate of decreasing the autocorrelation function appears in bubbly flow for $q_w = 0.396 \text{ l/min}$ and for slug flow (Fig. 5a). The low rate of decreasing the autocorrelation function appears for bubbly flow for $q_w = 0.057 \text{ l/min}$ and 0.094 l/min. The embedding dimension defines the number of independent variables describing the analysed system. The higher embedding dimension appears for small bubbles flow for $q_w$ from 0.057 l/min to 0.17 l/min. In bubbly flow the increase of water flow rate causes the decrease of embedding dimension. The opposite situation appears for slug flow.

In Figs. 6 and 7 it has been shown the values of RQA coefficients obtained for different air and water volume flow rates. The recurrence plots have been prepared for the number of samples equal to 1000.

When the channel is filled with water, the signal from the phototransistor sensor oscillates with small amplitude around a constant value of $\sim 3.4 \text{ V}$, and when the channel is filled with bubbles the signal oscillates around the value of $\sim 1.8 \text{ V}$. From the fragments of a time series, in which his value oscillates around the constant values, the algorithm of attractor reconstruction creates the points with coordinates $(\sim 3.4 \sim 3.4 \sim 3.4, \ldots)$ and $(\sim 1.8 \sim 1.8 \sim 1.8, \ldots)$. In the vicinity of those points the recursion usually occurs. Such recurrences create in the RP the diagonal lines as well as vertical lines. As a result, the frequency of occurrence of vertical and diagonal lines is very similar. In Fig. 6 it has been shown the length of the longest diagonal line and length of the longest vertical line.

In Fig. 6 black dots have been placed. Points show the locations of local minima of length of the longest diagonal line and length of the longest vertical line. The coefficient (1)length of the longest diagonal line) can be considered as a measure of chaos intensity.
in examined time series. This factor is associated with entropy KS (Kolmogorov–Sinai). This can be considered as the sum of positive Lyapunov exponents. The higher value of the coefficient (1/ length of the longest diagonal line) indicates the air and water flow rates, for which the two phase flow pattern becomes more unpredictable. In the results the dots shown in Fig. 6 indicate the air and water flow rates, where behaviour of two phase flow is more unpredictable. Dots shown in Fig. 6a form the borders between areas, where the two phase flow patterns are more predictable.

The analysis of dynamics of recorded data allows distinguishing the five two phase patterns. The patterns were marked with Roman numbers in Fig. 6a. We can distinguish: (I) flow of micro-bubbles, (II) flow of micro- and mini-bubbles. (III) flow of micro- and mini-bubbles with confined bubbles, (IV) slug flow, (V) stratified flow.

Fig. 7 shows the changes of coefficients: recurrence rate and recurrence period density entropy as a function of water and air volume flow rates. The maximum values of recurrence period density entropy indicate the ranges of water and air flow, where the chaotic behaviour of analysed signal is the most intensive. Both coefficients indicate the same area in the central part of Fig. 7a and b. The intensity of chaotic behaviour decreases for small bubbles flow with high value of water flow rate and for low water flow rate, and high air volume flow rate. The increase of water flow rate in the bubbly flow decreases the intensity of chaos appearance, while for the slug flow this intensity is increased.

5. Identification of two-phase flow patterns

In the windowed recurrence quantification analysis [19] the subset of fixed size of recorded data is defined. The first RP is obtained by taking the initial subset of the series. Then, the subset is modified by “shifting forward”. This creates a new subset of recorded data, which is used for calculation of the next RP. This process is repeated over the entire time series. Such analysis creates the set of RQA coefficients obtained for different parts of recorded data. The signal from the laser–phototransistor changes chaotically during the time, therefore, the values of coefficients $C_{RQA}$ obtained for subsequent subset of recorded data vary. In order to evaluate, whether the values of coefficients $C_{RQA}$ can be used for identification of flow patterns, the following coefficients have been calculated.
where \( \sigma(C_{\text{RQA}}) \) is standard deviation of coefficients \( C_{\text{RQA}} \) and \( \bar{C}_{\text{RQA}} \) is a mean values of coefficients \( C_{\text{RQA}} \).

The coefficient \( \Delta C_{\text{RQA}} \) is a measure of accuracy of evaluation of the system dynamics by the coefficient \( C_{\text{RQA}} \).

In Table 1 it has been shown the values of coefficients \( \Delta C_{\text{RQA}} \) for different air volume flow rates for \( q_w = 0.094 \text{ [l/min]} \), values lower than 10% have been marked. We can conclude that such coefficients as: determinism, averaged diagonal length, Entropy of diagonal length, laminarity, trapping time and recurrence period density entropy can be treated as the measure of two phase flow dynamics.

These coefficients describe the different aspects of dynamical system but they cannot be treated as independent variables describing the system. For obtaining the set of independent variables which characterise the dynamics of system under consideration the principal component method has been used.

The principal component analysis (PCA) is a method that uses the orthogonal transformation to convert an input set of data (in our case it is RQA coefficients stored in matrix \( A \)) into a new set of data, in a new set of coordinates called the principal components. Such method has been applied for RQA analysis in the papers [20–22]. This transformation is defined in such a way that the data (in a new set of coordinates) has the largest possible variance around the first principal component. For the successive components the variance of data decreases. In each water flow rate the matrix, \( A \), contains the values of 6 coefficients, which characterise the RP-s (name of columns) and 13 rows, which represent the values of air volume flow rates.

In the first step of PCA the data in columns of matrix \( A \) is normalised in such a way:

\[
z_i = \frac{(x_i - \bar{x})}{\sigma}
\]

where \( \sigma \) is a standard deviation of data in each column of matrix \( A \).

In the next step the covariance matrix is created:

\[
\text{Cov} = (AA^T)/(N - 1)
\]

where \( N \) is a number of measurements.

In cases under consideration the dimension of covariance matrix is 6 \( \times \) 6. The eigenvectors and eigenvalues of the covariance matrix are calculated using the SVD decomposition. In this method a rectangular matrix \( \text{Cov} \) can be broken down into the product of three matrices – an orthogonal matrix \( U \), a diagonal matrix \( S \) and the transpose of an orthogonal matrix \( V \). The SVD decomposition has the following form:

\[
\text{Cov} = U S V^T
\]

where \( S \) is a diagonal matrix containing the square roots of ordered eigenvalues. The columns of \( U \) are orthogonal eigenvectors of \( \text{Cov} \), the columns of \( V \) are orthogonal eigenvectors of \( \text{Cov}^T \).

Columns of matrix \( U \) contain the eigenvectors of the covariance matrix, which define the new coordinates characterising the data. In the end step of analysis the data is expressed in the new coordinates (called components) by the multiplication of eigenvectors by normalised data matrix. Usually, the first few components explain the most of input data variation.

For \( q_w = 0.042 \text{ l/min} \) first two components explain the 60% + 24% = 84% of input data variation. Therefore, the two first components can be used for reconstruction of 2D map of dynamics of two-phase flow patterns. The location of points on this map depends on the dynamical properties of recorded time series.

<table>
<thead>
<tr>
<th>( q_w ) [l/min]</th>
<th>0.013</th>
<th>0.042</th>
<th>0.200</th>
<th>0.500</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Recurrence rate</td>
<td>22%</td>
<td>18%</td>
<td>14%</td>
<td>21%</td>
</tr>
<tr>
<td>2 Determinism</td>
<td>4%</td>
<td>2%</td>
<td>3%</td>
<td>3%</td>
</tr>
<tr>
<td>3 Averaged diagonal length</td>
<td>3%</td>
<td>4%</td>
<td>1%</td>
<td>8%</td>
</tr>
<tr>
<td>4 Length of longest diagonal line</td>
<td>11%</td>
<td>42%</td>
<td>16%</td>
<td>78%</td>
</tr>
<tr>
<td>5 Entropy of diagonal length</td>
<td>7%</td>
<td>6%</td>
<td>3%</td>
<td>6%</td>
</tr>
<tr>
<td>6 Laminarity</td>
<td>2%</td>
<td>1%</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>7 Trapping time</td>
<td>4%</td>
<td>6%</td>
<td>2%</td>
<td>8%</td>
</tr>
<tr>
<td>8 Length of longest vertical line</td>
<td>13%</td>
<td>40%</td>
<td>24%</td>
<td>53%</td>
</tr>
<tr>
<td>9 Recurrence time of 1st type</td>
<td>21%</td>
<td>19%</td>
<td>14%</td>
<td>21%</td>
</tr>
<tr>
<td>10 Recurrence time of 2nd type</td>
<td>19%</td>
<td>14%</td>
<td>12%</td>
<td>18%</td>
</tr>
<tr>
<td>11 Recurrence period density entropy</td>
<td>4%</td>
<td>4%</td>
<td>4%</td>
<td>5%</td>
</tr>
</tbody>
</table>
Points corresponding to the time series, which have the similar dynamical properties, are located close to each other. In such a way the points corresponding to similar two-phase flow patterns create clusters in the map. The points on the map are characterised by values of $q_a$ and $q_w$ for which the time series have been recorded. The 2D map of dynamics of two-phase flow patterns is shown in Fig. 8a and b. The arrows in Fig. 8b indicate the direction of $q_a$ changes.

![2D map of dynamics of two-phase flow patterns](image)

**Fig. 8.** 2D map of dynamics of two-phase flow patterns in square (3 x 3 mm) minichannel. (a) Points location in 2D map. (b) Separated groups of points corresponding with different flow patterns. (c) 2D map of two-phase flow patterns in coordinates $v_w$ and $v_a$. I – flow of micro-bubbles, II – flow of micro- and mini-bubbles, III – flow of micro- and mini-bubbles with confined bubbles, IV – slug flow, V – stratified flow.
In the 2D map of dynamics of two-phase flow patterns the points are gathered in the five separated groups (Fig. 8b), which correspond to micro-bubble flow (Fig. 8b, I), flow of micro- and mini-bubbles (Fig. 8b, II), flow of micro- and mini-bubbles with confined bubbles (Fig. 8b, III), slug flow (Fig. 8b, IV), stratified flow (Fig. 8b, V). In Fig. 8c it has been shown the 2D map of two-phase flow patterns in coordinates $v_w$ and $v_a$. The areas where the flow patterns appear have been marked with Roman numbers.

In the papers [21,22] RQA coefficients were determined at constant values of time delay and embedding dimension. In the works the variation of those parameters (time delay and embedding dimension) together with change of water and air flow rates was not taken into account. Their constant values were determined for a signal recorded for bubble flow and they were used for analysis of other types of flow patterns. The application of obtained in such a way coefficients for the PCA did not allow to construct a 2D map describing the dynamics of two-phase flow for all water volume flow rates under consideration. In this case the points representing the different flow patterns were located on the 2D map in the same area. In [21] it has been shown results obtained only for two water flow rates. In this paper the PCA was performed for all 11 RQA coefficients. In [22] the PCA was used to determine which RQA coefficients were suitable for describing the dynamics of flow patterns vs. water and air flow rates. Two coefficients have been identified: determinism and recurrence rate.

The analyses carried out in the present paper show that the time delay and embedding dimension vary with the water and air flow rate. Not taking into account of this fact was one of the reasons for impossibility of preparing the 2D map for all water volume flow rates under consideration. The next issue which was solved in the present paper was the reducing the errors of accuracy of flow pattern identification by choosing the limited number of RQA coefficients. Only coefficients which vary slightly in stationary flows have been considered.

The comparison of present results with results obtained in the papers [21,22] shows that the proposed method is sensitive to the proper choosing of the RQA coefficients. Some coefficients cannot be treated as flow pattern identifiers because they vary during the stationary flow pattern.

6. Conclusions

In the paper the dynamics of changes of void fraction in time has been analysed. The analysis resulted in the creation of 2D map which described the dynamics of changes of void fraction in time. The map shows the character of recorded signal dynamics vs. the control parameters (water and air flow rates). Based on analysis of photographs taken using a high speed camera the areas of appearance of particular flow patterns have been set on the map. The numbers of flow patterns were identified based on the analysis of recorded movies and character of changes of the recorded signal (shown in Fig. 2). The borders obtained in such a way define the areas of the occurrence of flow patterns as well as they characterise the dynamics (of changes of void fraction in time) while the flow patterns change.

The aim of the proposed method is to analyse the dynamics of void fraction changes in time with using the RQA. In the paper the signal from the laser–phototransistor sensor has been analysed. However, the RQA has been successfully used for the analysis of signals recorded by other types of sensors.

The method of selection of RQA coefficients and the use of PCA, proposed in the paper, amplifies the differences that exist between dynamics of two phase flow patterns under considerations during the changes of control parameters. In the present paper the control parameters were the air and water flow rates. The detection of the influence of various parameters (such as temperatures, surface roughness of the channel and shapes of the channel) on the dynamics of two phase flow requires the collection of experimental data obtained for different values of those parameters, which are to become control parameters. In such a way the proposed map can be extended by defining the additional areas which characterise the flow patterns occurring for different values of considered control parameters. Also the proposed method can be used for analysis of data from other type of sensors.

When the map of dynamics of two-phase flow patterns is created, then it can be used for automatic detection of flow pattern. After the measurement and the RQA the results can be converted for the point on the map. The point location on the map indicates the flow pattern.

The proposed combination of RQA and PCA can detect differences between dynamics of flow patterns under considerations, but it does not directly indicate the physical processes responsible for those differences. Identification of the processes is possible after a comparison of the results of data analysis with values of other parameters describing the system. In the present work we compiled analysis results with images of flow patterns.

In the first step of quantification recurrence analysis the recorded signal is normalised, so the average values of the signal do not affect the results of the analysis. Despite of the neglect of quantitative signal characteristics, the qualitative analysis of its dynamics allows for the identification of the two-phase flow patterns. It has been shown that the proposed method is useful to identify the: flow of micro-bubbles, flow of micro- and mini-bubbles, flow of micro- and mini-bubbles with confined bubbles, slug flow, stratified flow.

The borders between two-phase flow patterns shown in Fig. 8 are similar to borders defined by the coefficient of value equal to (1/length of the longest diagonal line) (Fig. 6a). Therefore, we can conclude that the borders define the areas on the 2D map, inside which the behaviour of two phase flow is more predictable in comparison with two-phase flow behaviours on the border lines.

In the 2D map shown in Fig. 8 the points obtained for different air volume flow rates create the specific trajectory. Location of points on this trajectory corresponds to a certain two-phase flow pattern, which is created for a certain air volume flow rate. Therefore, this location of points on the trajectory can be used for more precise identification of two-phase flow pattern in comparison with proposition shown in Fig. 8b.

The obtained results confirm that this type of analysis can be treated as an alternative way of identification of two-phase flow patterns in the minichannel.

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References


