Entropy Analysis of Two Phase Flow Pattern Identification in Vertical Tube

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Abstract: This paper aims to analyze the time domain marginal spectral entropy of differential pressure signals collected from the gas-liquid two-phase flow pattern vertical tube bundle channel on the experimental platform. By comparing the visualized and measured differential pressure signals, four flow patterns were found, namely, bubble flow, bubble-mixed flow, agitated flow, and annular flow. The marginal spectral entropy values of the four flow patterns are calculated, and it is found that the spectral entropy distribution regions of the different flow patterns are different. Putting the aforementioned four flow patterns that is regarded as the feature quantity into artificial neural network support vector machine for flow pattern recognition. The experimental results show that the marginal spectral entropy can better reflect the flow difference between different flow patterns. The support vector machine has the advantages of fast calculation speed and high recognition rate. The overall recognition rate of the four flow patterns (the transition flow is included) is as high as 95.31% by combing the marginal spectral entropy with the support vector machine, which is suitable for online identification of flow patterns.

1. Introduction

Gas-liquid two-phase flow phenomena are widely found in various industrial pipelines, such as evaporator heat exchange tubes, water wall tubes.¹ The flow pattern of gas-liquid two-phase flow affects the flow and heat transfer of two-phase flow, which has an extremely important impact on the safe operation of equipment. Most of the previous research results are aimed at flow pattern recognition of horizontal and circular pipes ², and the research on flow pattern identification for longitudinally colliding vertical tube bundles ³ is still not perfect. Therefore, the identification of the flow pattern of the gas-liquid two-phase flow in the vertical tube bundle channel has always been an important issue in the field of two-phase flow.

Entropy can describe the complexity of nonlinear systems. Since the Shannon entropy is proposed, the research of entropy has been deepened. Approximate entropy, sample entropy, fuzzy entropy ⁴, multi-scale entropy ⁵, etc. are applied in signal processing, achieving certain results. However, these are all time domain entropy. The calculation of time domain entropy often depends on the parameter selection of data, such as delay time and embedding dimension. Improper parameter selection usually leads in large differences in results, causing difficulties in flow pattern recognition. Previous studies have shown that compared with signal time domain analysis, signal frequency domain analysis can better reflect the essential characteristics of signal. Power spectral entropy is a frequency domain entropy analysis method, which has been well applied in ECG analysis ⁶, rotor vibration fault diagnosis, centrifugal pump fault vibration signal processing ⁷. The theoretical basis of power spectral...
entropy is Fourier transform, which is very effective for stationary signal analysis with frequency variation with time. But it is difficult to analyze Fourier transform for non-stationary signal with frequency variation with time. Based on this, N.E. Huang and other engineers proposed a new signal analysis method in 1998, Hilbert-Huang transform (HHT), putting forward many new concepts such as empirical mode decomposition (EMD), Hilbert spectrum and marginal spectrum. It is pointed out that the amplitude of the Fourier spectrum can only reflect the probability that the frequency actually exists in the signal, while the amplitude of the marginal spectrum can reflect whether the frequency exists in the signal or not. The HHT transform can solve the deficiency of the Fourier transform.\(^8\)

Based on the HHT theory and the concept of generalized entropy, this paper proposes a new method of frequency domain entropy analysis—marginal spectral entropy analysis. According to the four types of differential pressure fluctuation signals of gas-liquid two-phase flow in the vertical tube bundle, the marginal spectral entropy value is calculated. Combing with the artificial neural network, it was used as the eigenvalue for flow pattern identification, attaching great significance for convective online identification.

2. Marginal Spectral Entropy Feature Extraction

2.1. Introduction to HHT Principle

The HHT algorithm includes empirical mode decomposition (EMD) and Hilbert transform. Firstly, EMD decomposition is performed on nonlinear non-stationary signals, obtaining a set of intrinsic mode functions (IMF) which characterize the time scale of signal characteristics. The Hilbert transform is conducted on each IMF component, obtaining the instantaneous frequency and the instantaneous amplitude, the Hilbert amplitude spectrum and the Hilbert marginal spectrum. The specific algorithm is as follows\(^9\),

(1) EMD decomposition of the signal, which is expressed as the sum of the limited IMF components.

\[ x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \]

(2) After Hilbert transform of each IMF component, it comes to:

\[ H[c(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{c(t)}{t} dt \]

(3) The instantaneous amplitude and instantaneous frequency: the analytical signal of \( c(t) \) can be expressed as \( z(t) = c(t) + jH[c(t)] \), and \( c(t) = a(t) \cos(\phi(t)) \) the amplitude function is \( a(t) = (c^2(t) + H^2[c(t)])^{1/2} \), the phase function is the instantaneous frequency of \( c(t) \) can be calculated from the phase function:

\[ f^I(t) = \frac{1}{2\pi} \frac{d}{dt} (\phi(t)) \]

(4) Hilbert spectrum:

\[ H(f^I,t) = \text{Re} \sum_{k=1}^{n} a_k(t)e^{2\pi jf^I_k(t)} dt \]

(5) Integrating \( H(f^I,t) \) with time to obtain the marginal spectrum:

\[ h(f^I) = \frac{1}{T} \int_{0}^{T} H(f^I,t) dt \]

2.2. Introduction to Marginal Spectral Entropy

Combined with the definition of information entropy, the marginal spectral entropy is defined as

\[ \text{HHE} = - \sum_{k=1}^{n} p_k \ln(p_k) \]

\[ p_k = h(k)/\sum h(k) \]

indicates the probability of occurrence of the corresponding value of the kth frequency. In order to avoid the influence of time series length and sampling frequency on spectral entropy, the spectral
entropy is normalized as
\[ HHE = \frac{HHE}{\ln N} \]  
\[ N \] is the length of the h(k) sequence.

2.3. Typical Signal Analysis
In order to verify the extensive application and anti-interference of the marginal spectral entropy theory, six typical signals are selected for analysis and calculation. The conditions for the generation of several time series are as follows:

1. Logistic mapping:
   \[ x_{n+1} = ax_n (1-x_n) \]  
   \[ a=3.9, x_0=0.4; \]  
   \[ x_{n+1} + 30 \text{dB} \]  

2. Logistics+ Noise:
   \[ y_n = ax_n + y_n \]  
   \[ a=1.4, b=0.3, x_0=0, y_0=0 \]  

3. Henon Mapping
   \[ x_{n+1} = 1 - ax_n^2 + y_n, y_{n+1} = bx_n, \]  
   \[ a=1.4, b=0.3, x_0=0, y_0=0 \]  

4. Sinusoidal signal \[ y = 3\sin(x), \text{ sampling interval is } \pi/50 \]

5. Sine + Gaussian noise: \[ y = 3\sin(x) + p \cdot y_1; \]  
   \[ y_1 \] is the Gaussian noise sequence, and \( p \) is the proportion of random components, taking \( p=0.2 \)

By intercepting 1000 data points of several typical signal sequences, it is found that the marginal spectral entropy of white noise is close to 1, and the marginal spectral entropy of logistic and henonen chaotic sequences is significantly larger than that of sinusoidal signals, indicating that chaotic sequences are more complex and sinusoidal. The signal has a nature of regularity, so the marginal spectral entropy is small. The calculation results also shows that the marginal spectral entropy method has better anti-noise ability, and the anti-noise ability of the chaotic sequence is better than that of the sinusoidal signal.

3. Support Vector Machines
The support vector machine is a neural network model based on statistical theory. The basic principle is to project the complex input vector nonlinearly into the high-dimensional linear space and construct the optimal hyperplane in the new space. The specific algorithm is as follows:

1. Given a sample set \( (x_i, y_i) (i=1,2,\ldots,n) \), in which \( x_i \in R^d \), \( y_i \in \{-1,1\} \) is a category label, maps the input vector to an n-dimensional space by nonlinear transformation \( \varphi : R^d \to R^n \);

2. Establishing a hyperplane in a high dimensional space: \( a\varphi(x) + b = 0 \), in which \( a = \sum_{i=1}^{n} a_i \varphi(x_i) \)

3. Classification hyperplane optimization, that is under constraint of \( y_i(a\varphi(x_i) + b) \geq 1 \), \( \Phi(a) = \|a\|^2/2 \) gets the minimum;

4. Introducing Lagrange multipliers \( a_i \geq 0 \), transferring it into quadratic programming problems:
   \[ \begin{align*}
   \max_{a, \omega, b} & \quad Q(a) = \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i,j=1}^{n} a_i a_j y_i y_j \varphi(x_i) \cdot \varphi(x_j) \\
   & \quad \sum_{i=1}^{n} a_i y_i = 0 \\
   & \quad a_i \geq 0, i=1,2,\ldots,n
   \end{align*} \]  
   (12)

Get the optimal \( a, \omega, b \);

5. The optimal classification function is \( f(x) = \text{sgn}(\omega^T \varphi(x) + b) = \text{sgn}(\sum_{i=1}^{n} a_i \varphi(x_i) \varphi(x)) \)  
   (13)

In order to avoid complex operations in high-dimensional space, kernel functions \( K \) was introduced,
In this paper, the SVM kernel function uses a radial basis kernel function, and the classifier uses a one-to-one algorithm.

4. Signal Acquisition
The experiment is carried out on a vertical tube bundle gas-liquid two-phase flow test bench and it is shown in Figure 1. The experimental device mainly includes three parts: a fluid control system, an image acquisition system, and a dynamic data acquisition system. The experimental section is a 1100 mm vertical tube bundle. The material is made of transparent plexiglass, and six pressure measuring points are set. The middle two points are the pressure difference measuring points. The working fluid is air-water, and the experimental acquisition frequency is 1000 Hz.

5. Result Analysis
In the experiment, four flow patterns were taken by a high speed camera. Considering the data integrity and the calculation speed, the differential pressure signal collected by the collector intercepts 6000 data points after the flow is stabilized.

Whether the selection of characteristic parameters can reflect the flow pattern characteristics directly determines the effect of flow pattern recognition. In this paper, a total of 142 sets of differential pressure signals were collected from the bubble flow, bubble-mixed flow, mixed flow and annular flow, and the marginal spectral entropy and power spectral entropy were calculated as characteristic parameters.

Spectral entropy is a measure of system complexity from a frequency domain perspective. The smaller the spectral entropy is, the more concentrated the spectral distribution is, and the lower the complexity of the system is. The larger the spectral entropy is, the flatter the spectral distribution is, and the higher the complexity of the system is. If it is a single frequency component, the theoretical spectral entropy is 0. If it is white noise, that is, the spectral density is 1/N at each frequency, the spectral entropy of the system is the maximum value log N.

The marginal spectral entropy distribution regions of different flow patterns are different, indicating that the complexity is different. The main channel of the bubble flow is the liquid phase, the bubbles are randomly distributed in the liquid phase, and flow upwards with the liquid phase macroscopically, so the marginal spectral entropy is the largest and the flow is the most complicated. For the bubble-mixed flow, the bubble gradually becomes larger through the narrow sub-channel, and the disturbance is gradually intense. Due to the cutting of the adjacent sub-channel, there is no slug flow, but transition to the mixing flow. The entropy value is located between the bubble flow and the agitated flow, with the characteristics of a bubble flow and a mixed flow. For the mixing flow, the bubbles are continuously polymerized and twisted in the channel, forming a strong disturbance, and
the liquid alternately moves up and down, causing strong oscillation. Due to the lateral mixing in the adjacent channels, the random phenomenon of gas phase and liquid phase vibration is not obvious, so the entropy value is lower than the bubble flow. For the annular flow, the gas phase volume ratio is much larger than the liquid phase volume ratio, and the gas phase and the liquid phase flow are continuous to form a relatively stable interface. At this time, the signal has a certain periodicity, the marginal spectral entropy is the smallest, and the flow is relatively regular.

The marginal spectral entropy of the four flow patterns is more distinguishable than the power spectral entropy. In order to realize streamline online identification, the marginal spectral entropy is taken as the characteristic parameter. 78 groups were selected from 142 groups as training samples, and were sent to the support vector machine for training, and the others are used as test samples for identification test. Tested on 64 groups of samples, the results show that the overall recognition accuracy rate is 95.31%, the test time is 0.11s, 3 cases were misidentified (2 cases of bubble-mixed flow and 1 case of annular flow), the recognition rate of the mixed flow reached 100% and part of the data experimental results are shown in Table 1. It proves that the marginal spectral entropy and the support vector machine can identify four experimental flow patterns quickly and accurately.

| Serial number | Marginal spectral entropy | Actual flow pattern | Recognition result |
|---------------|---------------------------|---------------------|--------------------|
| 1             | 0.6470                    | Bubble flow         | Bubble flow        |
| 2             | 0.6867                    | Bubble flow         | Bubble flow        |
| 3             | 0.6747                    | Bubble flow         | Bubble flow        |
| 4             | 0.5425                    | Bubble-mixed flow   | Bubble-mixed flow  |
| 5             | 0.5072                    | Bubble-mixed flow   | Bubble-mixed flow  |
| 6             | 0.4555                    | Mixing flow         | Mixing flow        |
| 7             | 0.4668                    | Mixing              | Mixing             |
| 8             | 0.4563                    | Mixing              | Mixing             |
| 9             | 0.4491                    | Mixing              | Mixing             |
| 10            | 0.4540                    | Mixing              | Mixing             |
| 11            | 0.3424                    | Annular flow        | Annular flow       |
| 12            | 0.3640                    | Annular flow        | Annular flow       |

In order to verify the effectiveness of the combination of marginal spectral entropy with the support vector machine to identify the flow pattern, this paper combines the marginal spectral entropy with the commonly used BP neural network and compares it with the support vector machine. The experimental results are shown in Table 2. The experimental results show that the combination of marginal spectral entropy with the support vector machine can identify the four flow patterns faster and the recognition accuracy is higher.

| Method | Recognition time(s) | Correct identification number | Recognition rate (%) |
|--------|---------------------|--------------------------------|----------------------|
| BP     | 0.23                | 55                             | 85.93                |
| SVM    | 0.11                | 60                             | 95.31                |

The reason for misidentification of flow pattern is summarized as follows: (1) The transitional flow type parameter has a large range, being easy to generate fluctuations, and it easily crosses with adjacent flow patterns, which is the main reason for reducing the recognition rate; (2) The training sample is not large enough to contain all the feature points, and the recognition rate is low; (3) Due to the allowable error of the experimental equipment, there is error accumulation in the experimental process, which makes the measured experimental data contaminated and misidentified. Although there is misidentification, the recognition rate can meet the requirements of engineering applications, and
has the advantage of high speed, which can be used for online identification of flow patterns.

6. Conclusion
(1) Marginal spectral entropy is a kind of frequency domain entropy, which can reflect the complexity of four types of flow patterns from the frequency domain angle, and it, as a characteristic parameter of flow pattern differentiation, has good identification;

(2) SVM has the characteristics of fast calculation speed and high recognition rate. It is especially suitable for small sample calculation. When marginal spectral entropy is input into SVM as a characteristic parameter, it can identify four flow patterns accurately, and the overall recognition rate is 95.31%. Especially for the typical flow pattern of mixed flow, the recognition rate can reach 100%, which is suitable for online recognition of flow patterns;

(3) For the transitional flow pattern of bubble-stirring flow, the recognition effect of combining the marginal spectral entropy with SVM is not very satisfactory. Improving the recognition rate of the transitional flow pattern is the next step to be studied.

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