

Time-Frequency Signal Processing for Gas-Liquid Two Phase Flow Through a Horizontal Venturi Based on Adaptive Optimal-Kernel Theory^{*}

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Abstract A time-frequency signal processing method for two-phase flow through a horizontal Venturi based on adaptive optimal-kernel (AOK) was presented in this paper. First, the collected dynamic differential pressure signal of gas-liquid two-phase flow was preprocessed, and then the AOK theory was used to analyze the dynamic differential pressure signal. The mechanism of two-phase flow was discussed through the time-frequency spectrum. On the condition of steady water flow rate, with the increasing of gas flow rate, the flow pattern changes from bubbly flow to slug flow, then to plug flow, meanwhile, the energy distribution of signal fluctuations show significant change that energy transfer from 15–35 Hz band to 0–8 Hz band; moreover, when the flow pattern is slug flow, there are two wave peaks showed in the time-frequency spectrum. Finally, a number of characteristic variables were defined by using the time-frequency spectrum and the ridge of AOK. When the characteristic variables were visually analyzed, the relationship between different combination of characteristic variables and flow patterns would be gotten. The results show that, this method can explain the law of flow in different flow patterns. And characteristic variables, defined by this method, can get a clear description of the flow information. This method provides a new way for the flow pattern identification, and the percentage of correct prediction is up to 91.11%.

Keywords adaptive optimal-kernel, two-phase flow, time-frequency spectrum, time-frequency ridge, flow pattern identification

1 INTRODUCTION

The features of gas compression, effect of slip gravitation between two phases and complexity of two phase interface make gas-liquid two-phase flow in horizontal pipe a complicated and multivariable stochastic process. So the accurate measurement of parameters of gas-liquid two-phase flow system remains unsolved thoroughly. Recently, with the development of measurement technique and signal processing technique, two-phase flow system parameters could be estimated by processing and analyzing the dynamic signal, which seems significant and effective [1–4]. Because the dynamic signal from gas-liquid two-phase flow has strong nonlinear characteristics, the advanced method of nonlinear signal processing is a key technique in studying gas-liquid two-phase flow [5]. Zheng and Jin [6] had made a detailed research in fluid mechanics of two-phase flow and explained its nonlinear nature.

Bakshi *et al.* [7] had studied the local structure and pattern transition in a gas-liquid bubbly column using a wavelet-based technique to calculate the local gas holdup signal. His experimental analysis had showed that the energy discontinuity of the gas holdup signal in time and frequency was related closely to pattern transition in the bubbly flow. Wang *et al.* [8] had accomplished intelligent identification of gas-liquid flow regimes through adopting the technique based on

wavelet energy distribution and revealed its good performance in bubbly flow, stratified flow, annular flow and plug flow. Sun *et al.* [9] processed and analyzed the dynamic differential pressure signal from gas-liquid two-phase flow using the wavelet transformation theory and discovered that the characteristic vector from information entropy of wavelet packet analysis could identify different flow patterns. Chen *et al.* [10] presented a method for online identification of flow regimes of gas-liquid two-phase flow system based on the wavelet transform. In that study, the pipeline pressure drop was acquired for signal processing and the Harr wavelet was selected as the mother wavelet. Stratified flow, wavy flow, plug flow and slug flow could be feasibly identified by using this method. Nguyen *et al.* [11] presented an application of the wavelet analysis technique to two-phase flow pattern identification by using the void fraction signals obtained from a multi-channel impedance void meter in a vertical-upward air-water flow. The results showed that the method had a high precision for characterizing different flow regimes in two-phase flow, and was considerably more promising for online recognition of two-phase flow patterns due to the short time of data processing.

Lao [12] used Wigner-Ville distribution (WVD) to analyze the dynamic differential pressure signal, from the analysis result of WVD, the typical flow patterns of gas-liquid two-phase flow in horizontal pipe

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could be identified. The stability of dynamic signal from gas-liquid two-phase flow had close relation to flow pattern. When signal had good stability, the WVD represented favorable conformance in time domain and was similar to fast Fourier transform (FFT) results in frequency domain; when transient differential features turned up in flow system, WVD could provide time-frequency distribution of the signal, but the accuracy of the time-frequency distribution would be impaired by the nonlinear nature of the signal and the existence of multiple components. Recently, great progress had been achieved by employing Hilbert-Huang transform (HHT) [13–15] in dynamic signal progressing of gas-liquid two-phase flow. HHT method, characterized by adaptive decomposition and good resolution in both time domain and frequency domain, was helpful to two-phase flow mechanism study. Flow pattern identification had ideal accuracy by using HHT. But the HHT theory system was still incomplete and influenced by interface effect. Further study was needed to explain the physical significance of decomposition model.

Adaptive optimal-kernel (AOK) is a time-frequency analysis method which has good resolution in both time domain and frequency domain. AOK had application in inter-harmonics analysis successfully [16]. AOK time-frequency theory was developed and improved based on WVD. Classic Wigner-Ville distribution had nice time-frequency resolution and its time-bandwidth product could keep above the prescribed minimum according to the Heisenberg uncertainty theory. But WVD was a bilinear process, which could cause intense cross-term interference when the signal contained multiple components, which might influence the interpretation of WVD time-frequency representation. As for the AOK theory, the adaptive optimal-kernel time-frequency representation method could separate the independent term in signal effectively by restraining the influence of cross-terms, and it was suitable to long time nonstationary signal processing. In view of strong nonlinear characteristics of gas-liquid two-phase flow, the AOK theory was introduced into signal processing in this paper. The AOK method was applied to analysis the dynamic differential pressure signal and the flow rules of different flow regimes was studied according to the time-frequency representation from this method. The marginal distribution was extracted from AOK time-frequency representation spectrum; also the characteristic variables were obtained from the AOK time-frequency representation spectral and the marginal distribution respectively in order to study the relationship between flow regime and AOK eigenvectors.

2 AOK THEORY

2.1 Optimal kernel time-frequency representation

Many time-frequency distributions were designed to separate the independent term in signal and restrain

the influence of cross-terms. Among them, the optimal kernel time-frequency representation is given by

$$P(t, \omega) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} A(\theta, \tau) \Phi(\theta, \tau) e^{-j\theta t - j\tau \omega} d\theta d\tau \quad (1)$$

Here, $A(\theta, \tau)$ is called the fuzzy function of signal $s(t)$, and is given by

$$A(\theta, \tau) = \int_{-\infty}^{+\infty} s\left(t + \frac{\tau}{2}\right) s^*\left(t - \frac{\tau}{2}\right) e^{j\theta t} dt \quad (2)$$

Function $\Phi(\theta, \tau)$ is a low-pass kernel function, θ is the frequency offset and τ is the time delay, and “*” stands for complex conjugate. Different choices for the kernel function yield widely different time-frequency representations.

2.2 Adaptive optimal-kernel (AOK) time-frequency representation

The signal dependent time-frequency representation based on a radial Gaussian kernel, which is an entire algorithm, is similar to short time Fourier transform. As only one kernel is designed to the whole signal, the method is not suitable for long time nonstationary signal processing. To solve this problem, AOK time-frequency representation is proposed. We define short time ambiguity function as $A(t; \theta, \tau)$, which is an ambiguity function of a windowed signal:

$$A(t; \theta, \tau) = \int_{-\infty}^{+\infty} s^*\left(u - \frac{\tau}{2}\right) \omega^*\left(u - t - \frac{\tau}{2}\right) \cdot s\left(u + \frac{\tau}{2}\right) \omega\left(u - t + \frac{\tau}{2}\right) e^{j\theta u} du \quad (3)$$

where $\omega(u)$ is a symmetrical window function, t indicates the center position of $\omega(u)$. Set $\omega(u) = 0$ when $|u| > T$ (T is the length of time window), so at any time t , the signal's ambiguity function is calculated only in the interval of $[t - T, t + T]$. The short term ambiguity function can accurately depict any detail part of the signal. At this time, the adaptive optimal kernel function $\Phi_{\text{opt}}(t; \theta, \tau)$ can be obtained by solving the following optimization problem:

$$\max_{\Phi} \int_0^{2\pi} \int_0^{\infty} |A(t; r, \psi) \Phi(t; r, \psi)|^2 r dr d\psi \quad (4)$$

subject to

$$\left. \begin{aligned} \Phi(t; r, \psi) &= \exp\left[-\frac{r^2}{2\sigma^2(\psi)}\right] \\ \frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} |\Phi(t; r, \psi)|^2 r dr d\psi &= \frac{1}{2\pi} \int_0^{2\pi} \sigma^2(\psi) d\psi \leq \alpha, \\ \alpha &\geq 0 \end{aligned} \right\} \quad (5)$$

where the function $\sigma(\psi)$ controls the spread of the Gaussian at radial angle ψ ; we call $\sigma(\psi)$ the spread

function. The angle $\psi = \arctan(\gamma/\theta)$ is measured between the radial line through the point (θ, γ) and the θ axis. $r = \sqrt{\theta^2 + \gamma^2}$ is the radial coordinate.

Then, the AOK representation of the signal in interval $[t-T, t+T]$ can be calculated by

$$P_{\text{AOK}}(t, \omega) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} A(t; \theta, \tau) \Phi_{\text{opt}}(t; \theta, \tau) e^{-j\theta t - j\tau \omega} d\theta d\tau \quad (6)$$

2.3 Ridge extraction of AOK time-frequency representation

The AOK time-frequency representation has a fine time-frequency resolution in nonstationary signal processing. Because of the action of adaptive optimal kernel function, there would be diffused distribution in AOK time-frequency representation when closed components exist in time-frequency coordinates, and this kind of distribution will affect the result of time-frequency spectral analysis. To improve the time-frequency conglomeration of AOK and enhance readability of time-frequency platform, the ridge of AOK is extracted by using the concept of ridge extraction in the spectrum rearrangement theory. The way to get ridge of AOK is that the local frequency domain modulus maxima are sought out and highlighted at any time points in AOK time-frequency representation within a given threshold value. The threshold value chosen is a compromise between attenuation of useful information and readability of time-frequency spectrum.

3 EXPERIMENTAL RESULTS ANALYSIS

3.1 Experimental condition

Multiphase experimental device is shown in Fig. 1, which mainly consists of air compressor, water pump, gear oil pump, oil tank, water tank, oil surge tank, gas surge tank and water surge tank. Surge tanks stabilize the pressure of the liquid and gas sources.

The $\phi 50$ mm pipe system and instruments were set up in accordance with the requirements of experiment. A Venturi tube, whose ratios of throat diameter to tube diameter was 0.5501, was chosen here as the throttle device, and the Keller PD23 diffused Si-piezoresistive differential pressure sensor, which has 1 kHz frequency response, 0.2% accuracy, and 0–50 kPa measuring range, were used to collect differential pressure signals. The length of flow development sector is 4 m, that of observation is 65 cm, the length from observation to Venturi tube is 50 cm and length from Venturi tube to export is 1 m. Fig. 2 shows the physical devices of test pipeline, Fig. 2 (a) is the Venturi tube and differential pressure sensor, Fig. 2 (b) is the structure of Venturi (50 mm). Many experiments have done to decide the position of pressure taps. The tilt of 45 degrees off the topmost position was the best for the pressure taps and used in this paper. The experiment signals were acquired to PC104 computer *via* a data acquisition (DAQ) card with the sample frequency 200 Hz. In the experiment process, bubbly flow, slug flow and plug flow were generated through changing the flow rate of water and gas. In addition, the standard flow patterns were judged visually.

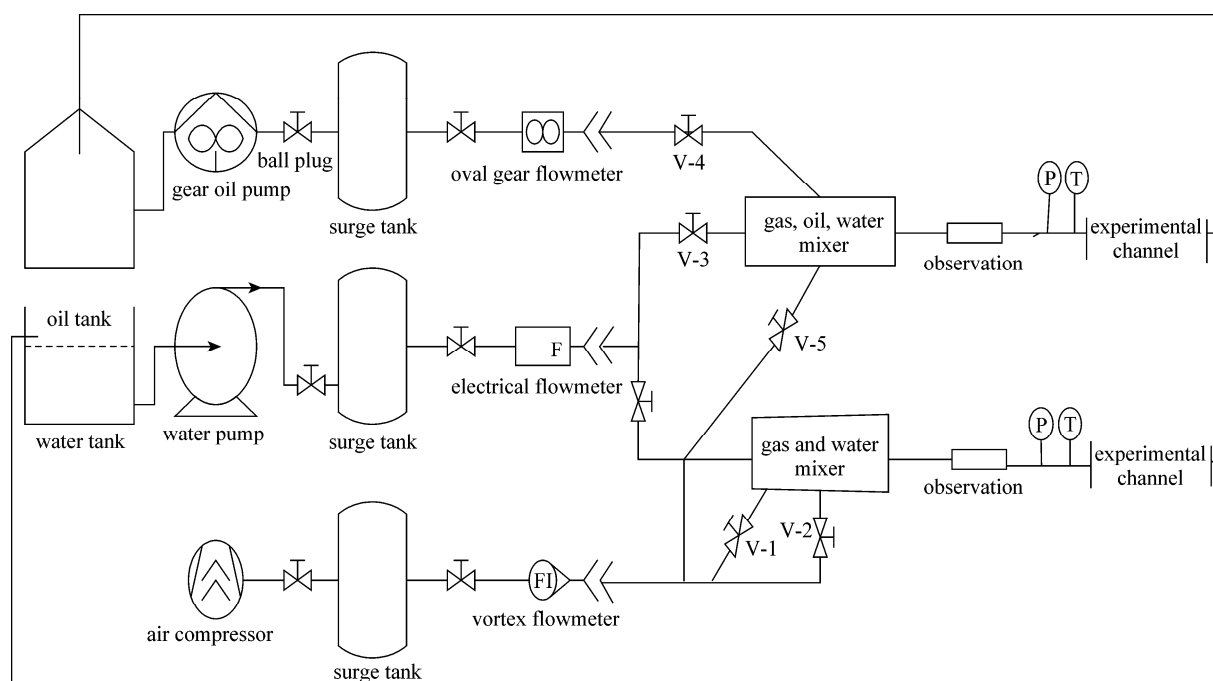
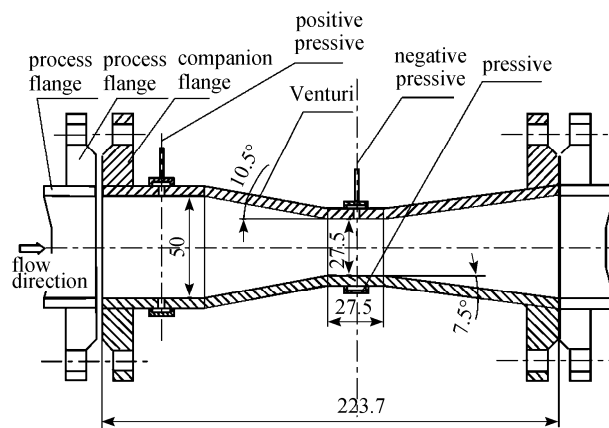


Figure 1 The schematic of experimental device

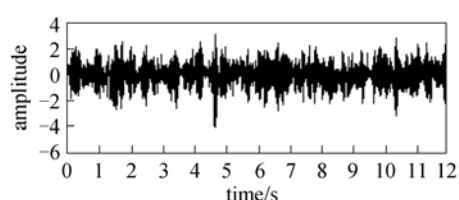


(a) Venturi tube and differential pressure sensor

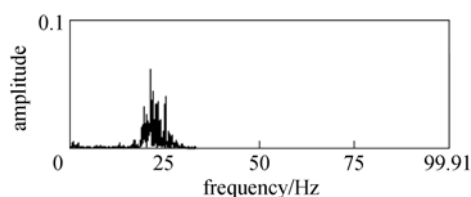


(b) Structure of Venturi

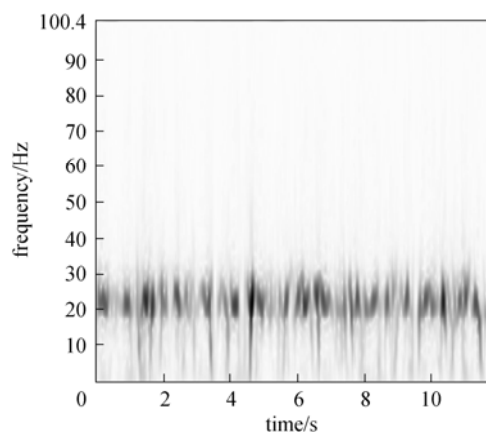
Figure 2 The physical devices of test pipeline



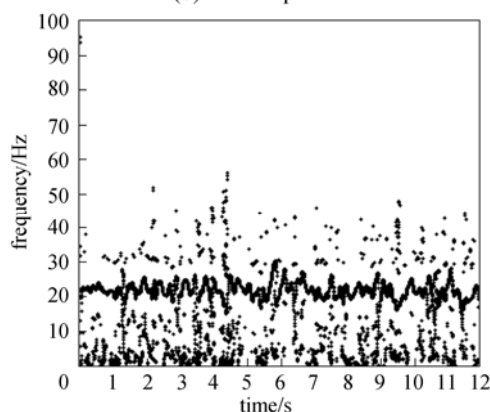
(a) Signal after preprocessing



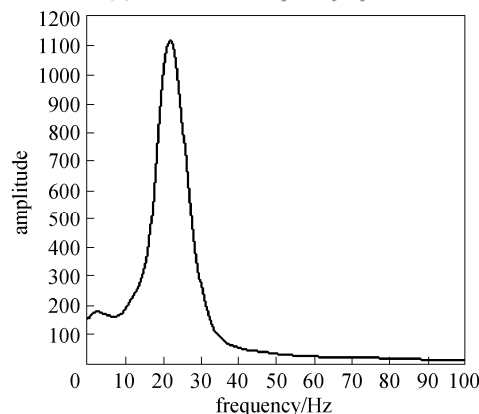
(b) Power spectrum



(c) AOK time-frequency spectrum



(d) Extraction graph of AOK ridge



(e) Marginal spectrum

Figure 3 Analysis results of bubbly flow ($Q_L = 8.99 \text{ m}^3 \cdot \text{h}^{-1}$, $Q_g = 1.10 \text{ m}^3 \cdot \text{h}^{-1}$)

3.2 Gas-liquid two-phase flow fluctuation signal analysis

Firstly, the acquired original differential pressure fluctuation signals were preprocessed with the methods such as filtering, eliminating, zero mean, and removing trend term, in addition normalization was also

required. Then, these signals are ready for being analyzed by AOK time-frequency spectrum.

Figure 3 shows the typical analysis result of bubbly flow. Fig. 3 (a) shows the signal of bubbly flow after preprocessing; Fig. 3 (b) shows the power spectrum; Fig. 3 (c) is the AOK time-frequency spectrum; Fig. 3 (d) is the extraction graph of AOK ridge; Fig. 3 (e) is the marginal spectrum, which is extracted from

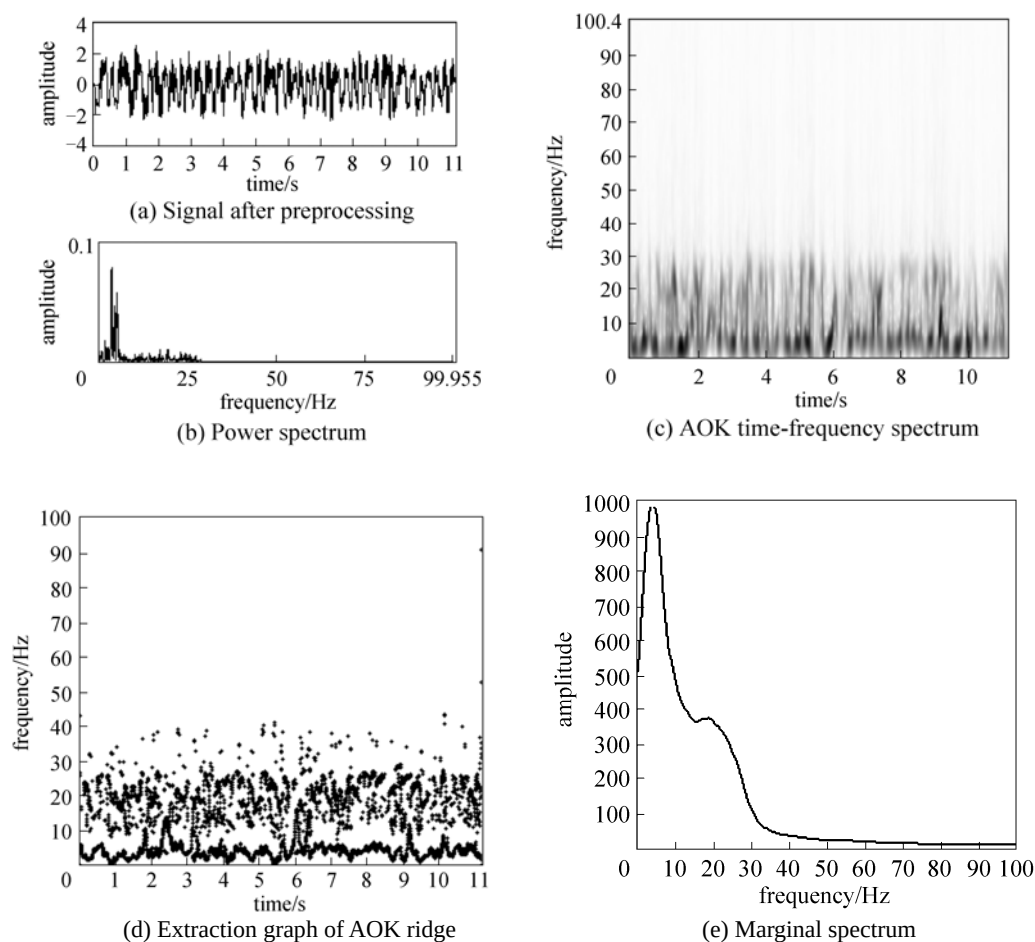


Figure 4 Analysis results of slug flow ($Q_L = 8.99 \text{ m}^3 \cdot \text{h}^{-1}$, $Q_g = 2.25 \text{ m}^3 \cdot \text{h}^{-1}$)

the AOK time-frequency spectrum.

From Fig. 3 (c), it is obvious that the energy of bubbly flow mainly concentrated between 18–28 Hz which is defined as high-frequency band. From Fig. 3 (e), the highest energy value shows up at approximately 23 Hz. Due to the low flow rate of gas and relatively high flow rate of water, intensive gas bubbles flow at the top of the pipe. The differential pressure transducer is also installed at the top the pipe, that the signal fluctuations show a high frequency because of the action of gas bubbles. So the energy of bubbly flow is mainly concentrated in the high-frequency band.

From Fig. 3 (d), it's obvious that between 18–28 Hz the ridge forms a narrower band. Because of this, the ridge signal extraction improves largely the time-frequency resolution ratio, at the same time the readability of time-frequency dimension information is enhanced.

Figure 4 shows the analyzed results of slug flow. From Fig. 4 (c), the energy of slug flow distributes from 0 Hz to 35 Hz. From Figs. 4 (d) and 4 (e), actually the energy of slug flow mainly exists in two bands, one is between 0–10 Hz which is defined as low frequency band, and another is between 15–25 Hz which is defined as mid-high frequency band. Due to the

increasing of gas flow rate, some bubbles become slugs; the signal energy mainly concentrates in the fluctuation when these slugs go through the pressure transducer. However, the small bubbles still exist between two slug, making the energy has a distribution in high frequency band, so two wave peaks show up in the slug flow time-frequency spectrum.

Figure 5 shows the plug flow results. The gas goes through the pipe in a gas plug form, which makes the differential pressure fluctuate intensively. From Fig. 5, the energy of plug flow mainly shows up between 0–8 Hz, which is low frequency band. Just like the analysis results mentioned above, the AOK ridge extraction has highest time-frequency resolution ratio, and the AOK analysis takes a second place.

Generally speaking, on the condition of steady water flow rate, with the increasing of gas flow rate, the flow pattern changes from bubbly flow to slug flow, then to plug flow, meanwhile the energy distribution of signal fluctuations in differential pressure show significant change that energy transfer from 15–35 Hz band (high frequency band) to 0–8 Hz band (low frequency band); moreover, when the flow pattern is slug flow, there are two wave peaks showed in time-frequency spectrum.

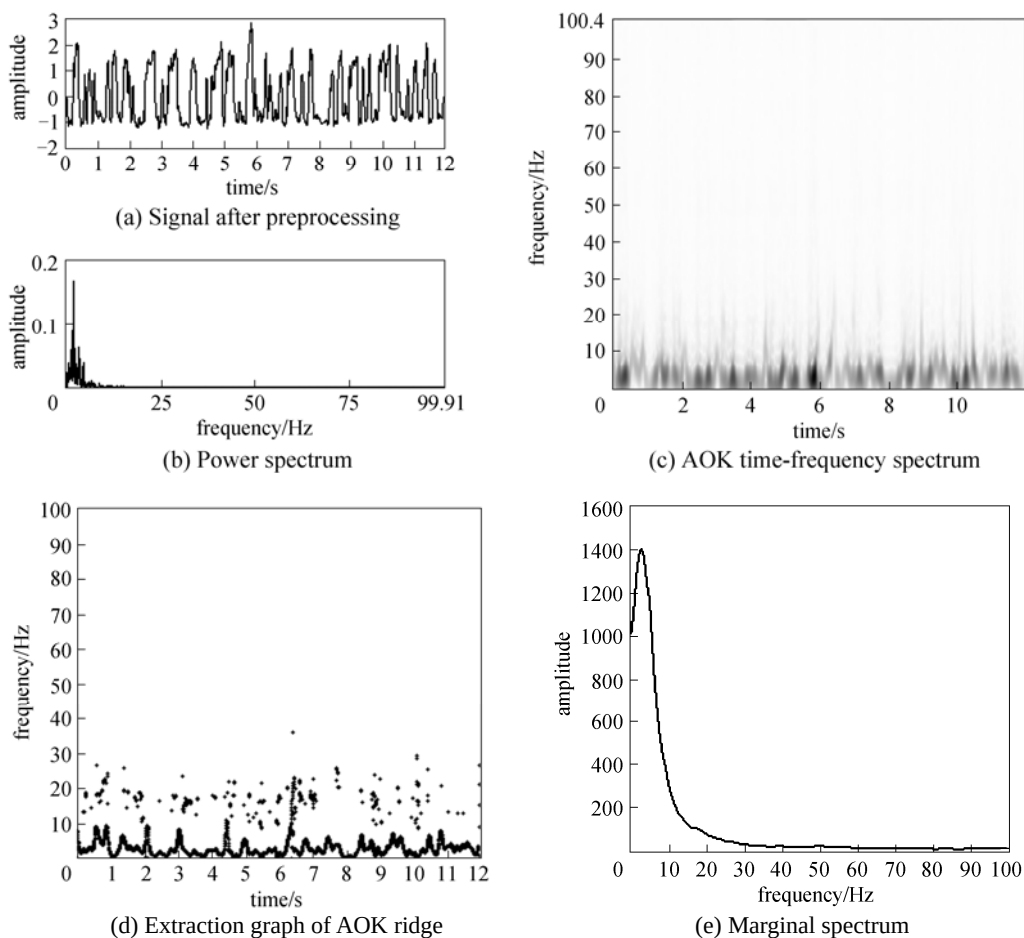


Figure 5 Analysis results of plug flow ($Q_L = 8.99 \text{ m}^3 \cdot \text{h}^{-1}$, $Q_g = 4.45 \text{ m}^3 \cdot \text{h}^{-1}$)

3.3 Feature extraction from gas-liquid two-phase flow fluctuation signal

Feature extraction is one of the most important parts in the gas-liquid two-phase flow pattern identification. The identification performance depends on the selecting of characteristic variables [17–21]. Five characteristic variables related to the flow pattern are defined in the paper through analysis of time-frequency spectrum.

(1) Characteristic variables extracted from AOK time-frequency spectrum

F_1 : frequency domain coordinates of energy centroid in AOK time-frequency spectrum:

$$F_1 = \frac{\sum_{j=1}^N f R(f)}{\sum_{i=1}^M \sum_{j=1}^N R(t, f)} \quad (7)$$

In Eq. (7), $R(t, f)$ is the energy distribution of AOK time-frequency spectrum. (t, f) indicates the coordinates of AOK time-frequency spectrum. M is the total points of the collected data in frequency domain

and N is the number of frequency intervals.

F_2 : Low frequency band energy accounted for total energy percentage, and

F_3 : High frequency band energy accounted for total energy percentage:

$$F_2 = \frac{\int_{f_1}^{f_2} \int_0^T |P_{\text{AOK}}(f, t)|^2 df dt}{\int_{f_1}^{f_4} \int_0^T |P_{\text{AOK}}(f, t)|^2 df dt},$$

$$F_3 = \frac{\int_{f_3}^{f_4} \int_0^T |P_{\text{AOK}}(f, t)|^2 df dt}{\int_{f_1}^{f_4} \int_0^T |P_{\text{AOK}}(f, t)|^2 df dt} \quad (8)$$

$P_{\text{AOK}}(f, t)$ is adaptive optimal-kernel time-frequency distribution. According to the analysis results mentioned above, 0–10 Hz is defined as the low frequency band, indicated as (f_1, f_2) ; 15–35 Hz is the high frequency band, indicated as (f_3, f_4) . T is the total sampling time.

(2) Characteristic variable extracted from marginal spectrum

F_4 : The frequency corresponding to maximum peak value of the marginal spectrum, which is defined as

$$p(F_4) = \max[P(f)] = \max \int_0^T P_{\text{AOK}}(f, t) dt \quad (9)$$

where T is the total length of the signal. $p(f)$ presents the signal amplitude changing along with the frequency on the whole frequency band.

(3) Characteristic variables extracted from extraction graph of AOK ridge

F_5 : Frequency domain coordinate of centre:

$$F_5 = \frac{1}{n} \sum_{i=0}^{n-1} f_i \quad (10)$$

where n indicates the number of extracted ridge, (t_i, f_i) indicates the coordinates of the i th ridge.

3.4 Flow characteristics analysis of gas-liquid two-phase flow

First, five characteristic variables that mentioned above were extracted from each flow pattern, and the correlation between each pairs of these variables were examined to observe the relationship of each characteristic variable with flow pattern. Also the change rules of the fluctuation signal were investigated under different flow pattern. Figs. 6 to 15 were the scatter plots using the combinations among F_1 , F_2 , F_3 , F_4 and F_5 .

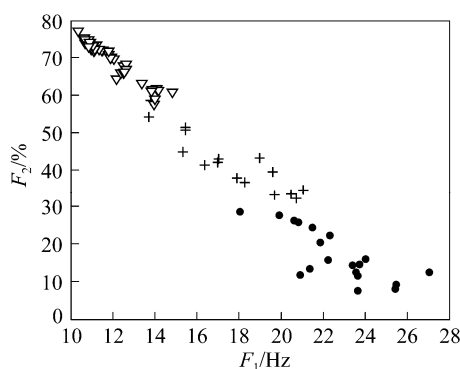


Figure 6 Scatter plot of pair of F_1 - F_2
● bubble flow; + slug flow; ▽ plug flow

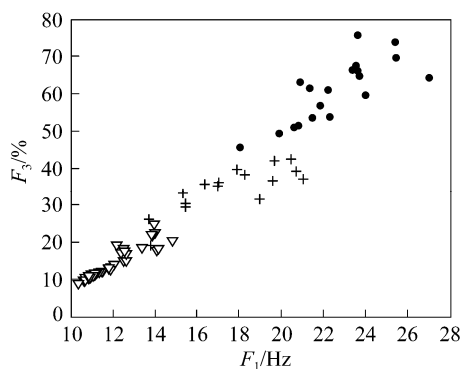


Figure 7 Scatter plot of pair of F_1 - F_3
● bubble flow; + slug flow; ▽ plug flow

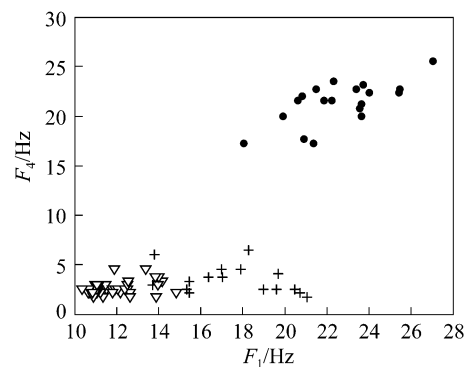


Figure 8 Scatter plot of pair of F_1 - F_4
● bubble flow; + slug flow; ▽ plug flow

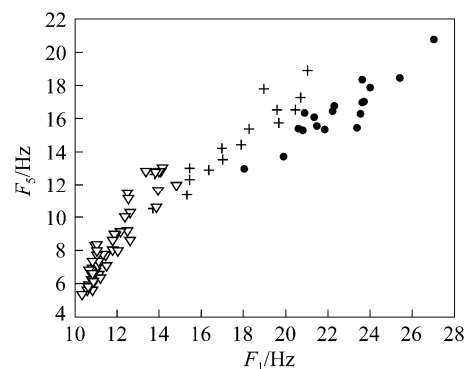


Figure 9 Scatter plot of pair of F_1 - F_5
● bubble flow; + slug flow; ▽ plug flow

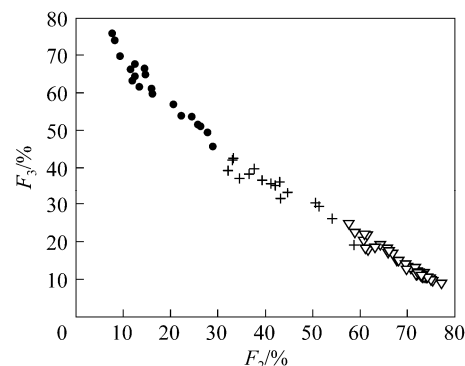


Figure 10 Scatter plot of pair of F_2 - F_3
● bubble flow; + slug flow; ▽ plug flow

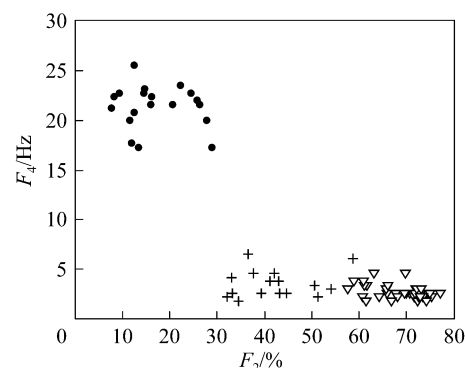


Figure 11 Scatter plot of pair of F_2 - F_4
● bubble flow; + slug flow; ▽ plug flow

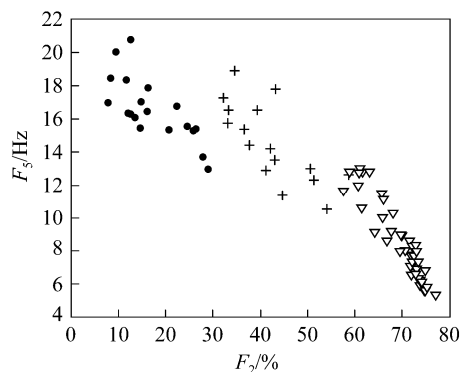


Figure 12 Scatter plot of pair of F_2 - F_5
 ● bubble flow; + slug flow; ▽ plug flow

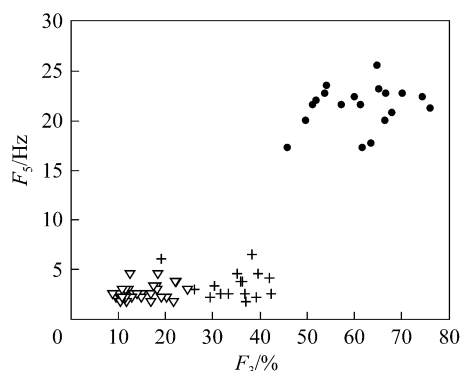


Figure 13 Scatter plot of pair of F_3 - F_4
 ● bubble flow; + slug flow; ▽ plug flow

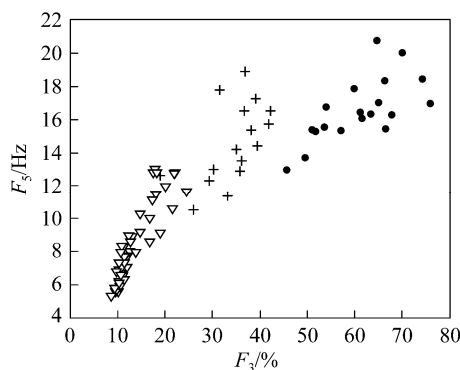


Figure 14 Scatter plot of pair of F_3 - F_5
 ● bubble flow; + slug flow; ▽ plug flow

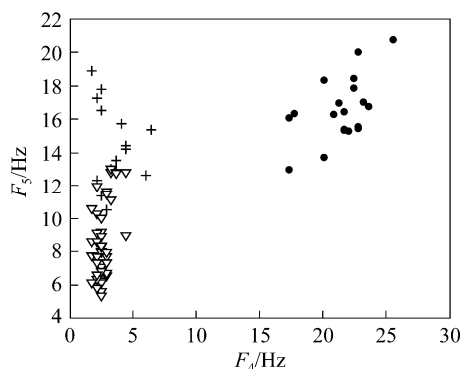


Figure 15 Scatter plot of pair of F_4 - F_5
 ● bubble flow; + slug flow; ▽ plug flow

From Figs. 6 to 9, the changes of F_1 could be seen clearly. Energy centroid of the bubbly flow was in the range of 20–30 Hz (high frequency band); energy centroid of the slug flow was in the range of 15–20 Hz (middle frequency band); energy centroid of the plug flow was in the range of 10–15 Hz (low frequency band). With the increasing of gas flow rate, flow pattern changed from bubbly flow to slug flow, then to plug flow; energy centroid of differential pressure signal changed gradually from high frequency band to low frequency band step by step.

From Figs. 6, 10, 11 and 12, the relationship between F_2 and flow pattern could be seen. From Figs. 7, 10, 13 and 14, the relationship between F_3 and flow pattern could be seen obviously. Bubbly flow, slug flow, plug flow took up 5%–30%, 30%–55%, 55%–80% of F_2 respectively. Meanwhile, bubbly flow, slug flow, plug flow took up 45%–80%, 25%–45%, lower than 25% of F_3 respectively. From the above, it was clear that when the flow rate of gas was increasing, the flow pattern changed from bubbly flow to slug flow, then to plug flow; in this process, low frequency ratio increased gradually, and high frequency ratio gradually decreased.

From Figs. 8, 11, 13 and 15, the relationship between F_4 and flow pattern could be seen clearly. The frequency corresponded to the maximum peak value of marginal spectrum of bubbly flow mainly focused in high frequency band, and that of slug flow and plug flow mainly focused in low frequency band. As a result, when flow pattern changed from bubbly flow to plug flow, the frequency corresponded to the maximum peak value of marginal spectrum shifted from high frequency band to low frequency band.

From Figs. 9, 12, 14 and 15, the relationship between F_5 and flow pattern was seen clearly. Bubbly flow's center of AOK ridge extraction graph mainly focused in high frequency band, slug flow's focused in middle frequency band, and plug flow's focused in low frequency band. As a result, when the flow rate of gas was increasing, the flow pattern changed from bubbly flow to slug flow, then to plug flow, meanwhile the center of AOK ridge extraction graph moved from high frequency band to low frequency band.

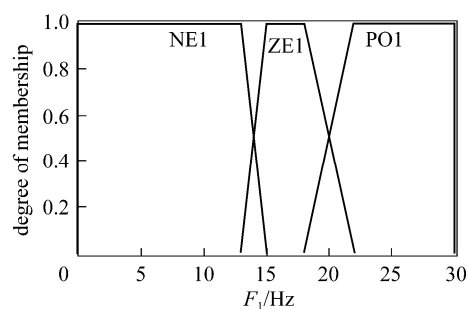
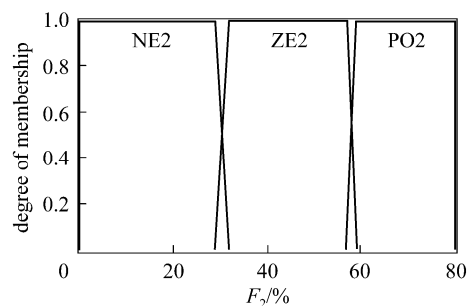
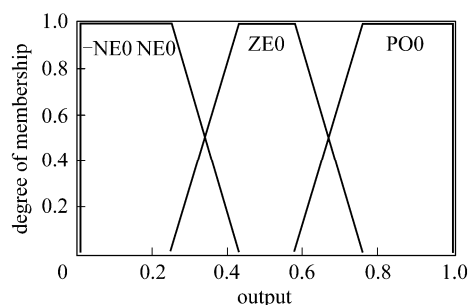
3.5 Flow pattern prediction

From the above analysis, different ranges of characteristic variables correspond accurately to different flow patterns. Therefore, after setting up the dividing values of characteristic variables, the flow pattern can be identified accurately by judging the range of characteristic variables. Table 1 shows the range of characteristic variables.

Total 90 data (19 from bubbly flow, 27 from slug flow and 44 from plug flow) were taken for testing. Fuzzy inference method was used to observe the flow pattern identification effect. A "two inputs-one output" model is used in designing the fuzzy inference system. Here we take F_1/F_2 for example. Figs. 16 to 18 show

Table 1 The range of characteristic variables for predicting flow patterns

Flow pattern	F_1/Hz	$F_2/\%$	$F_3/\%$	F_4/Hz	F_5/Hz
bubbly flow	18–28	7–29	45–76	17–26	12–21
slug flow	13–22	32–59	19–43	1–7	10–19
plug flow	10–15	57–78	8–25	1–5	5–13

**Figure 16** Membership functions of F_1 **Figure 17** Membership functions of F_2 **Figure 18** Membership functions of output**Table 2** Fuzzy rule table of F_1/F_2

F_2	Output		
	NE1(F_1)	ZE1(F_1)	PO1(F_1)
NE2	–NE0	–NE0	NE0
ZE2	–NE0	ZE0	–NE0
PO2	PO0	–NE0	–NE0

the membership functions of input variables F_1 , F_2 and output variables. F_1 is divided into three areas (0–15, 13–22, 18–30), which are recorder as NE1,

ZE1, PO1. F_2 is divided into three areas (0–32, 29–59, 57–80), which are recorded as NE2, ZE2, PO2. Output is the flow pattern, which are No flow, bubbly flow, slug flow, plug flow, which are recorded as –NE0, NE0, ZE0, PO0. Table 2 is the fuzzy rule table of F_1/F_2 . The entire fuzzy inference process was based on Mamdani-type algorithm (Max-Min), and the de-fuzzification is based on the center area method (the centroid method).

Table 3 shows the identification rates of characteristic variables pairs. From Table 3, the lowest identification rate is 84.44% and the identification rates of F_1/F_2 , F_2/F_3 and F_3/F_4 are higher than others.

Table 3 Identification rates of characteristic variables pairs

Characteristic variables pair	Total number of test data	Number of correct identification	Identification rate
F_1/F_2	90	82	91.11%
F_1/F_3	90	81	90%
F_1/F_4	90	81	90%
F_1/F_5	90	76	84.44%
F_2/F_3	90	82	91.11%
F_2/F_4	90	82	91.11%
F_2/F_5	90	81	90%
F_3/F_4	90	81	90%
F_3/F_5	90	79	87.78%
F_4/F_5	90	78	86.67%

4 CONCLUSIONS

(1) The AOK method not only has a high frequency resolution, but also has a strong ability to suppress cross-terms. In this article, AOK was introduced for two-phase flow dynamic signal processing, providing a new method for studying time-varying characteristics of gas-liquid two phase flow.

(2) Ridge signal extraction, which is based on the analysis of AOK theory, has higher time-frequency resolution than AOK, at the same time the readability of time-frequency dimension information was enhanced.

(3) By the analysis of AOK time-frequency spectrum and AOK extracted ridge graph, five characteristic variables related to the flow pattern were defined. After these characteristic variables were combined and visual analyzed, different combinations of these five characteristic variables could be attained for flow pattern identification. Through experimental results it is shown that the identification rate is high.

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