Classification of Flow Regimes in Bubble Column Using the Integration of Ultrasound and KNN Algorithm

Wongsakorn Wongsaroj[1], Jiddilok Pulsawat[1], Naruki Shoji[2], Natee Thong-Un[1], Weerachon Treenusorn[3] and Hiroshige Kikura[4]

[1] Dep. of Instrumentation and Electronics Engineering, King Mongkut's University of Technology North Bangkok, 1518 Wongsawang, Bangsue, Bangkok 10800, Thailand
[2] Robotics and Mechanical Engineering Research Unit, Muroran Institute of Technology, 27-1 Mizumoto-cho, Muroran, Hokkaido 050-0071, Japan
[3] Office of Atoms for Peace, Ministry of Science and Technology, 2-12-1 Ookayama, Meguro-ku, Tokyo 152-8550, Japan
[4] Lab. for Zero-Carbon Energy, Tokyo Institute of Technology, 2-12-1 Ookayama, Meguro, Tokyo 152-8550, Japan

This paper presents the integration of ultrasound technology and the KNN algorithm to classify the flow regimes in bubble columns. An ultrasonic velocity profiler is employed to obtain the standard deviation of bubble velocity distributed in the column. The characteristic of echo signal influenced by each flow regime is collected. Both data and three flow regimes known were used to make the KNN model for the classification. The circular-shaped tank, including a bubble generator and gas hold-up monitoring, was utilized as the experimental apparatus. The flow regime of the experimental fluid is found. The classification with the weighted nearest neighbors method was demonstrated. The accuracy of the classification under acceptable trend.

Keywords: Ultrasonic, Flow regime, KNN

1. Introduction

Bubble columns [1] are an important class of multiphase reactors that are used widely in several industries. In order to operate the bubble column to high efficiency and in accord with the production requirement, the flow regime in the column is crucial to be operated at the correct region. For example, in the bioreactors, the reactor is operated at low superficial gas velocities for a highly efficient process. On the contrary, in an FT – synthesis reactor, it is executed at high superficial gas velocity to enhance efficient heat and mass transfer.

A Bubbly flow regime has almost uniform bubble size distribution and less bubble-bubble interaction. This phenomenon happens at a low superficial gas velocity. A churn turbulent flow regime occurs when the gas is applied at a higher superficial velocity. Width range of bubble size distribution, bubble coalescence, and high liquid phase turbulence are observed obviously. Between both regions, the transition flow regime is found. Slug flow is not considered in this research. It has a large bubble size covering the internal length scales of the column diameter, generally not seen in bubble columns, especially in large columns.

As the above explanation, the flow regime should be identified in real-time. Therefore, the measurement technique to identify the flow regime is needed.

An optical sensor was applied [2]. It works with the machine learning algorithm to classify the two-phase flow regime. This technique contacts the flow intrusively, which reduces the sensor lifetime. Moreover, if the fluid in the column is in harsh conditions or the bubble column is an opaque vessel with no optical access, the technique is difficult to operate. Hence, a measurement technique that works non-intrusively and can operate in the opaque condition is required.

This research presents the combination of ultrasonic techniques and machine learning to identify flow regimes in a bubble column.

The ultrasonic velocity profiler (UVP) is an ultrasound-based measurement technique to obtain velocity distribution in liquid flows with high spatial-temporal resolution [3]. The ultrasonic wave is able to transmit through various materials without the requirement of transparency. This method's measurement works non-intrusively and is ably conducted in a non-transparency fluid. In the UVP, an ultrasonic pulse is emitted into the liquid by the transducer that works in transmission mode. The same transducer operating in reception mode derives the echo signal reflected from the moving reflector dispersed in the liquid. As the repetition of ultrasonic pulse emission, the echo signals are sequentially derived according to the repetition of pulse emission, and the Doppler signal affected by moving particle velocity can be extracted from the echo signals under pulse repetition. The Doppler frequency $f_D(i)$ is associated with particle velocity (i means the particle position). Hence, the velocity of the moving particle at position $V(i)$ can be calculated as

$$V(i) = \frac{c f_D(i)}{2 f_0} \quad (1)$$

Where c is the speed of sound of the fluid, f_0 is the center frequency of the ultrasonic pulse.

In the two-phase flow, the UVP measurement was applied in many works, whether the both-phase (bubble and liquid) velocity measurement [4] or only measure bubble velocity [5], where the bubble velocity measurement concept is utilized in our work.

Ultrasonic measurement data on the two-phase flow in the bubble column derived are inputted to the machine learning algorithm for model development of the flow regime identification. These parameters contain valuable information on the operating flow regime of two-phase flow in the bubble column.

K-nearest neighbors algorithm (KNN) [6] is a machine learning methodology in the type of supervised classification algorithm applied in this research. Some of the measurement data is used to test the performance of the model in identifying the flow regime.

2. Methodology

2.1 k-nearest neighbors algorithm

The k-nearest neighbors algorithm (KNN) is a supervised learning classifier that uses proximity to make classifications or predictions about the grouping of an individual data point, as shown in figure 1. This technique is non-parametric. The KNN model is made by training data, which consists of attributes or inputs (x_i) and categories or outputs (y_i). Then, the k value in the KNN algorithm defines how much neighbor data is checked to determine the classification of a specific query point.

In order to determine which data points are closest to a given query point, the distance between the query point and the other data points (training data) needs to be calculated. The weighted nearest neighbors work as the decision-making method for classification in this research. For the KNN to classify the flow regime in the two-phase flow in this research, two attributes are used to make the model, which are the standard deviation of bubble velocity and the characteristic of the echo signal, respectively. The categories of classification are based on three flow regimes occurring in two-phase flow: bubbly, transition, and churn turbulent regime.

2.2 Standard deviation of Bubble velocity

Based on the Eq.1., the velocity profile of the particle can be obtained. Hence, if the ultrasonic reflector is a bubble,

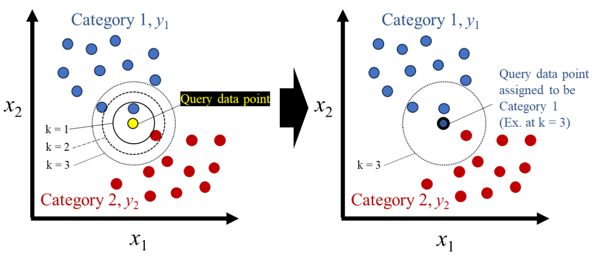


Figure 1: k-nearest neighbors algorithm.

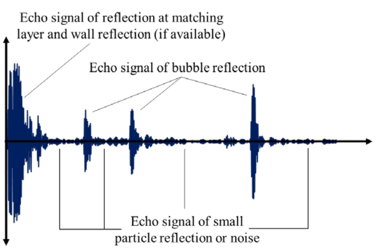


Figure 2: Echo signal of two-phase air-water flow.

the reflection index is high, and a huge echo amplitude can be observed when the echo signal is reflected from the bubble, as illustrated in figure 2. The autocorrelation method is used as the velocity estimator. The bubble velocity data is separated by putting the threshold value on the autocorrelation function amplitude. Then, the velocity of a bubble is able to be extracted. The bubble velocity profile is obtained when a massive number of the bubbles are distributed available to cover a two-phase flow area. Then, the standard deviation of bubble velocity in the interested region is determined from high amount number of velocity profiles. Lastly, it is utilized as the first attribute for the flow regimes classification model of the KNN algorithm.

2.2 Characteristics of echo signal

The effect of the bubble dispersed in the two-phase flow on the ultrasonic measurement is illustrated via the characteristic of the echo signal. The characteristic can be used to be the second attribute of the flow regimes classification model. Figure 3. shows the echo characteristic influenced by the bubbly and churn-turbulent flow at the interested region. High amplitude level dense in the signal obtained from a churn-turbulent flow. It is also observed in the bubbly region at the zone close to the transition regime. The density of the high echo amplitude is enhanced mainly as the increasing of bubble number. In this research, the slope value of the autocorrelation function of the echo signal at low values of time shifts is utilized as a characteristic of the echo signal. The slope of the function varies increasingly following the massive density of high amplitude echo. The bubble size affects the magnitude of echo amplitude. However, it has less influence on the slope value due to the amplitude threshold applied, except the bubble size is bigger than the ultrasonic beam width, which blocks the signal penetration into the fluid behind the bubble and makes disability of the measurement respectively. The schematic of signal processing is shown in figure 4. The autocorrelation function $r_{xx}(k)$ in the processing is expressed as follows.

$$r_{xx}(k) = \sum_{n=0}^{N-1} x(n)x(n+k) \tag{2}$$

"Where k is the time lag and $x(n)$ is the time domain signal.

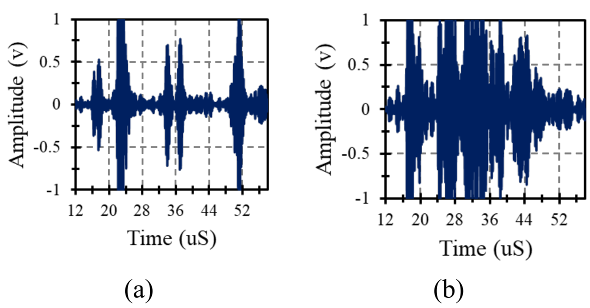


Figure 3: Echo signal in two-phase flow (a) bubbly regime and (b) churn-turbulent regime.

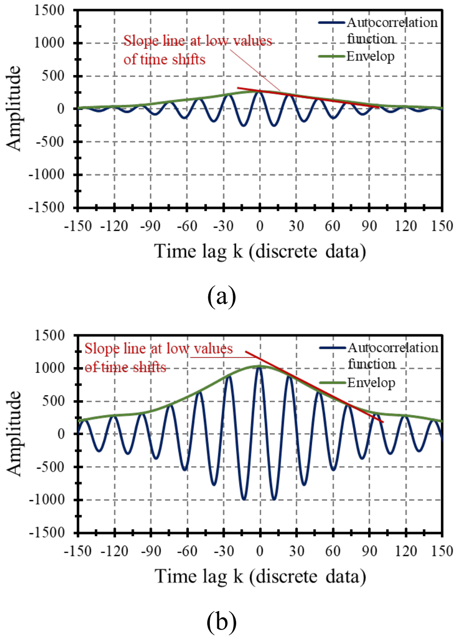


Figure 4: Slope value of the autocorrelation function of the echo signal at low values of time shifts (a) bubbly regime and (b) churn-turbulent regime.

3. Experimental setup

Figure 5 illustrates the experimental apparatus and measurement system. The circular tank was used as a bubble column. The internal diameter of the tank was 80 mm. The wall thickness was 2 mm. The bubble generator was put at the bottom of the tank. The bubble generated was supplied by the air compressor and controlled by the airflow controller. There are three types of liquid utilized in the experiment: 1) tap water, 2) tap water mixed with glycerin 5 %v/v, and 3) tap water mixed with glycerin 20 %v/v. The pressure meter was installed at positions A and B to measure the fluid pressure in order to calculate the gas hold-up in the bubble column.

The UVP system comprises an ultrasonic transducer, Pulser/receiver, a Digitizer, and a Computer. The LabVIEW version 2021 was used as a measurement processing tool. The equipment specification and parameter configuration is shown in Table 1 and 2, respectively.

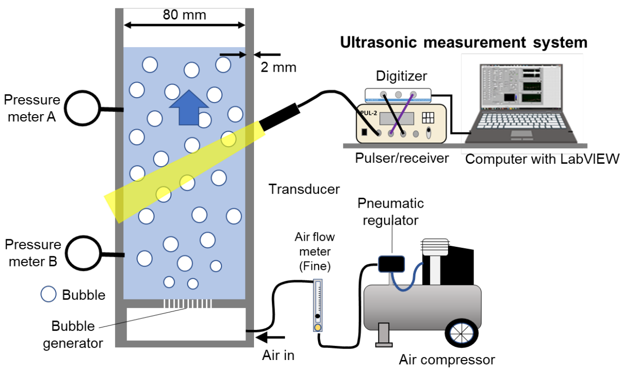


Figure 5: Experimental apparatus and measurement system.

Table 1: UVP measurement system specification.

Equipment	Description
Transducer	4 MHz, Model: TX-4-5-8, MFG: Met-Flow, Lausanne, Switzerland
Pulser/receiver	Model: PUL-2, MFG: Honda Electronics, Aichi, Japan
Digitizer	Model: NI USB 5133,MFG: National Instrument, Texas, USA
Computer	Model: ThinkPad, MFG: Lenovo, Beijing, China

Table 2: UVP Parameter configuration.

Parameter	Value
Center frequency (f_0)	4MHz
Number of cycles	4
Emission voltage	140 Vp-p
Receiving gain	30 dB
Pulse repetition frequency (f_{PRF})	8 kHz
Number of repetitions (N_{REP})	64

4. Result and discussion

4.1 Experimental data of gas hold-up and flow regimes

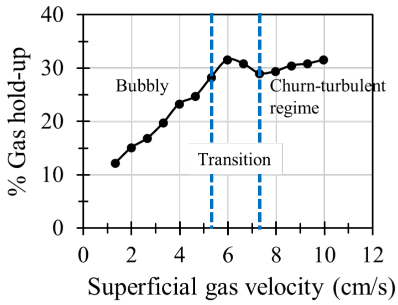
Figure 6 represents the graph that shows the relation between the gas hold-up (ε) and superficial gas velocity (U_g). The experimental data to define the relation was obtained from the conducting experiment in the apparatus explained in the previous section. The tap water, tap water mixed with glycerin 5 %v/v, and tap water mixed with glycerin 20 %v/v were the working liquid in the experiment. The flow regimes were mapped on the graph, which was the essential data for making the KNN classification model.

4.2 KNN classification model and accuracy evaluation

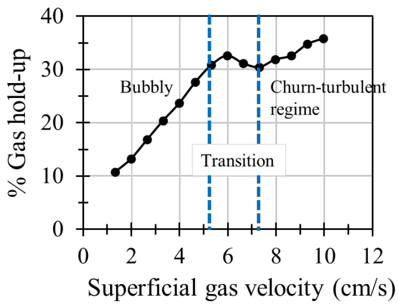
Figure 7 illustrates the KNN model for flow regime classification. The standard deviation of bubble velocity and the slope of the autocorrelation function of the echo signal worked as the model attributes. There are three flow regime categories in the model: bubbly, transition, and churn turbulence. One hundred sixty-eight training data was inputted to make the model. The training data is the information that the categories accorded to attributes were known.

4.3 Testing result and accuracy evaluation

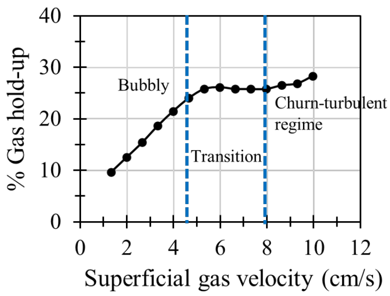
In the last step, the 28-testing data set that the known flow regime was used to confirm the accuracy of the model. All data was collected from the water, which is a working liquid that was injected by the air with a superficial gas velocity between 1.3 and 9.9 cm/s. The data cover three flow regimes. The k = 3 was set for the evaluation. The testing result is shown in Table 3. The model accuracy in the testing is 96.4%. Figure 8 illustrates the tested result on the KNN model. The result in transition regime is used in this example.



(a)



(b)



(c)

Figure 6: Relation between the gas hold-up and superficial gas velocity (*U*g), (a) tap water, (b) tap water mixed with glycerin 5 %v/v, and (c) tap water mixed with glycerin 20 %v/v.

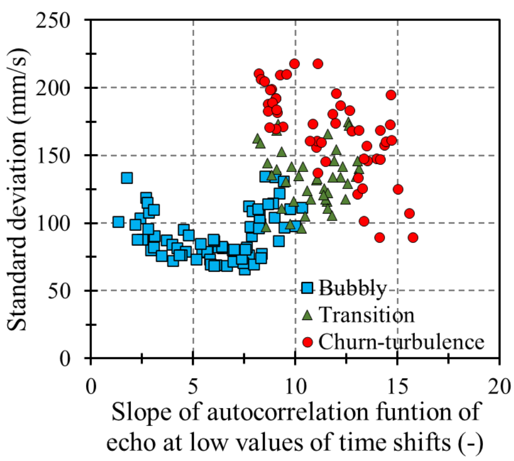


Figure 7: The KNN model for flow regime classification.

Table 3: Testing result

No.	Flow regime	Prediction	No.	Flow regime	Prediction
1	bubbly	Correct	15	Trans	Correct
2	bubbly	Correct	16	Trans	Correct
3	bubbly	Correct	17	Trans	Correct
4	bubbly	Correct	18	Trans	Correct
5	bubbly	Correct	19	Trans	Wrong
6	bubbly	Correct	20	Churn	Correct
7	bubbly	Correct	21	Churn	Correct
8	bubbly	Correct	22	Churn	Correct
9	bubbly	Correct	23	Churn	Correct
10	bubbly	Correct	24	Churn	Correct
11	bubbly	Correct	25	Churn	Correct
12	bubbly	Correct	26	Churn	Correct
13	bubbly	Correct	27	Churn	Correct
14	Trans	Correct	28	Churn	Correct

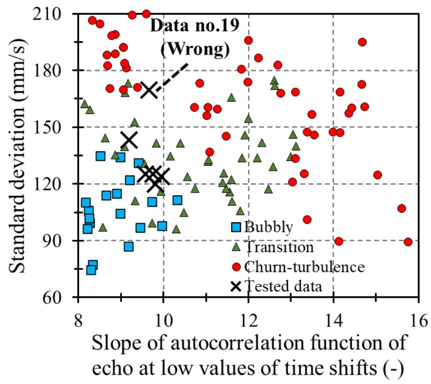


Figure 8: The KNN model for flow regime classification.

5. Summary

The integration of the UVP technique and the KNN algorithm to identify the flow regimes in bubble columns was proposed. The standard deviation of bubble velocity distributed in the column and the characteristic of the echo signal influenced by each flow regime were collected by the UVP. The experiment was conducted in a circular shaped tank that bubble generated, and gas hold-up was monitored. The KNN model for the flow regime classification was made. The weighted nearest neighbors method was used to make the decision for classifying the flow regime. The accuracy of the classification was higher than 95%.

References

[1] Deckwar W-D: Bubble Column Reactors, John Wiley & Sons, England (1992).

[2] Manjrekar O N, *et al.*: Identification of flow regime in a bubble column reactor with a combination of optical probe data and machine learning technique, Chem. Eng. Sci. 2 (2019), 100023.

[3] Takeda Y: Velocity Profile Measurement by Ultrasonic Doppler shift method, Int J Heat Fluid Flow. 7 (1987), 313-318.

[4] Wongsaroj W, *et al.*: Extended Short-Time Fourier Transform for Ultrasonic Velocity Profiler on Two-Phase Bubbly Flow Using a Single Resonant Frequency, Appl. Sci. 9 (2019), 50.

[5] Batsaikhan M, *et al.*: Visualisation of air–water bubbly column flow using array Ultrasonic Velocity Profiler, Theor. App. Mech. Lett. 7 (2017), 379-385.

[6] Zhang S, *et al.*: Learning k for kNN Classification, ACM Trans Intell Syst Technol. 8 (2017), 43:1-43:19.