Comparison of differential pressure model based on flow regime for gas/liquid two-phase flow

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Abstract. Gas/liquid two-phase flow in horizontal pipe is very common in many industry processes, because of the complexity and variability, the real-time parameter measurement of two-phase flow, such as the measurement of flow regime and flow rate, becomes a difficult issue in the field of engineering and science. The flow regime recognition plays a fundamental role in gas/liquid two-phase flow measurement, other parameters of two-phase flow can be measured more easily and correctly based on the correct flow regime recognition result. A multi-sensor system is introduced to make the flow regime recognition and the mass flow rate measurement. The fusion system is consisted of temperature sensor, pressure sensor, cross-section information system and v-cone flow meter. After the flow regime recognition by cross-section information system, comparison of four typical differential pressure (DP) models is discussed based on the DP signal of v-cone flow meter. Eventually, an optimum DP model has been chosen for each flow regime. The experiment result of mass flow rate measurement shows it is efficient to classify the DP models by flow regime.

1. INTRODUCTION

Research work of gas/liquid two-phase flow in horizontal pipe receives great attention in the research field of multi-phase flow. It was found that because of the complexity and variability of two-phase flow, the real-time parameter measurement becomes a difficult issue in the field of engineering and science (Hetsroni, 1982).

The flow regime, which ties up with the pressure, temperature and flow rate, could reflect the flow pattern and inner structure of two-phase flow. Other parameters of two-phase flow could be measured more easily and correctly in case of the flow regime has been correctly recognized. The mass flow rate measurement is achieved by utilizing a multi-sensor data fusion system which contains temperature sensor, pressure sensor, cross section system and v-cone flow meter. It was found that multi-sensor data fusion combines the data from multiple sensors and relates the information from associated databases to achieve improved accuracies and more specific inferences than that could be achieved by the use of a single sensor (Llinsa et al., 1998). Multi-sensor data fusion has already been widely used in the field of military and robot but just comes to a start in the field of multi-phase flow.

Cross-section information technology is an on-line measurement technique with the advantages of non-invasion, non-radiation. it could provide us with two/three dimensional information which is far more than other conventional techniques. The measured voltage contains rich information of the cross-section and could be used to make the flow regime recognition and cross fraction calculation. D-S evidence theory is adopted to recognize the flow regime based on the measured voltage.
V-cone flow meter is a new kind of throttling set which appeared in the middle of 1980s. It was found that because of the special shape, it has the advantages of small pressure drop, high repeatability, good linear ability, wide measurement scale and so on (Stewart et al., 2002). In the field of single-phase flow, v-cone flow meter has achieved pretty high accuracy, at the mean time it has become a popular device for two-phase flow measurement by combine with differential pressure (DP) models. Steven (2003) found its efficient use in the measurement of wet gas.

A method to measure the mass flow rate of gas/liquid two-phase flow in horizontal pipeline is put forward. According to the flow regime, a comparison of DP models has been made based on the DP signal from v-cone flow meter. The most suitable DP models for v-cone flow meter have been respectively adopted under different flow regime which has been recognized by the cross-section information system. The experiment result shows this method is acceptable.

2. MULTI-SENSOR FUSION SYSTEM

The multi-sensor system contains temperature sensor, pressure sensor, cross-section information system and v-cone flow meter. Fig 1 shows the simplified structure of the multi-sensor data fusion system. The cross-section information system is used to recognize the flow regime while other sensors are used to make the mass flow rate calculation.

The physics fundamental of cross-section information system is different medium has different conductivity. Dong (2005) found that the medium distribution can cause the change of conductivity distribution which could be measured by the system. There are two electrode-plane in the cross-section information system in which 16-electrode and adjacent exciting mode are adopted. 16 electrodes are uniformly installed around the pipe in each plane. Each plane of electrode could be regarded as an independent sensor of the same kind which can be used in the data fusion. It was found that the adjacent exciting mode refers to the exciting current is injected into the measured area through a pair of adjacent electrodes, and the voltages are measured through successive pairs of neighboring electrodes except the exciting electrodes. After all the voltages have been measured, the current is injected through the next electrodes until all the independent voltage measurements have been done (Dong et al., 2001). In this mode every circle contains 16 excitations and each excitation contains 13 voltage data, in order to get one frame information of the cross-section 208 voltage data need to be gathered.

The dual-plane cross-section information system used in the experiment could provide us with 50 frames data per second in every plane. Differential pressure signal is obtained across a v-cone flow meter whose $\beta$ is 0.65, front angle is 45°, and back angle is 65°.

The experiment is carried out in Tianjin University Multi-phase Flow Laboratory. The horizontal pipe is made of organic glass, so that the flow regime could be observed more clearly in the experiment. The pipe is about 40m long and the inner diameter is 50mm. The flow rate of water is about 0.1-16.0 m$^3$/h, and gas is 0.06-82.0 m$^3$/h. Different flow regime could be formed by controlling the valve of water and gas pipe. Of these flow regimes bubble flow, short plug flow, long plug flow and annular flow are objective flow regimes to be recognized.
3. FLOW REGIME RECOGNITION

3.1 Feature Extraction

In the adjacent exciting and measure strategy, one frame information of the pipe cross-section is consists of 208 measured voltage data. It was found that it is difficult to make the flow regime recognition directly and data pretreatment is needed in order to reduce the data dimension, \( R_i \) is defined as follows (Tan et al., 2007):

\[
R_i = \frac{1}{13} \sum (V_{ij} - V_{ij0})
\]

(1)

Where \( V_{ij} \) is the \( j \)-th voltage data at the \( i \)-th excitation, \( V_{ij0} \) is the \( V_{ij} \) vale when the pipe is full of water.

An array \( V_{Ras} \) (where \( n = 16m \)) could be formed through the time axis, In order to get a better known about how well \( V_{Ras} \) represents the void fraction at different flow regime on a large scale, set \( m = 500 \). three features: \( \overline{X} \), \( SD \), \( SK \) are extracted from the above \( R_i \) series in order to reduce the data demension at a further step:

\[
\overline{X} = \frac{1}{n} \sum_{i=1}^{n} R_i
\]

(2)

\[
SD = \left( \frac{1}{(n-1)} \sum_{i=1}^{n} (R_i - \overline{R})^2 \right)^{1/2}
\]

(3)

\[
SK = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left( \frac{R_i - \overline{R}}{SD} \right)^3
\]

(4)

The experiment results show the three features have good capability of differentiating (shown in Tab.1), so they could be used to identify the flow regime separately.

| Flow Regime       | \( \overline{X} \) | \( SD \) | \( SK \) |
|-------------------|-------------------|-----|-----|
| Bubble Flow       | 0.828             | 8.511 | 2.491 |
|                   | 1.192             | 8.768 | 1.982 |
|                   | 1.047             | 9.119 | 2.272 |
|                   | 8.345             | 20.521 | 0.511 |
| Short Plug Flow   | 7.832             | 19.898 | 0.414 |
|                   | 8.9259            | 20.850 | 0.5295 |
|                   | 12.5947           | 32.578 | 0.797 |
| Long Plug Flow    | 11.674            | 34.176 | 0.631 |
|                   | 10.889            | 28.729 | 0.615 |
|                   | 5.743             | 50.434 | 0.894 |
| Annular Flow      | 5.650             | 49.438 | 0.824 |
|                   | 4.870             | 50.535 | 0.861 |
3.2 D-S Evidence Theory
Dempster-Shafer (D-S) evidence theory is a statistical-based data fusion classification algorithm. It was found that D-S evidence theory is based on a non-zero set \( \Theta \), which is called Frame of Discernment (Shafer, 1976).

3.2.1 Basic Probability Assignment Function
In the theory a basic probability assignment over \( \Theta \) is defined as \( m: 2^\Theta \to [0,1] \), such that:

\[
\begin{align*}
  m(\emptyset) &= 0 \\
  \sum_{x \in \Theta} m(A) &= 1
\end{align*}
\]

(5)

If \( A \subseteq \Theta \), and \( m(A) > 0 \), \( A \) is called focal element and \( m(A) \) is an evidence which represents how well \( A \) is supported.

3.2.2 Combination Rule
The key point of D-S evidence theory is that the single evidence BPAF may be combined to an integrated BPAF, this is the evidence combination. The combination rule is as follows:

\[
m(A) = \begin{cases} 
  0, & A = \emptyset \\
  K \sum_{A \cap B \cap \cdots \cap \emptyset \neq A} m(A)m(B) \cdots, & A \neq \emptyset
\end{cases}
\]

(6)

where \( K = (1 - \sum_{A \cap B \cap \cdots \cap \emptyset \neq \emptyset} m_{1}(A)m(B)\cdots)^{-1} \).

3.3 Recognition Process and Result
Features extracted from both planes of cross-section information system are used to get the basic probability assignment function \( m_i(A_j) \) (\( i = 1,2, \ldots, 6 \), \( j = 1,2,3,4 \)) which represent how well the \( i \)th feature supports the \( j \)th flow regime. The features \( X, SD \) and \( SK \) from both planes are respectively defined as \( S_i, i = 1,2, \ldots, 6 \) and the four objetivelflow regimes: bubble flow, short plug flow, long plug flow and annular flow, which appointed as the elements of the frame of discernment in D-S evidence theory, are respectively defined as \( A_j, j = 1,2,3,4 \). The concepts of Union Core, Distance and proportion coefficient \( K \) are introduced to get the value of \( m_i(A_j) \):

\[
C_i = \frac{1}{N} \sum_{i=1}^{N} S_{ij}, i = 1, \ldots, 6
\]

(7)

\[
D_i = \sqrt{(S_{ij} - C_i)^2}, i = 1, \ldots, 6
\]

(8)

\[
K_i = \frac{D_i}{C_i}, i = 1, \ldots, 6
\]

(9)
In the equation, \( S_i \) is the sample data, \( S_i' \) is the recognized object.

The sample data \( S_i \) is used to get the Union Core \( C_i \) and then the basic probability assignment function \( m_i(A_j) \) could be acquired through normalizing the four \( K \) from these four flow regimes. Through utilizing the combination rule with \( m_i(A_j) \), the recognition result is obtained (shown in Tab.2). In this experiment, 30 sets of data of each flow regime are used as the sample data to get the Union Core \( C_i \) (six Cores of each regime), and another 30 sets data of each flow regime are used as the recognizing objects with the regime recognition method based on D-S evidence theory.

| Tab.2 Recognition result under the method based on D-S evidence theory |
|---------------------------------------------------------------|
| Flow regime       | Data sets | Right recognized | Success rate |
| Bubble Flow       | 30        | 29               | 96.7%        |
| Short Plug Flow   | 30        | 26               | 86.7%        |
| Long Plug Flow    | 30        | 27               | 90%          |
| Annular Flow      | 30        | 30               | 100%         |

Only one set data of bubble flow is taken as short plug flow, totally 7 sets data of short plug and long plug flow are mistaken as each other, and all the annular flow have been right recognized. The experiment results shows the flow regime can be recognized with high accuracy by cross-section information system, and the recognition method based on D-S evidence theory is acceptable. If a better way is found to get the BPAF in evidence theory, better recogniton result would be achieved.

4. DIFFERENTIAL PRESSURE MODEL

It was found that in the field of gas/liquid two-phase flow measurement based on differential pressure, there are already some differential pressure (DP) models, such as Homogeneous model, Murdock model, Chisholm model, Lin model and so on (Murdock, 1962; Chisholm, 1977; Lin, 1982). However the above DP models are deduced from the orifice plate meter and venturi tube not v-cone flow meter, the direct use of these DP models to v-cone flow meter would cause considerable larger measurement error. Since every model has its own adaptive condition, an optimum DP model from them could be found under a certain flow regime for v-cone flow meter.

4.1 Homogeneous Model

In this model, gas/liquid two-phase flow is considered as well-mixed single-phase flow with a mixed density, so single-phase flow DP model could be used. The measurement error of this model is considerable big especially when the gas mass quality \( x \) is small and pressure is low.

\[
W = \frac{\varphi CA \sqrt{2 \rho_g \Delta P}}{\sqrt{1 - \beta^2} \left[ \frac{\rho_g}{\rho_L} + \left( \frac{1 - \rho_g}{\rho_L} \right) \right]} \tag{10}
\]

4.2 Murdock Model

Murdock model is derived from separated model to which a coefficient 1.26 has been added. The experiment condition for Murdock model is that gas mass quality: 0.11-0.98 and the pressure: 0.1-4 MPa.
4.3 Chisholm Model
Slip model is taken into consideration in Chisholm model. When the experiment pressure is 1.0-7.0 MPa and the gas mass quality \( x \leq 0.1 \), the prediction error of this model is about 20%. This error reduces with the increase of experiment pressure and gas mass quality.

\[
W = \frac{\varphi CA \sqrt{2\Delta P_{Tr} \rho_G}}{\sqrt{1 - \beta^4 [x + 1.26(1 - x)\sqrt{\rho_G / \rho_L}]}} \quad (11)
\]

4.4 Lin Model
On the basis of a modified separated flow model, a simple and rational relationship for the flow rate is put forward by introduction of a corrective coefficient \( \theta \) in this model. \( \theta \) is a function of \( \rho_G / \rho_L \) and is derived from the experiment of high \( \rho_G / \rho_L \) condition across a sharp edged circular orifice. Lin model performs well especially when the \( \rho_G / \rho_L \) is high or the gas mass quality \( x \) is large.

\[
W = \frac{\varphi CA \sqrt{2\rho_G \Delta P_{Tr}}}{x \sqrt{1 - \beta^4} \left[ 1 + \left( \frac{\rho_L}{\rho_G} \right)^{0.25} + \left( \frac{\rho_G}{\rho_L} \right)^{0.25} \right] \chi + \chi^2} \quad (12)
\]

Where \( \chi = \frac{\Delta P_L}{\Delta P_G} = \left( \frac{W_L}{W_G} \right) \frac{\rho_G}{\rho_L} = \left( \frac{1 - x}{x} \right) \sqrt{\frac{\rho_G}{\rho_L}} \).

5. EXPERIMENT RESULT
The DP models mentioned above have been applied to each objective flow regime using the differential pressure signal acquired by the v-cone flow meter. Fig. 2 shows the mass flow rate error of the models under each flow regime.

The first part of this figure show the DP models’ experiment error at bubble flow. The gas mass quality \( x \) is small and the pressure is low in bubble flow and Murdock model has done a good job at this flow regime, the experiment error mostly shakes within 5% while others models beyond 10%. When the gas mass quality \( x \) and pressure increases, bubble flow turns into short plug flow, Murdorck model continues its good performance in short plug flow, the mean value and standard deviation is the smallest of the four models. Chisholm model becomes the best behaved model at long plug flow, the error curve is smooth and within 5%, while the error of others is variable and big. At annular flow, the standard deviation of these models is smaller than other flow regimes, while the mean value is biggest of all the flow regimes. Gas/liquid two-phase flow becomes more mixed when the pressure is high and gas mass quality is large, so Homogenous model suits annular flow much better than other flow regimes. However the mixture could not becomes so well mixed that it could be seen as single-phase flow or rather Homogenous model is an ideal model, the experiment error of it is considerable big. The last part of the figure shows Lin model is supperier to others.
After the error comparison of the models at certain flow regimes, in this experiment Murdock model is the most suitable model for bubble flow and short plug flow, or rather Murdock model well worked in the condition of low pressure and small gas mass quality, Chisholm model is the best for long plug flow, and Lin model for annular flow. The optimum model would be applied to certain flow regime which has been recognized after the error comparison of the models.

Based on the flow regime recognition and optimum model selection, the mass flow rate result is given by every 10 sets measured data of each flow regime which have been right recognized. Fig. 3 shows the mass flow rate error.

The experiment error of long plug flow with Chisholm is smallest while the error of others is more variable but mostly centralized within 10%. Only one experiment point of bubble flow and one point of annular flow is beyond 10%. The error is acceptable for the flow rate measurement of gas/liquid two-phase flow. A higher accuracy could be achieved if these DP models have been modified.

6. CONCLUSION
A method of mass flow rate measurement for gas/liquid two-phase flow based on flow regime recognition and differential pressure model is put forward in this paper. The experiment result is achieved by a multi-sensor fusion system which is mainly consists of cross-section information system
and v-cone flow meter. Firstly the flow regimes have been recognized by a dule-plane cross-section information system. D-S evidence theory as an important fusion method in decision-fusion level has been used to recognize the objective flow regimes. The high recognition accuracy indicates the feasibility of this recognition method. After the flow regime recognition, an error comparision among four typical DP models has been made according to objective flow regimes. Finally a optimum DP model has been selected for each objective flow regime which has been recognized, that is Murdock model for bubble flow, Chisholm model for long plug flow, and Lin model for short plug flow and annular flow. By utilizing the optimum DP model, the mass flow rate error is within 10%, it is shown that the method based on multi-sensor fusion is acceptable for flow rate measurement of gas/liquid two-phase flow.

Because of the complexity and variability of multi-phase flow, it is needed to observe and measure the flow process from multi-aspect in both time and space. This provide us a good opportunity to apply multi-sensor data fusion to the field of multi-phase flow measurement. With the research work get deeper, more fusion methods and fusion strategies will be applicated in this research area.

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NOMENCLATURE
\(x\) gas mass quality  
\(m\) frame number  
\(n\) length of the pre-treatment data series  
\(A\) minimum cross sectional area of v-cone \([m^2]\)  
\(C\) discharge coefficient of the V-cone flow meter  
\(N\) sample data number  
\(R\) pre-treatment data series  
\(V\) measured voltage  
\(W\) mass flow rate of gas/liquid two-phase flow \([kg/s]\)  

Greek Letters
\(\beta\) diameter ratio of the v-cone flow meter  
\(\phi\) thermal expansion factor  
\(\rho\) density of gas and liquid \([kg/m^2]\)  
\(\theta\) corrective coefficient.  
\(\Delta P\) differential pressure of two-phase flow \([Pa]\)  

Subscripts
\(i\) \(i\)-th excitation  
\(j\) \(j\)-th voltage data  
\(G\) gas phase  
\(L\) liquid phase  
\(0\) the pipe is full of water

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