Identification of flow regime using multi-resource information

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Abstract: - Most two-phase flow measurements depend on correct flow regime identification. Many methods have been proposed to identify the flow regime, but none of them can work well across different flow conditions. In this paper we apply a non-intrusive instrument of different types of sensor to extract the data under different flow conditions. In light of these different sensor information, evidence theory of Dampster-Shafer is applied to realize the information fusion. Based on a clustering technique of self-organized feature map, the basic probability assignment for Dampster-Shafer is determined, and at the same time the calculation of combination rule using the evidence theory can result in new interpretation and insight of different flow regimes. The experimental results show that the principle of data fusion helps improve the identification quality of flow regimes greatly.

Key-Words: - flow regime; two-phase flow; evidence theory.

1 Introduction

The flow regime, reflecting the pattern and intrinsic structure of flow, is one of the important parameters to describe two-phase flows, and identification of two-phase flow regimes is becoming increasingly important in many industrial processes[1, 2]. On-line identification of two-phase flow regimes can not only help analyze the effect of flow pattern on phase fractions and flow rate but also play an important role in the safety of operation and the reliability of practical processes [3,4]. However, so far there is no valid method to identify two-phase flow regimes. In most cases, two-phase flow regimes are determined subjectively. On the other hand, two-phase flow is more complex than single-phase flow due to the existence of relative movement and variable interfaces between two phases. Consequently, there is no effective method available to gather the accurate information that can reflect the true flow regimes. Up to now there are two tendencies used to improve the identification qualify for two- phase flow regimes: mending measure instrument and ameliorating identification algorithm. Many attempts have been made to identify two-phase flow regimes using linear or nonlinear classifiers derived from machine learning algorithms[5-7] based strictly on data obtained from laboratory experiments. These new methodology for flow pattern identification have been successful with researchers reporting promising accuracy rates. However, these methods strongly depend on very limited flow conditions and difficult to satisfy general applications. In particular, there is no exact theory for the characterization of these patterns, and the subjective character of the flow pattern identification often causes disagreements between researchers due to imprecise and incomplete data. Facing such disagreements, an effective way is to use data fusion toward an objective conclusion.

Recently, more and more methods show that it is useful to apply the data fusion technique to original information of different sensors in order to obtain higher accuracy and more believable classification or identification of data. In the direction, it is expected that the flow regime types can be effectively identified due to the systematic use of multi-resource information from different sensors. Data fusion deals with the synergistic combination of information made available by various knowledge sources such as sensors, in order to provide a better understanding of a given scene. Flow regime identification requires a way that matches information gathered by various information sources and generates the useful decision-making rules through the information features. For the identification of flow regime, it is suffered from the uncertain flow mechanism and imprecise or incomplete of data. Evidence theory proposed Dempster-Shafer (D-S) [8, 9] is a powerful and flexible mathematical tool for handing uncertain, imprecise and incomplete information. That is so for at least for three reasons. First, by representing the uncertainty and the imprecision of a body of knowledge via the notion of evidence, belief can be committed to single hypothesis (singleton) or a composite hypothesis (union of hypotheses), Second, the evidence combination rule of the D-S evidence theory provides a useful operator to integrate multiple information from different sources. Finally, the decision on the optimal hypotheses choice can be made in a flexible and rational manner. So in this paper we use the evidence theory to integrate the data from different resources. After synthesizing the information features and calculating the basic probability assignment, the combination evidence is presented. In this way, the correctness of flow regime identification in two-phase flow is greatly increased.

In the paper, the identification results in two-phase flow are integrated based on the following considerations: (1) to construct a classifier by a visual learning data of time series or historical data for the identification of flow regimes; (2) to identify the flow regimes by analyzing the characteristic of raw voltages of the electrodes and (3) to adopt integrative data acquisition instrument.

2 Flow regimes and data acquisition

2.1 Typical flow regimes in two-phase flow

Definitions of flow regimes are based on linguistic descriptions and graphical illustrations (see Fig.1).

(a) Bubby flow (b) Annular flow (c)Churn flow

Fig.1. Illustration of three different flow regimes

The visual flow pattern classification is determined through subjective descriptions, which might vary for different viewers. Normally there is no clear boundary between two adjacent patterns in two-phase flow, i.e. one pattern changes to another pattern gradually with transition regions found between adjacent patterns. In most cases, vertical two-phase flows might be divided into seven patterns: bubbly, flow, transition region between bubbly flow and slug flow, slug flow, transition region between slug flow and churn flow, churn flow, transition region between churn and annular flow, and annular flow. Usually, one thinks that the transitions between churn flow and other flows are not as clear as the transition between bubbly flow and slug flow [1] .

2.2 Data acquisition

The structure of the measurement system for data acquisition is plotted in Fig.2. The system employs three pairs of dual-planes of electrode array sensors, Sensor 1, Sensor 2 and Sensor 3, except a pair of excitation electrodes that locate respectively at the axial separated cross-section. Each sensor consists of a sine-wave generator, voltage control current source, plane selection, multiplexer for the 8-electrode array, amplifier, phase sensitive demodulator, and A/D converter. Sensor 1 and Sensor 2 have different shapes of electrode. All electrodes are non-intrusive type, and the original flow is free of disturbance by them. Sensor 1 and Sensor 2 work in an adjacent measurement strategy that is called “multiple alternating current driven and voltage sensing electrode” protocol with serial measurement channels55], and measure the variances and the related pressures of the data of time series of two 8 conductance fluctuating signals. Sensor 3 takes the pressure measure in pipe wall based on the principle of the cross-correlation technique. E_1 and E_2 are excitation electrodes (plotted by red circle in Fig.2. The data of each sensor are transmitted into the computer by an independent channel to further possess.

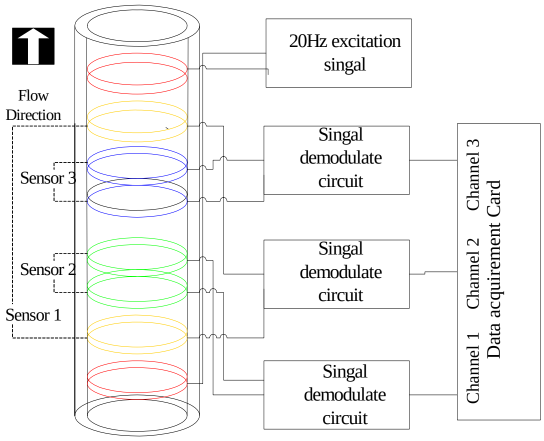

Fig.2. Data acquisition system based on a designed multi-sensor system.

3 Integrating multi-resource information

3.1 D-S evidence theory

The D-S evidence theory allows one to manipulate non-necessarily exclusive events and thus to represent explicitly process uncertainty. This theory assumes the definition of (i) a frame of discernment X consisting of the exhaustive and exclusive hypothesis and (ii) the reference set 2^X of all the disjunctions of the elements of *X*. In the evidence theory, a basic probability assignment (BPA) is an elementary mass function: *m*: $2^X \rightarrow [0,1]$ satisfying: $m(\phi)=1$ and $\sum_{A\subseteq 2^X} m(A)=1$. A BPA is characterized by two functions: the belief function *Bel* and the plausibility function *Pl*. The belief in a subset *A* $\in 2^X$ is the sum of all pieces of evidence that support *A* and the plausibility of *A* the sum of pieces of evidence not supporting $\overline{A}$:

$$Bel(A)=\sum_{B\subseteq A} m(B) \quad and$$
$$pl(A)=\sum_{B\cap A\neq\phi} m(B)=1-bel(\overline{A}) \tag{1}$$

Based on these definition, combination operators can be characterized. It is possible to build a unique elementary mass function *m* from *n* elementary mass functions m_1, m_2, …,m_n arising from *n* distinct and independent sources but characterized on the same set, such that

$$m(A)=\frac{\sum_{A_i\cap B_j=C} m(A_i)m(B_j)}{(1-\sum_{A_i\cap B_j=C} m(A_i)m(B_j))}, \tag{2}$$

where $\oplus$ denotes the combination operator. The Dempster's rule consists of calculating:

$$Bel(A)=(((bel_1\oplus bel_2)\oplus bel_3)\oplus ...)\oplus bel_n \tag{3}$$

3.2. Determining BPA

The basic determinations of the BPA of each resource in X are different shapes or densities of pattern clusters formed during unsupervised analysis of the pattern data. In the paper, we first apply a method of augmenting the Self-Organizing feature Map (SOM) [10] clustering algorithm to aggregate all data (see Fig.3). The SOM algorithm can extract the prototypes from the training patterns more reliable while retaining neighbourhood information through mapping the original pattern data to feature layer. The procedure to identify the clusters in the SOM feature layer is as follows: the pattern data of each resource is a piece of time series *l*, and the distance of any two pattern data, f_1 and f_2, is defined by

$$d(f_1,f_2)=\int_l |f_1-f_2|dx \tag{4}$$

All training patterns were presented to the SOM algorithm for clustering. For each class, the node in the feature map that won most frequently were identified as the core node of that class. Those nodes that were in the neighbourhood of the core node was highlighted as the clusters. The number of won core node is interpreted as the importance of the individual information sources in the whole clustering process. In this study, for each flow pattern C, we define the BPA as follows:

$$\tilde{m}(C)=N_r/N \tag{5}$$

where *N* is the number of training patterns used in the flow regime *C* and N_r is the number of times core node wins in the feature map layer. Note that we set all densities equal to the same value for each flow regime. Clearly, we will have a higher density value(i.e. higher confidence that the core node is the prototypical member) if N_r is high. In this direction, the BPA of any two-element subset is defined as

$$\tilde{m}(C_i,C_j)=(d(C_i)+d(C_j))/(d(C_i,C_j)+d(C_j,C_i)) \tag{6}$$

$d(C_i)$ is the average of all distances inside the neighbourhood of *i*-th won node to its own, and $d(C_i, C_j)$ the average of all distances inside the neighbourhood of *i*-th won node to *j-th* won node. In the sense of flow regime identification, it is meaningless to calculate the mass value of any subset of more than three elements. Therefore, the final mass function *m* is obtained after normalization with respect to the entire set 2^X, that is

$$m(A_i)=\frac{\tilde{m}}{\sum_{A_i\in 2^X}\tilde{m}(A_i)}, s.t. \sum_{A_i\in 2^X} m(A_i)=1 \tag{7}$$

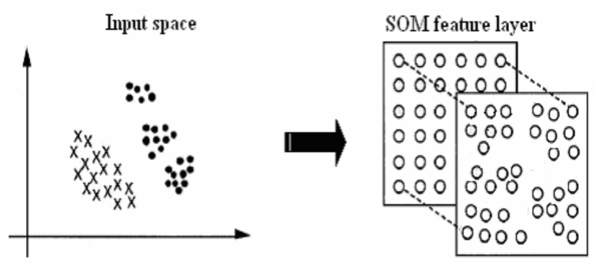

Fig.3. Determination of BPA using SOM classification.

4 Experiment

We apply the data acquisition system illustrated in Fig.2 to take three classes of data from three pairs of sensor simultaneously. All experiments are performed under the following flow conditions: Water cut: 44–75%, Total flow rate: 26–66 m^3/d, Gas density: 0.75 g/cm^3, Water density: 1.00g/cm^3, Gas viscosity: 3.26 centipois. We change the gas density and flow rate in total 28 times of experiment to simulate deferent two-phase flow conditions. Only five kinds of flow regime can be observed in all experiments and denoted as , , , , and corresponding to Bubble, Slug, Churn, Annular, and Wispy-Annular flows, individually.

We apply three kinds of method respectively to identify the flow patterns. The method 1 and method

2 directly classify all data of series time by SOM method to create a classifier for all flow regimes, depending on the data of the Sensor 1 and sensor 2. Based on the pressure data in pipe wall, Method 3 classify these data to construct classifier. At the same time, we regard the three sensors as three information resources, use the D-S evidence theory to construct the probability density function, combine different rules by Eq.(6), and finally integrate all three resources to make the decision/identification of flow regimes. The comparative results are listed in Table1, and the following conclusions can be observed:

1) All three methods have the "blind area of identification" on their own, i.e., some real flow regimes cannot be identified or be incorrectly classified, but the correct identification fraction is heightened to a great extent after integrating all three information resources in together using the D-S evidence theory. Here the final flow regime *F* is determined if the following equations are satisfied:

$$F=\max_j\{(Bel(j)+pl(j))/2\} \text{ and } Bel(j)>\varepsilon\,, \qquad (8)$$

j is label of flow regimes ~ including their two-element combinations, ε =0.6.

2) The belief degree of each information resource is enhanced toward majority of the combinations of flow regimes thus their identification become easier. Likewise the uncertainty interval [*Bel*, *pl*] was thinned after the information fusion. Here the *Bel* and [*Bel*, *pl*] are calculated across 28 times of experiment averagely.

3) Some transition flow regimes between two different flow regimes, such as flow regime between and , are more important than five typical ones, and richen the interpretation a of flow regimes.

Table1 Threes of Candidate Decision-Making Elements on Data Fusion Results

Class	Method1	Method2	Method3	Fusion Results
	CR /[*Bel*, *pl*]	CR/[Bel, *pl*]	CR/[*Bel*, *pl*]	CR/[*Bel*, *pl*]
	57/[0.60, 0.68]	34/[0.14, 0.26]	56/[0.03, 0.88]	78/[0.61, 0.77]
	65/[0.67, 0.71]	37/[0.12, 0.38]	48/[0.05, 0.38]	68/[0.70, 0.75]
	64/[0.63, 0.77]	56/[0.56, 0.78]	72/[0.16, 0.57]	68/[0.55, 0.64]
	53/[0.54, 0.78]	75/[0.76, 0.81]	67/[0.12, 0.19]	81/[0.84, 0.94]
	57/[0.41, 0.59]	67/[0.58, 0.69]	36/[0.27, 0.48]	73/[0.93, 0.98]
	75/[0.16, 0.34]	65/[0.39, 0.62]	76/[0.57, 0.78]	84/[0.87, 0.95]
	58/[0.01, 0.18]	30/[0.15, 0.18]	63/[0.56, 0.81]	69/[0.75, 0.76]
	26/[0.04, 0.17]	38/[0.04, 0.18]	67/[0.03, 0.16]	72/[0.74, 0.81]
	13/[0.16, 0.19]	19/[0.03, 0.08]	49/[0.16, 0.23]	63/[0.46, 0.54]

Therefore, the integrated results by D-S evidence theory have higher correctness rate of the flow regime identification. Likewise the fusion results may in fact define some new useful flow regimes based on the combination of flow regimes, such as the combination of original flow regimes , , and , although they are difficult to be observed in the experimental conditions. Nevertheless, these transition flow regimes can correspond to real physical background. Consequently, to pay more attention on these new developed flow regimes are likely promising to find the natural principle contained the two-phase flow.

5. Conclusions

A new approach of the identification of flow regime based on D-S evidence theory was presented through the analysis of the measurable voltages obtained from a multi-sensor system. This approach was verified by flow conditions of a number of rather different settings. Unlike the existing single method that may suffer from the poor accuracy of the classification, this method would make a group of imprecise and incomplete information become more accurate and stable. Meanwhile, this method is applicable to two-phase flows with conductive liquid being the continuous phase, and the correctness of the identification of flow regime can be greatly improved. In discussion of Dempster-Shafer evidence theory, the usefulness and meaning of basic probability assignment and belief functions are introduced, then the calculating equation of combination rule on the identification of flow regime is developed.

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