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Digital Image Processing Based Flow Regime Identification of Gas/Liquid Two - Phase Flow

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Abstract: In most of the industries the two-phase flow pattern is obtained when gas and liquid flow simultaneously in a pipe. These two phase flows are complex, dynamic and are difficult to measure. An approach for identifying the flow pattern using Neural Network and Support vector machine is developed. Flow images are captured using high speed SLR camera and are preprocessed. After preprocessing the images, the textural features such as entropy, homogeneity, contrast, correlation and energy are extracted. The textural features extracted are given as the input to the neural network and support vector machine. Four typical flow regimes such as bubbly flow, slug flow, stratified flow and annular flow are captured from the experimental set-up. The results obtained shows that support vector machine method of classification is very effective with accuracy of 98.03 percent and hence higher recognition is done.

Keywords: Flow Regime, Image processing, neural network, support vector machine, pattern recognition;

1. INTRODUCTION

Two-phase flow widely exists in various fields such as power plant, chemical industry, nuclear energy and metallurgical industry. The simultaneous flows of more than one phase are almost ubiquitous particularly in the field of chemical engineering. These multiphase flows are complex because of the infinitely deformable nature of the interface in gas-liquid and liquid-liquid flows. In general the two phase flows are basically classified into four patterns namely, Bubbly flow, in which air is distributed as discrete bubbles in continuous water. Slug flow, which has the diameter of the air bubble approximately same as the up riser pipe and the nose of that slug will be in spherical form, Stratified flow, the regular flow and Wavy Annular flow, in which air occupies the core of the pipe and water film is formed on the pipe wall. Flow regime plays an important role in two-phase flow because it affects not only the flow behaviour, the diathermancy and matter propagation properties, but also the precise measurement of two-phase flow parameters. It is an important parameter that also influences system stability, and mass transfer and pressure drop characteristics. Therefore it is necessary to identify the flow regime in a two- phase flow.

There are several studies to identify the flow regime in two-phase flow based on microwave radiation, process tomography, particle image velocimetry and fuzzy logic. All these methods have their application limits. The textural features of images can reflect the dynamic and complex characteristics of two-phase flow. Gang Huang et.al(2011) proposed a method to extract the textural features by Gray Level Co-occurrence Matrix (GLCM).The extracted features are energy, entropy, contrast, homogeneity, correlation. Then mean and standard deviation of the textural feature series are used as the inputs to Support Vector Machine (SVM) to identify the current flow regimes.

Pedram Hanafizadeh et. al(2011), experimentally investigated the visual detection of gas-liquid two phase flow regime in the airlift pump in which one of the main parameters affecting the performance of the air lift pumps is the two-phase flow regime in the main pipe of the pump. The gas phase velocity is measured in two-phase flow from the data obtained by the high-speed camera and the three main flow regimes namely slug, churn and annular are visually detected in the airlift pump. Mayor.T.S. et.al (2007) measured the flow parameters by the automatic analysis of a sequence of video frames with the purpose of object tracking and characterization. Expressions are also derived for the computation of overall uncertainty in parameters. Van Hout R et al(2001) used a feature evaluation method to calculate the evaluation features and the corresponding sensitive features and input into the SVM to automatically identify flow regime.

Lilan Shi et. al(2007) and ,Mi Y,Ishii M et al(1998) proposed a method for fuzzy Recognition of Gas-Liquid Two phase Flow pattern based on image processing in which flow images are captured by a high speed CCD camera in horizontal pipe. First a Fuzzy reasoning method is used to identify stratified flow and annular flow. Then fuzzy neural network is used to identify the flow pattern of the bubbly, slug and plug flow. Levenberg-Marquart optimized algorithm is used to learn the network. Monji H et al., L.H.Tsoukalas(1998),Embrechts M J et al(1996) and Lilan shi et al(2005) developed flow regime identification approaches based on Neural network approaches that are explained in Pattern Identification using Multi scale entropy and RBF neural network. The image moment invariants and GLCM matrix features are extracted. To improve the performance of multiple classifier system, rough set theory is used for reducing the inessential factors. SVM is trained by using Eigenvectors to reduce the dimension of the flow regime samples. Bui Dinh et.al(2006),Noguerira.S et al. (2006),sun Bin et al(2010) visualized the two-phase flow using a Charge Coupled Device (CCD) camera and flow regimes are determined by examining the video images.

This paper deals with an identification of flow regime using textural features and support vector machine. The extracted textural features were entropy, homogeneity, contrast, correlation and energy. The features extracted are given as input to the neural network and support vector machine. Based on the feature values, accurate identification of flow patterns using support vector machine is done.

The rest of the paper is organized as follows. Section II discusses the Experimental test facility and flow regime identification methodology. Section III describes about the textural feature extraction. Section IV discusses the about pattern identification using Neural network and support vector machine classifier. Section VI deals with Results and discussions, Section VII is the Conclusion.

2. EXPERIMENTAL TEST FACILITY

Atmospheric air is compressed and is given to the air flow line through regulated valve. At the same time, water from overhead tank is regulated and is sent to the water line. At the T-joint air and water gets mixed together and is allowed to flow through the transparent glass pipe. High speed Image acquisition SLR camera at the speed of 25 frames per second is used for capturing the images of liquid-gas two- phase flow. Depending upon the different air flow rates, different flow patterns are obtained. Since there is the possibility of liquid pressure to be higher than the air pressure, there is a non return valve connected to the air flow side to prevent the liquid entering into the air flow side. The rotameter used for measuring liquid flow rate is of acrylic type with minimum flow rate of 2000 LPH and a maximum flow rate of 20000 LPH and the rotameter for measuring air flow rate ranges from 0 LPM to 300 LPM. Both the flow meters are at ambient temperature and have no pressure loss. Figure 1(a) & (b) shows the experimental set-up of the two-phase liquid-gas flow measurement.

Fig. 1. (a).Experimental set-up of Liquid-Gas two - phase flow measurement.

3. FLOW REGIME IDENTIFICATION METHODOLOGIES

The Images of different flow patterns that are captured using high speed SLR camera are pre-processed and are made available for pattern identification. The flow pattern identification approaches are shown in Fig.2.

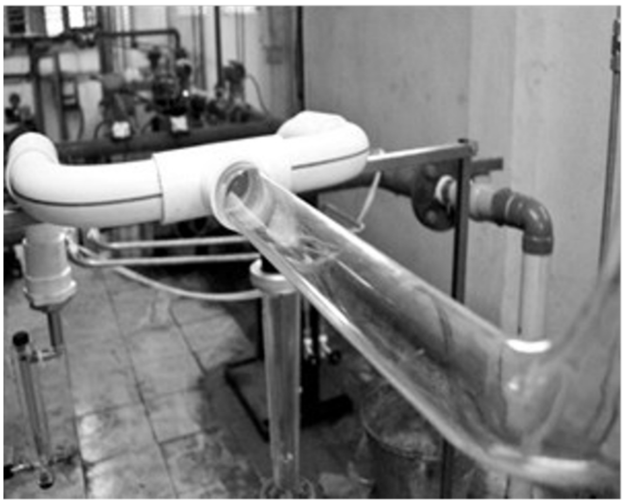


Fig.1.(b).Experimental set-up T-Junction

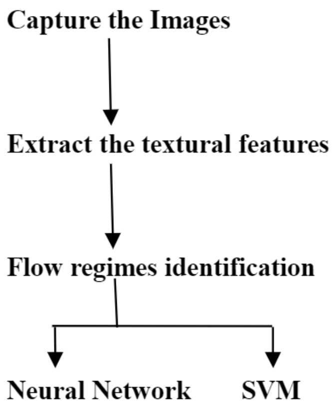


Fig. 2. Flow pattern identification approaches

4. FEATURE EXTRACTION

The images of different flow patterns captured using SLR camera are taken for pattern recognition. The pattern recognition is done by using neural network approach and SVM classifier. In both the methods the textural features such as Entropy, Correlation, Contrast, Homogeneity and Energy that are obtained from Gray Level Co-occurrence Matrix (GLCM) are given as inputs and the targets are assigned. The procedure for determining GLCM matrix and extracting the features are explained below.

4.1 Gray level co-occurrence matrix

A Gray Level Co-occurrence Matrix (GLCM) contains information about the positions of pixels having similar gray level values. A co-occurrence matrix is a two-dimensional array, **P**, in which both the rows and the columns represent a set of possible image values. A GLCM **Pd**[i,j] is defined by first specifying a displacement vector **d**=(dx,dy) and counting all pairs of pixels separated by **d** having gray levels i and j. The GLCM is defined by:

$$P_d[i,j] = n_{ij} \quad \text{...............(1)}$$

Where n_{ij} is the number of occurrences of the pixel values **(i,j)** lying at distance **d** in the image. The algorithm for determining Gray Level Co-occurrence Matrix (GLCM) is explained below,

1. Creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value *i* occurs in a specific spatial relationship to a pixel with the value *j*.

2. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent).

3. Each element (*i,j*) in the resultant GLCM is simply the sum of the number of times that the pixel with value *i* occurred in the specified spatial relationship to a pixel with value *j* in the input image.

4. The number of gray levels in the image determines the size of the GLCM.

4.2 Numerical Features of GLCM

Gray level co-occurrence matrices capture properties of a texture but they are not directly useful for further analysis, such as the comparison of two textures. Numeric features are computed from the co-occurrence matrix that can be used to represent the texture more compactly. Numeric quantities or statistics that describe a texture can be calculated from the intensities (or colours) themselves. Various features of GLCM are discussed below.

Entropy: Entropy is a measure of information content. It measures the randomness of intensity distribution.

$$C_e = -\sum_i \sum_j P_d[i,j] \ln P_d[i,j] \text{..............(2)}$$

When the image is not texturally uniform, many GLCM elements have very small values, which imply that entropy is large.

Correlation: Correlation is a measure of image linearity.

$$C_c = -\sum_i \sum_j [ijP_d[i,j]] - \mu_i.\mu_j / \sigma_i \sigma_j \text{.............(3)}$$

Where

$$\mu_i = \sum_i i P_d[i,j]$$

$$\sigma_i^2 = \sum_i i^2 P_d[i,j] - \mu_i^2$$

Correlation will be high if an image contains a considerable amount of linear structure and it returns a measure of how correlated a pixel is to its neighbour over the whole image. The range of correlation should be within -1 to +1.

Contrast: Contrast is a measure of the local variations present in an image.

$$C(k,n) = \sum_i \sum_j (i-j)^k P_d[i,j]^n \text{ ....(4)}$$

It returns a measure of the intensity contrast between a pixel and its neighbour over the whole image. If there is a large amount of variation in an image the P[i,j]'s will be concentrated away from the main diagonal and the contrast will be high. The range of correlation should be [0 (size (GLCM, 1)-1) ^2].

Homogeneity: Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$C_h = \sum_i \sum_j \frac{P[i,j]}{1+|i-j|} \text{.............}(5)$$

A homogeneous image will result in a co-occurrence matrix with a combination of high and low P[i,j]'s and homogeneity value is 1 for a diagonal GLCM.

Energy: Energy returns the sum of squared elements in the GLCM. It is also known as Uniformity and is 1 for constant image.

$$\sum_i \sum_j P[i,j]^2 \text{.............}(6)$$

5. PATTERN IDENTIFICATION

5.1 Neural Network

An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward back propagation neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern.

In this flow pattern recognition approach, the textural features extracted are given as input to the neural network. Hence in this case 5 neurons are considered for input layer and the output targets are assigned. The network is trained again and again by varying the hidden layer neurons until the desired accuracy is obtained.

5.2 Support Vector Machine Classifier

SVMs (Support Vector Machines) are a useful technique for data classification. A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one \target value" (i.e. the class labels) and several attributes" (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data, given only the test data attributes. The procedure for using Support vector machine is given below,

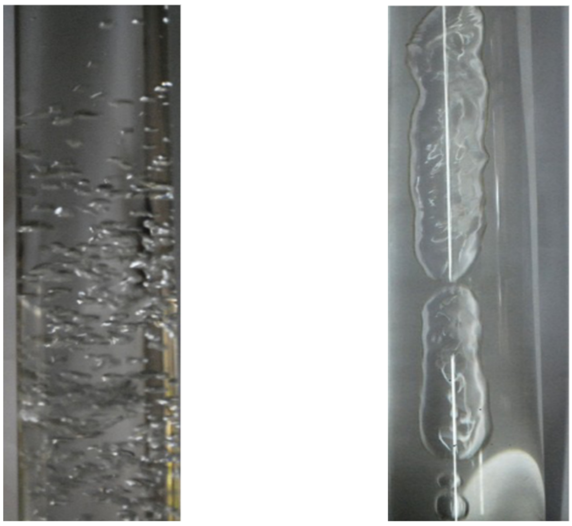
1. Transform data to the format of an SVM.
2. Randomly try a few kernels and parameters
3. Test

SVM requires that each data instance is represented as a vector of real numbers. Hence, if there are categorical attributes, we first have to convert them into numeric data. Before applying SVM, scaling is very important. The main advantage of scaling is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges. Another advantage is to avoid numerical difficulties during the calculation. Because kernel values usually depend on the inner products of feature vectors.

Data used for training is in matrix form, where each row corresponds to an observation or replicate, and each column corresponds to a feature or variable. Group is nothing but the column vector, character array, or cell array of strings for classifying data in training into two groups. It has the same number of elements as there are rows in training. Each element specifies the group to which the corresponding row in training belongs. Kernel function value specifies the string or function handle specifying the kernel function that maps the training data into kernel space. Kernel functions can be Linear, Quadratic, RBF, Polynomial or MLP. In this work Gaussian Radial Basis Function (RBF) is the kernel used for training.

6. RESULTS AND DISCUSSION

The real time images captured are pre-processed for further processing. To classify slug flow from other flow patterns, a pattern recognition approach using neural network and SVM are implemented. A set of 25 frames from each flow pattern are considered to train the neural network and SVM. Another set of 25 frames which are different from training images are considered as test images. The Figure.4 shows the input images taken for different flow patterns. From the pre-processed images, the textural features are extracted and the flow patterns are identified.

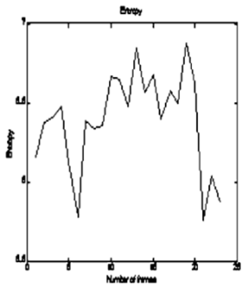


(a) (b)

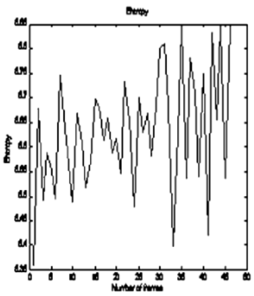
(c)

(d)

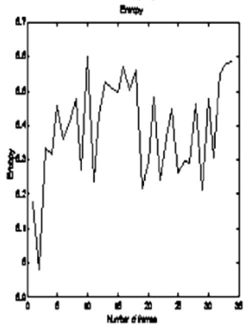
Fig. 4. Input Images (a) Bubbly flow (b) Slug flow (c) Stratified flow (d) Wavy annular flow



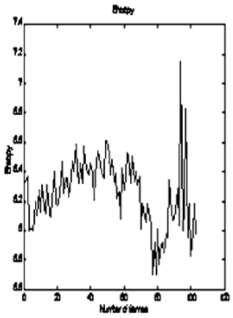
(a)



(b)



(c)



(d)

Fig. 5. Entropy Feature (a) bubbly flow (b) Slug flow (c) Stratified flow (d) Wavy annular flow

Gray Level co-occurrence matrices are identified from the gray converted images. From the GLCM matrices obtained, the textural feature series such as Entropy, Correlation, Contrast, Homogeneity, and Energy are extracted. These features are given as input to the both neural network and SVM and the patterns classified. The Entropy feature extracted for all different flow patterns are shown in Fig.5. The above features are given as input to the neural network and the target matrix is specified. 5 neurons in input layer, 20 neurons in hidden layer and 4 neurons in output layer are taken for pattern classification.

The features which are most suitable for classification are taken as input to SVM. The results obtained using SVM are classified with an identification accuracy of 98.03%.

7. CONCLUSION

Image processing techniques are employed for the study of continuous co-current gas-liquid slug flow in vertical pipe. In this paper textural features extracted are used as input to the network since it can reflect both the dynamic and complex characteristics of the two-phase flow. With features as input to the network, pattern identification of slug flow has been carried out by incorporating neural network and Support Vector Machine classifier. Slug flows are classified accurately by SVM with an identification accuracy of 98% when compared to the neural network classifiers. The results obtained shows that textural series method with SVM classifier is feasible and it can be applied to classification of two-phase flow and thus the obtained result has higher accuracy.

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