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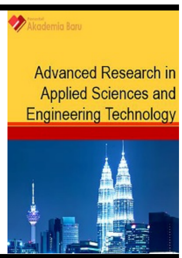

Flow Regime Identification in Gas-Liquid Two-Phase Flow in Horizontal Pipe by Deep Learning

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ABSTRACT

Two phase flow commonly occurs in industrial pipelines, heat exchangers and nuclear power plants. A characteristic feature of two-phase flow is that it can acquire various spatial distribution of phases to form different flow patterns/regimes. The first step to successfully design, analyze, and operate gas-liquid system is flow regime identification. Flow regime identification is of huge importance to the effective operation of facilities for the handling and transportation of multiphase fluids, and it represents one of the most significant challenges in petrochemical and thermonuclear industries today. The objective of this study is to develop a methodology for identification of flow regime using dynamic pressure signals and deep learning techniques. Three different flow regimes were simulated using a Level-Set (LS) method coupled with Volume of Fluid (VOF) method in a 6 m horizontal pipe with 0.050 m inner diameter. Dynamic pressure readings were collected at a strategic location and were converted to scalograms to be used as inputs in deep learning architectures like ResNet-50 and ShuffleNet. Both architectures performed effectively in classifying different flow regime and recorded testing accuracies of 85.7% and 82.9% respectively. According to our knowledge no similar research has been reported in literature, where various Convolutional Neural Networks are used along with dynamic pressure signals to identify flow regime in horizontal pipe.

Keywords:
Two-phase flow; Deep learning; Transfer learning; Continuous Wavelet Transform; Dynamic pressure

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1. Introduction

Two-phase flow commonly occurs in oil and gas industries, nuclear power plants and heat exchangers. An important characteristic of two-phase flow is its ability to acquire different spatial arrangements of phases, thus creating different flow patterns. Each pattern has its own hydrodynamic behaviour which influence properties like void fraction, pressure drop and heat transfer etc. For the successful operation of any two-phase flow, it is crucial to identify flow pattern. Different flow regime identification methods exist in literature [1-3]. Traditionally, Close Visual Inspection (CVI) was used to determine different flow regimes [4]. This method is highly subjective and only possible for easily accessible transparent pipes, which is not always the case in industries.

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Flow regime can also be identified using the fluctuations of natural flow parameters. This approach works on the principle that waveform of these fluctuations is closely related to different flow patterns. Example of such flow regime identification methods are void fraction measured by X-rays [5], rotating electric field conductance gauge [6], electrical capacitance tomography [7], conductivity [8], and electrical impedance [9]. The intrusive nature of some of these methods could alter flow regime change due to sensors placement within the flow stream. Although excellent results can be obtained using radiation techniques, the use of radiation source could lead to health and safety related problems. The use of pressure signals is considered a more practical approach because pressure data is readily available. That is why pressure fluctuations are widely used to identify flow regime [10-13].

Recently Machine Learning (ML) techniques are used to process such signals for flow regime identification. Mi *et al.* [9] used void fraction signals to train a neural network and then used the trained network to identify different flow regimes. Wang and Zhang [7] used Support Vector Machine (SVM) to identify different flow patterns by using capacitance signals from Electrical Capacitance Tomography (ECT) system as inputs, Trafalis *et al.* [14] also used the same method but used superficial velocities and pipe diameter as inputs. Neural networks have also been used to process signals from conductivity probe [8] and vortex flow meters [15] for flow regime identification.

Most of the literature is based on using differential pressure along with neural networks to identify flow regimes. Differential pressure data needs two pressure reading to be determined at different locations and is a cumbersome process. The present method proposes using dynamic pressure readings which can be obtained at single location. We will also be using deep learning techniques instead of neural networks as classifiers. According to our knowledge, dynamic pressure readings along with deep learning techniques have never been used before to identify different flow regime in water-air two phase system in horizontal pipe. The difference between traditional and deep learning methods is that the former needs hand crafted features extracted from the time and/or frequency domains to be fed into the ML algorithms, whereas, in deep learning, the Convolutional Neural Networks (CNNs) transform their representation in a more ambiguous manner. Deep learning model automatically learns the hidden patterns in the data. In this study, we used two different architectures namely ResNet50 and ShuffleNet and compared the performance in terms of classification accuracy.

2. Methodology

The methodology for identification of different flow regimes in two phase flow in a horizontal pipe is discussed in this section. This section will cover the simulation methodology used to collect dynamic pressure signals and neural networks used for classification.

2.1 Geometry

Geometry used in this research is a horizontal pipe with 6 m length and 0.050 m internal diameter. The inlet diameter is divided into air and water inlets as shown in Figure 1. Pressure readings were recorded for a total duration of 10 seconds at 80D from the inlet. From visual observation of contours, flow at this location was fully developed and thus considered appropriate for pressure readings.

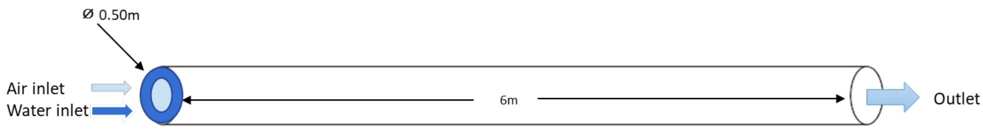
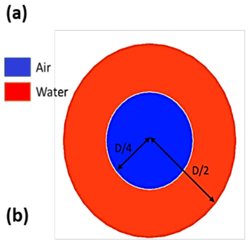


Fig. 1. Geometry of a horizontal pipe used in this study

2.2 Boundary Conditions

The inlet boundary condition was set to be velocity inlet type. Water and gas superficial velocities at inlet were chosen using Taitel and Dukler's flow regime map [4] as shown in Figure 2(c). As shown in the Figure 2(a) both phases were injected separately into the pipe. Gas phase was introduced into the pipe at the centre region while liquid phase was injected peripherally. The boundary condition at outlet was set to outlet pressure which is the value of atmospheric pressure. No slip boundary conditions were set on boundary wall. The atmospheric pressure was used as a reference and isothermal condition was applied. The surface tension of water-air was offset to 0.072 N/m. Physical properties of both working medium are listed in Figure 2(b).

(a)



(b)

Phase	Density (kg/m^3)	Viscosity (Pa s)
Water	998.2	1.003e-03
Air	1.225	1.7894e-05

(c)

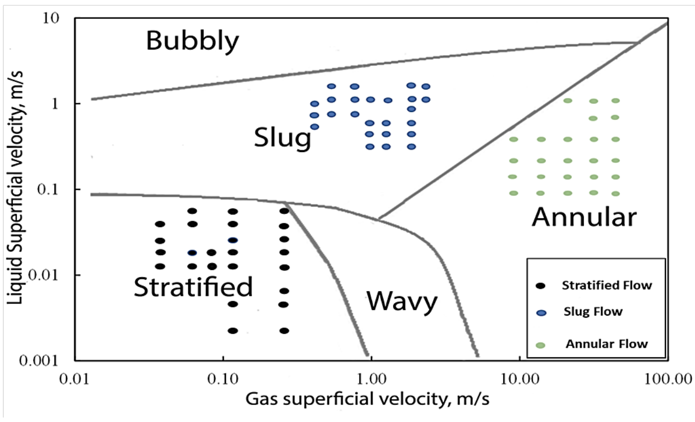


Fig. 2. Boundary Conditions; (a) Air and Water inlet, (b) Physical properties of air and water (at 20 ^{0}C), (c) Water and gas superficial velocities used for simulation of different flow regimes, shown in Taitel and Dukler flow regime map [4]

3.3 Data transformation

Continuous Wavelet Transform (CWT) is a tool that captures the time-frequency features of non-stationary signals like pressure signals [16]. The performance of CWT is excellent in the field of signal processing [17]. CWT convert pressure signals to scalogram images which are visual representation of continuous wavelet coefficients. These two-dimensional scalogram images can be used as input for CNN models. A CWT with source wavelet morlet with parameter = 8, was applied to the dynamic pressure signals and scalogram images were obtained, which can be expressed mathematically by Eq. (1). Some examples of scalogram images for different flow regimes are shown in Figure 3.

$$\Psi(\tau) = e^{i\omega_0\tau} e^{\frac{-\tau^2}{(2\vartheta^2)}} \quad (1)$$

The dilated version of Morlet wavelet in frequency domain is given by Eq. (6).

$$\Psi(\omega) = \vartheta\sqrt{2\pi e}^{\frac{-(a\omega-\omega_0)^2\vartheta^2}{2}} \quad (2)$$

where ϑ and ω are constants, the wavelet center frequency is denoted by ω_0.

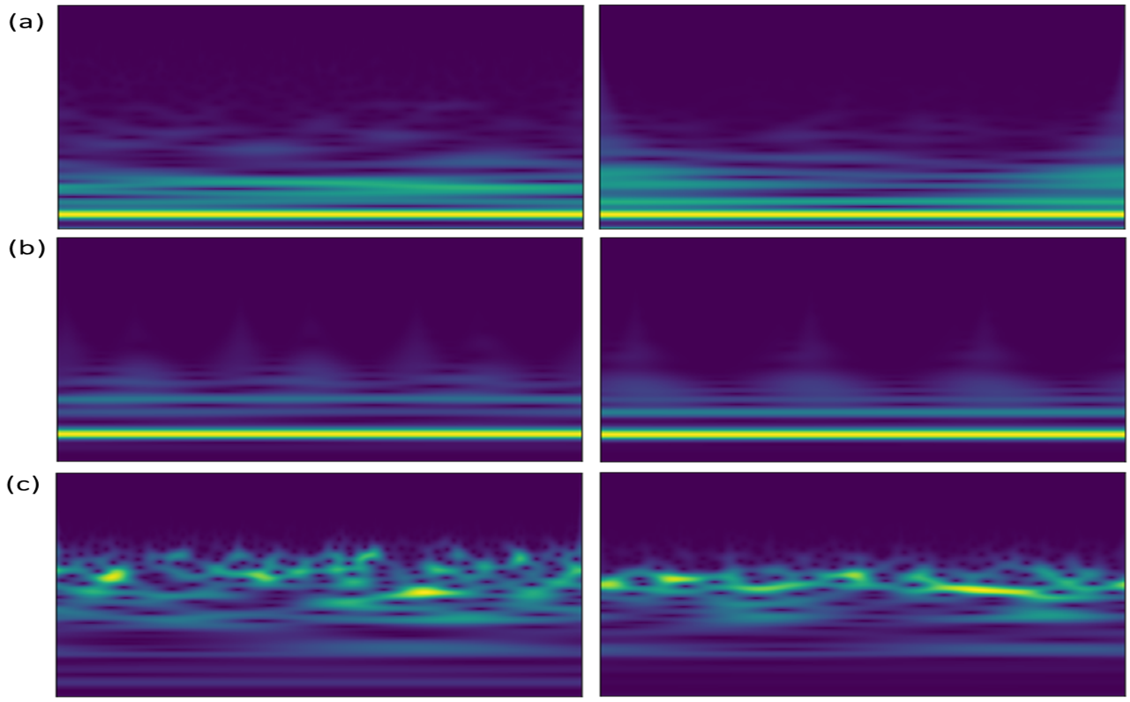


Fig. 3. Scalograms of different flow regimes (a) Stratified flow, (b) Slug flow, (c) Annular flow

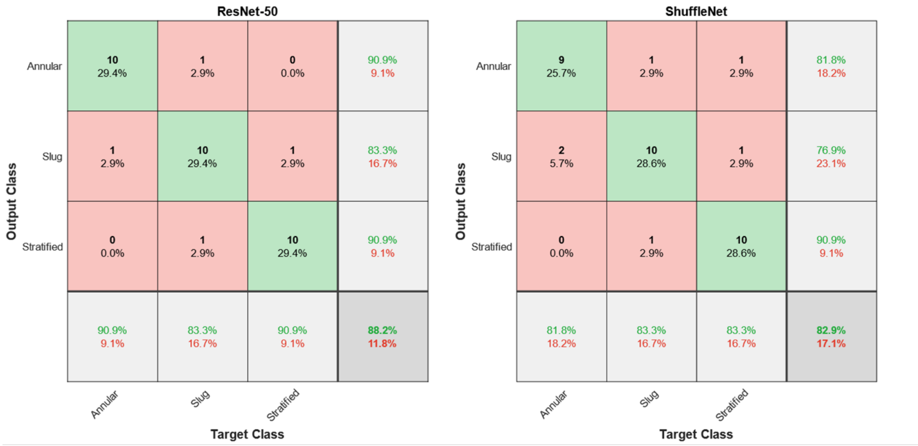
3. Results and Discussion

Different two-phase flow regimes have different pressure properties, which makes it possible to identify flow regimes using their pressure manifestation. These pressure signals are converted into scalograms as shown in Figure 3. These scalogram are used for training and testing of Convolutional Neural Networks (CNN), to classify different flow regimes. For the classification of different flow regimes using dynamic pressure signals, Resnet50 and ShuffleNet architectures were used. The accuracy was chosen as evaluation criteria for both the models. The Resnet50 achieved higher testing accuracy which was 85.7%, while that of ShuffleNet was 82.9%, as shown in Table 1. Both the training and validation losses were recorded. The training and validation loss for Resnet50 was 0.641 and 0.321 respectively, which was higher than ShuffleNet.

Table 1
Performance of ResNet-50 and ShuffleNet architectures

Classifier	Layers	Training Loss	Validation loss	Validation Accuracy	Testing Accuracy
ResNet-50	177	0.641	0.321	94.44	85.7
ShuffleNet	172	0.065	0.166	97.22	82.9

In Figure 4(a), the prediction accuracy for stratified, slug and annular flow regime are 90.9%, 83.3% and 90.9% respectively. Out of 11 signals for annular flow, Resnet50 correctly identified 10 signals. One of the slug signals was wrongly considered as annular signal. Total number of signals for slug flow were 12 and 10 signals were correctly classified while 1 stratified and 1 annular flow signal was wrongly predicted as slug. In case of stratified flow, 11 signals were used for testing and 10 of them were correctly identified while 1 slug signal was wrongly considered as stratified. In Figure 4(b), stratified, slug and annular flow regimes were predicted with 83.3%, 83.3% and 81.8% accuracy, respectively. Out of 11 signals for annular flow, ShuffleNet correctly classified 9 signals and one of the slug flow and one stratified flow signal was considered wrongly as annular signal. Total number of signals for slug flow were 13 and 10 signals were correctly classified while 1 stratified and 2 annular flow signals were wrongly predicted as slug. In case of stratified flow, 11 signals were used for testing and 10 of them were correctly identified while 1 slug signals were wrongly considered as stratified.



(a) (b)

Fig. 4. Confusion matrix of ResNet-50 and ShuffleNet for flow regime classification

4. Conclusions

A method for the identification of gas-liquid flow regimes in horizontal pipe was developed in this work. This method is based on acquiring dynamic pressure signals and its subsequent scalograms, followed by their classification using Convolutional Neural Networks (CNNs). Tests were performed to validate and weigh the performance of the proposed identification procedure. The designed deep learning model has been evaluated against testing dataset. The results suggested that the present model has high accuracy in flow pattern identification. The accuracies of predictions in stratified, slug and annular flows are all above 80%. The Resnet50 achieved higher overall testing accuracy which was 85.7%, while that of ShuffleNet was 82.9%. ResNet50, prediction accuracy for stratified, slug and annular flow regime was 90.9%, 83.3% and 90.9% respectively, while for ShuffleNet stratified, slug and annular flow regimes were predicted with 83.3%, 83.3% and 81.8% accuracy, respectively. Future work should include new experiments with different orientation of pipe, testing broader range of diameters and flow parameters. This work can be taken forward by testing more flow conditions near transition boundaries and defining transition boundaries on flow regime map. More deep learning architectures can be used to check their effect on accuracy.

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References

[1] Mandhane, J. M., G. A. Gregory, and K. Aziz. "A flow pattern map for gas—liquid flow in horizontal pipes." *International journal of multiphase flow* 1, no. 4 (1974): 537-553.

[2] Kaichiro, Mishima, and Mamoru Ishii. "Flow regime transition criteria for upward two-phase flow in vertical tubes." *International Journal of Heat and Mass Transfer* 27, no. 5 (1984): 723-737.

[3] Shaban, H., and S. Tavoularis. "Identification of flow regime in vertical upward air–water pipe flow using differential pressure signals and elastic maps." *International Journal of Multiphase Flow* 61 (2014): 62-72.
[4] Taitel, Yemada, and Abe E. Dukler. "A model for predicting flow regime transitions in horizontal and near horizontal gas-liquid flow." *AIChE journal* 22, no. 1 (1976): 47-55.
[5] Jones Jr, Owen C., and Novak Zuber. "The interrelation between void fraction fluctuations and flow patterns in two-phase flow." *International Journal of Multiphase Flow* 2, no. 3 (1975): 273-306.
[6] Merilo, M., R. L. Dechene, and W. M. Cichowlas. "Void fraction measurement with a rotating electric field conductance gauge." (1977): 330-332.
[7] Wang, H. X., and L. F. Zhang. "Identification of two-phase flow regimes based on support vector machine and electrical capacitance tomography." *Measurement Science and Technology* 20, no. 11 (2009): 114007.
[8] Juliá, J. Enrique, Yang Liu, Sidharth Paranjape, and Mamoru Ishii. "Upward vertical two-phase flow local flow regime identification using neural network techniques." *Nuclear Engineering and Design* 238, no. 1 (2008): 156-169.
[9] Mi, Y., M. Ishii, and L. H. Tsoukalas. "Vertical two-phase flow identification using advanced instrumentation and neural networks." *Nuclear engineering and design* 184, no. 2-3 (1998): 409-420.
[10] Elperin, T., and M. Klochko. "Flow regime identification in a two-phase flow using wavelet transform." *Experiments in fluids*32, no. 6 (2002): 674-682.
[11] Matsui, Goichi. "Automatic identification of flow regimes in vertical two-phase flow using differential pressure fluctuations." *Nuclear Engineering and Design* 95 (1986): 221-231.
[12] Vieira, Saon Crispim, Charlie van der Geest, Adriano Todorovic Fabro, Marcelo Souza de Castro, and Antonio Carlos Bannwart. "Intermittent slug flow identification and characterization from pressure signature." *Mechanical Systems and Signal Processing* 148 (2021): 107148.
[13] Bin, S. U. N., Hongjian Zhang, Lu Cheng, and Z. H. A. O. Yuxiao. "Flow regime identification of gas-liquid two-phase flow based on HHT." *Chinese Journal of Chemical Engineering*14, no. 1 (2006): 24-30.
[14] Trafalis, Theodore B., Olutayo Oladunni, and Dimitrios V. Papavassiliou. "Two-phase flow regime identification with a multiclassification support vector machine (SVM) model." *Industrial & engineering chemistry research* 44, no. 12 (2005): 4414-4426.
[15] Sun, Zhiqiang, and Hongjian Zhang. "Neural networks approach for prediction of gas–liquid two-phase flow pattern based on frequency domain analysis of vortex flowmeter signals." *Measurement Science and Technology* 19, no. 1 (2007): 015401.
[16] Gou, Linfeng, Huihui Li, Hua Zheng, Huacong Li, and Xiaoning Pei. "Aeroengine control system sensor fault diagnosis based on CWT and CNN." *Mathematical Problems in Engineering*2020 (2020).
[17] Pacheco-Chérrez, Josué, Diego Cárdenas, and Oliver Probst. "Experimental Detection and Measurement of Crack-Type Damage Features in Composite Thin-Wall Beams Using Modal Analysis." *Sensors* 21, no. 23 (2021): 8102.