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Classification of two-phase flow instability phases using convolutional neural networks

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1. Introduction

Natural circulation has been used in recent designs of nuclear power plants. This phenomenon is the core of passive systems that do not depend on pumps or active systems [1]. The main advantage of using natural circulation is its simplicity, implying cost reduction and proportional safety increase. The disadvantage is that natural forces are weak when compared to active systems. Natural circulation presents many two-phase flow instabilities in critical conditions which are particularly important to thermohydraulic studies. Heat transfer parameters are the focus of this research area. Most of these parameters can be obtained through flow patterns imaging due its non-invasive feature. Most of imaging studies have recently used artificial intelligence (AI) algorithms to investigate these flow patterns and parameters [2][3][4]. Typical AI classification is based on feature extraction. Recent Convolutional Neural Network (CNN) development has changed the need for previously extracting image-based features to classify patterns. CNNs have been demonstrating significant improvements when compared to conventional techniques [5] and other computational vision [6].

In such context, this work applies CNNs to experimentally acquired images to classify different *chugging* instabilities (described by Boure, Bergles and Tong [7]) which are typically present in natural circulation two-phase flow.

2. Methodology

The classification task was based on a previous formation of an experimental image database. These images were obtained in experiments performed on an experimental setup called Natural Circulation Circuit (NCC). This circuit is constituted of glass tubes arranged in U-shape allowing easy visualization of one-phase and two-phase flow under atmospheric pressure. Figure 1 shows a NCC scheme presenting different segments, including the visualization section.

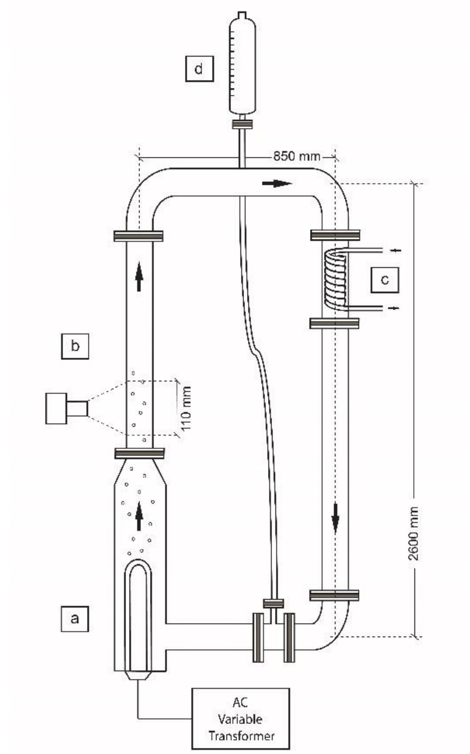

Figure 1: Natural Circulation Circuit (NCC) schematic showing: heating (a), visualization (b), cooling (c) and expansion tank (d) sections.

Three different chugging cyclical instabilities were studied on NCC experiments: Incubation (I), Expulsion (E) and Refill (R), as described by Boure, Bergles e Tong [7]. These phases and respective time intervals between each occurrence are illustrated in Figure 2.

The present study used 1152 images acquired on two-phase flow experiments [8]. These images were selected based on the occurrence time and, consequently, in general, correspond to typical patterns in the middle of each cycle phase. These images were preprocessed by extracting a common Region of Interest (ROI) and labelled according to each cycle phase. The neural networks were trained using these ROIs as direct input to the machine learning models used in this work.

Based on CNN traditional training methodology [10] images were split into subsets using 60% of the used database (692 images) for training, 20% (230 images) for validation and 20% (230 images) for testing. Three different models were trained to the classification task, and the one which presented best results was evaluated using test subset. This main model, VGG_GAP, was based on a traditional Convolutional Neural Network called VGG [10] using transfer learning option [11]. This neural network had a structure composed of a first block of thirteen convolutional layers interlaid with five max-pooling layers, followed by a global average pooling layer, a fully-connected layer with 1024 neurons (ReLU activation function), a dropout layer and a fully-connected layer with three output neurons correspondent to the three possible classes. To obtain a performance comparison, a neural network model with fewer layers, was called CONV_32x64 without using transfer learning. This model had a fist block composed of two convolutional layers interlaid with two max-pooling layers, followed by a global average pooling, a fully-connected layer with 128 neurons (ReLU activation function), a dropout layer and a fully-connected layer with three output neurons. The third model was trained to have a 'baseline' comparison parameter. This third model was composed of a single linear layer and, thus, nominated as LINEAR. The models' evaluation was performed based on the following metrics: precision, recall, average accuracy, and average F1-Score with weighting by each class.

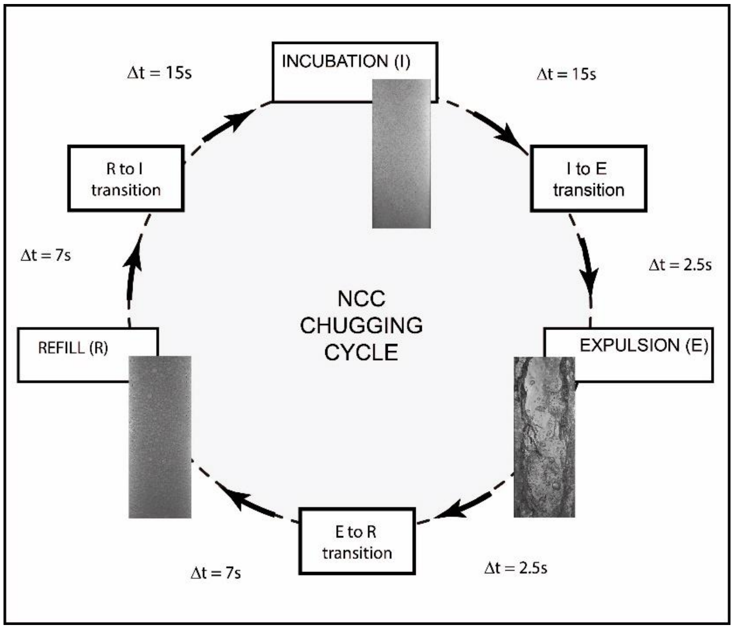

Figure 2: Chugging instability cycle observed in NCC and its typical phases and time intervals.

3. Results and Discussion

At first stage, a selection of the best model was performed using the trained models to the validation split. Table I shows obtained results.

Table I: Performance metrics of trained models on validation subset

	Precision	Recall	F1-Score	Accuracy
VGG_GAP	**1**	**1**	**1**	**100%**
CONV_32x64	0.99	0.99	0.99	99.57%
LINEAR	0.93	0.93	0.93	93.04%

The VGG_GAP model presented the best performance, correctly classifying all validation split images. This model was considered the best and was evaluated using the test split subset. The CONV_32X64 has wrongly classified one among 230 validation images. This fact suggests that much simpler models than VGG_GAP model could be developed to have the maximum classification performance. The LINEAR model also presented a very good perfomance suggesting that much complex problems can be dealt by this kind of model. Is important to emphasize that previous work on the same database from the same group [8], using traditional feature extraction from these images, had presented a much inferior performance

The VGG_GAP model was taken as the best performance model, and was applied to the test split, and the results are shown in Table II.

Table II: VGG_GAP model evaluation metrics obtained on test split

	Precision	Sensitivity	F1-Score	Number of Samples	Global Accuracy
Incubation	1	1	1	122	99.57%
Expulsion	0.96	1	0.98	28	
Refill	1	0.99	0.99	80	
Average	0.99	0.99	0.99	230	
Weighted Average	0.99	0.99	0.99	230	

From Table II, the VGG_GAP model wrongly classified one sample among the 230 split test samples which corresponds to a 99.57% accuracy. There was an expected performance decrease, but with strong F1-Score values.

4. Conclusions

This work has applied three different models of CNN to classify experimentally acquired images into three different phases of a typical chugging instability of two-phase flow in natural circulation. The work used a database of 1152 images. Among the tested models, the best model was the CNN model called VGG_GAP which was based on the VGG-16 model using transfer learning technique. On validation split subset, the model obtained 100% of global accuracy in classifying images while the 'baseline' model (a linear model) presented a 93.04% of global accuracy. The application of VGG_GAP over the test split subset obtained a 99.5% of F1-Score.

It is important to emphasize that the modern techniques of Deep Leaning are still scarcely applied on thermohydraulic area. This work shows that they can still be promisingly applied to predictive tasks associated with image classification.

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