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SELF-ORGANIZING MAPS APPLIED TO TWO-PHASE FLOW ON NATURAL CIRCULATION LOOP STUDIES

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ABSTRACT

Two-phase flow of liquid and gas is found in many closed circuits using natural circulation for cooling purposes. Natural circulation phenomenon is important on recent nuclear power plant projects for heat removal on “loss of pump power” or “plant shutdown” accidents. The accuracy of heat transfer estimation has been improved based on models that require precise prediction of pattern transitions of flow. Self-Organizing Maps are trained to digital images acquired on natural circulation flow instabilities. This technique will allow the selection of the more important characteristics associated with each flow pattern, enabling a better comprehension of each observed instability. This periodic flow oscillation behavior can be observed thoroughly in this facility due its glass-made tubes transparency. The Natural Circulation Facility (Circuito de Circulação Natural – CCN) installed at Instituto de Pesquisas Enérgeticas e Nucleares, IPEN/CNEN, is an experimental circuit designed to provide thermal hydraulic data related to one and two phase flow under natural circulation conditions.

1. INTRODUCTION

Periodic two-phase flow oscillations have been studied through the Natural Circulation Facility (Circuito de Circulação Natural – CCN) installed at Instituto de Pesquisas Enérgeticas e Nucleares, IPEN/CNEN [1-3]. This facility is an experimental circuit designed to provide thermal hydraulic data related to one and two phase flow under natural circulation conditions, and enables extensive visualization due its glass-made tubes transparency.

Natural circulation has been used in new generation power plant projects as a removal mechanism for "loss of pump power" or "plant shutdown" accidents [4].

Instabilities of two-phase flow patterns associated with natural circulation have been used as established by Delhaye in 1981 [1,5,6]. “Chugging” is the usual term to denominate the characteristic periodic expulsion of coolant from a flow channel [7]. This phenomena comprehension has been recently improved by new image processing and acquisition technology developments. Estimation of flow parameters and phase transition features are currently being investigated through artificial intelligence techniques.

Seleghim Jr and Hervieu [8] proposed a relation between flow type transitions and time-frequency covariances of void fraction signals and neural networks have been used to detect phase transitions based on signal changes by Crivelaro et al. [9].

The association of new image processing techniques and qualitative image analysis with flow related parameters has been studied [3,10-13]. Flow-type transitions, void fraction, dry angles are among many two-phase flow heat transfer examples [19-22].

This work proposes the use of Self-Organized Maps (SOM) to develop a flow pattern recognition algorithm able to identify chugging instability flow types observed on CCN experimental circuit. This neural network based algorithm is applied to digital images acquired through a visualization section. Instability phase denominations are based on classical Bour´e classification [7].

2. METHODOLOGY

Self-organizing Maps are trained based on these image features in order to observe how each of these features are important to classify each instability phase. The SOM will work as a pure clustering technique. The obtained map is used to classify different flow types.

2.1. Natural Circulation Facility

Natural Circulation Facility (NCF) (Figure 1) is an experimental circuit designed to provide thermal hydraulic data related to one and two phase flow under natural circulation conditions.

NCF is a rectangular loop of borosilicate glass tubes that are temperature resistant. The heated section (Figure 1(a)) has two Ni-Cr alloy electric heaters in U form and stainless steel cladded that can deliver up to 8000W. The cooling section (Figure 1(c)) consists of a heat exchanger/condenser, also made of glass, with two internal spiral coils where tap water flows. Circuit has an expansion tank opened to atmosphere in order to accommodate fluid level changes due to the temperature and void fraction changes. This tank is connected to the circuit through a flexible tube at its lower region in order to prevent steam entrance [1].

Visualization is possible in all regions of the circuit, and a visualization section with CCD (charge-coupled device) camera was adjusted with backlight illumination (Figure 3(b)). Temperature measurements and image acquisition were concomitantly done in order to characterize phase transition patterns and correlate them with the periodic static instability (chugging) measured cyclic period. Chugging instability cycles are usually divided in three different phases called incubation, expulsion and refill periods [1,5,6]. They are considered relaxation instabilities characterized by periodic expulsion of coolant from the channel. The experiments were adjusted to sustain a cyclic and periodic behavior of this instability.

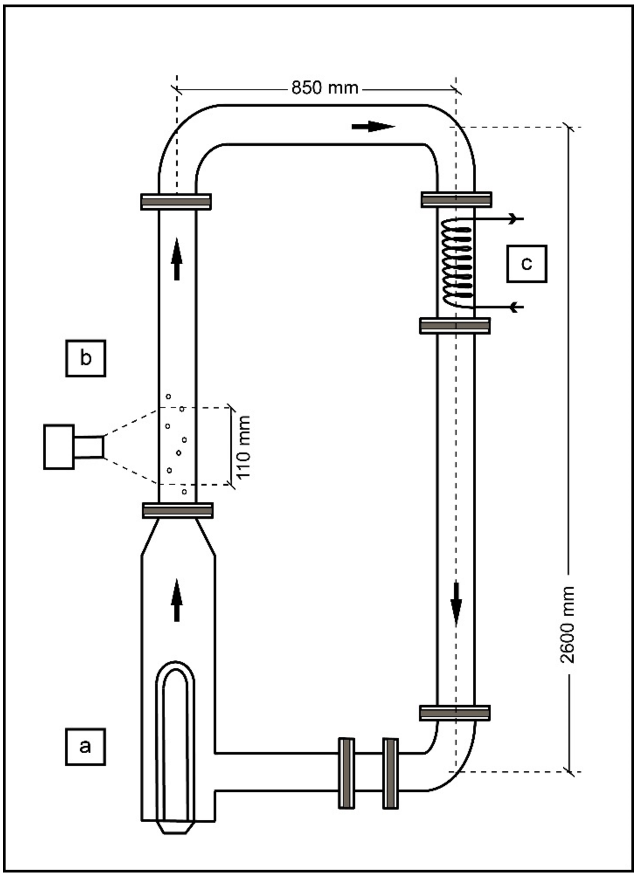

Figure 1: Schematics of natural circulation loop facility with: electrical heating section (a), visualization section (b) and cooling section(c).

The incubation phase has no net flow at the loop when vapor bubbles grow in number and size and vapor remains at upper horizontal leg. At this phase, the circuit pressure grows slightly expulsing the liquid from the cold leg to the expansion tank. The slug flow is replaced by churn flow at the called expulsion phase, when liquid entrained by vapor is expulsed from hot leg. The expansion tank level arises to its maximum value. The final phase is characterized by the inversion of flow rate direction caused by the difference of hydrostatic head, replacing the hot water at the heater by cold water coming from coil cooler. The vapor production at the heater decreases and the horizontal part of the hot leg is filled with water again, beginning the overall cycle once more [1]. This periodic flow oscillation behavior can be observed thoroughly in this facility due its glass-made tubes transparency.

2.2. Overall Classification System

The methodology used to apply SOM to flow images is represented on Figure 2. Images were acquired as is described in section 2.3 and were organized in proper folders in order to enable appropriate neural network training.

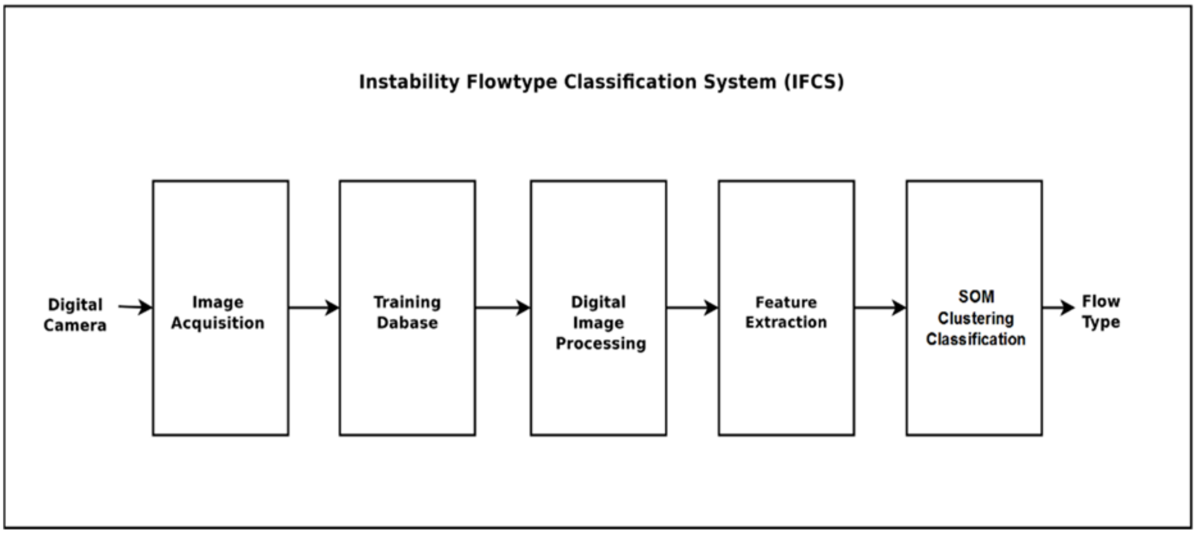

Figure 2: Instability Flow-type Classification System (IFCS) based on SOM clustering.

2.3. Image Acquisition Setup

Image acquisition was done simultaneously with temperature measurements using high resolution digital camera with 250 µs shutter speed. Lens mount was configured to enable macro focus and image acquisition was done at one frame per second rate during different cycles of 1000 to 1500 s long. Typical acquisition modes generated 3888x2592 pixels frames at longitudinal tube section with a resolution of approximately 0.03 mm/pixel. Backlight illumination technique showed to be the optimal condition to obtain image borders best definition. Images were acquired at an approximate 120 mm longitudinal section of the cylindrical hot leg tube (46.3mm external diameter) shown on Figure 1(b).

Image Database was organized based on three main chugging subtypes, Expulsion (E), Incubation (I), and Refill(R) (Figure 3). Pattern images were acquired simultaneously with circuit temperature measurements synchronized in time. The heating power was estimated to be raised up to 7270W with an ambient temperature of 25^{o}C. Cooling flow rates of 140 l/h were kept constant during the approximate 9500s experiment. Periodic behavior was confirmed by the detection of the refill-to-incubation phase transition image pattern. This detection is described with more detail elsewhere [2,3].

The instability two-phase flow cyclic behavior can be observed through temperature measurements and by cyclic flow pattern detection time interval. A regular T period of 49 seconds for a complete chugging cycle is estimated after stabilization occurs. The cycle is composed of an Incubation phase (T to (T+30)s), an Expulsion phase ((T+30)s to (T+35)s) and a Refill phase which lasts for the remaining 14 seconds of the cycle period.

The image database was composed of selected images related to each subtype phase of chugging cycle. Images corresponding to periods near to instability flow subtype transitions were not considered on this work in order to best estimate the fuzzy classification ability. From 2530 images, 32 sample images were selected to characterize each flow subtype.

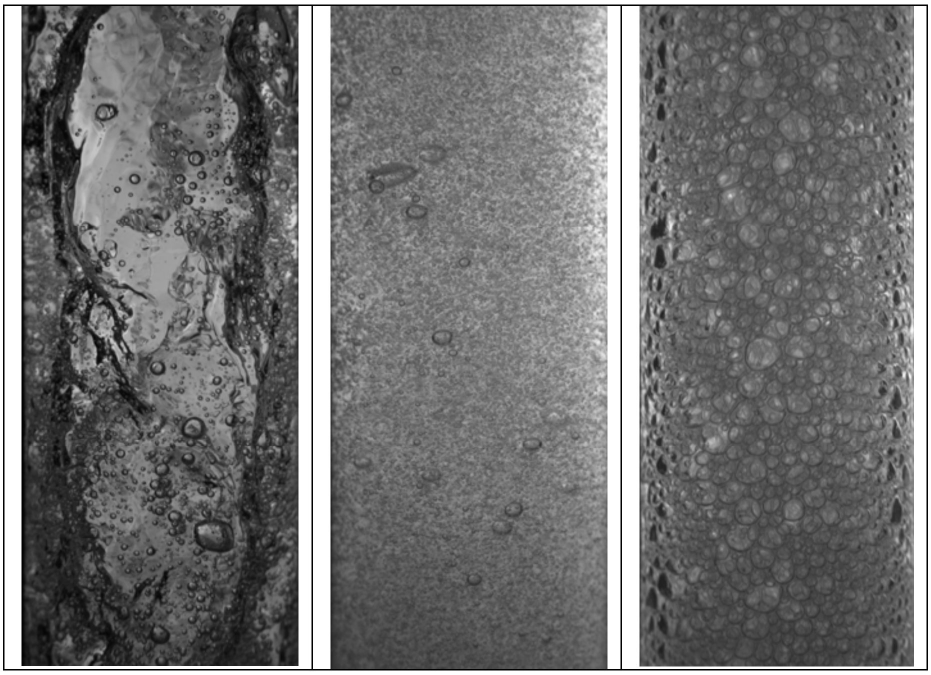

Figure 3: Typical images used to classification scheme. The three types are represented from left to right: Expulsion (E), Incubation (I) and Refill (R).

The images on Figure 3 show one example for each chugging subtype. From these images is possible to note that there are visual similarities and differences among the same subtype.

2.4. Digital Image Processing

Image database was composed of 96 full-sized 10^7 pixels “rgb” images (red-green-blue pattern) in compressed file format organized in three subtype classes in order to adjust FIS parameters. The image processing algorithm (Figure 2) was composed of a consecutive set of Matlab [18] functions. An interpolating gray-level transforming function (*rgb2gray*) produces a grayscale image as output. The following function is a histogram equalization function (*imadjust*) which maps the values in intensity image to new values in such that 1% of data is saturated at low and high intensities of this image. This increases the contrast of the output image. After these two steps a line extraction algorithm is applied in order to obtain grayscale profiles. From each sample, four longitudinal (top-down) and equidistant (inside tube) lines of 3888 pixels (Figure 4) were extracted. Acquired images originally included (inside the visual field frame) a focus calibration pattern beside the tube. This pattern was used to measure the field depth and the distance from the camera to the glass tube surface

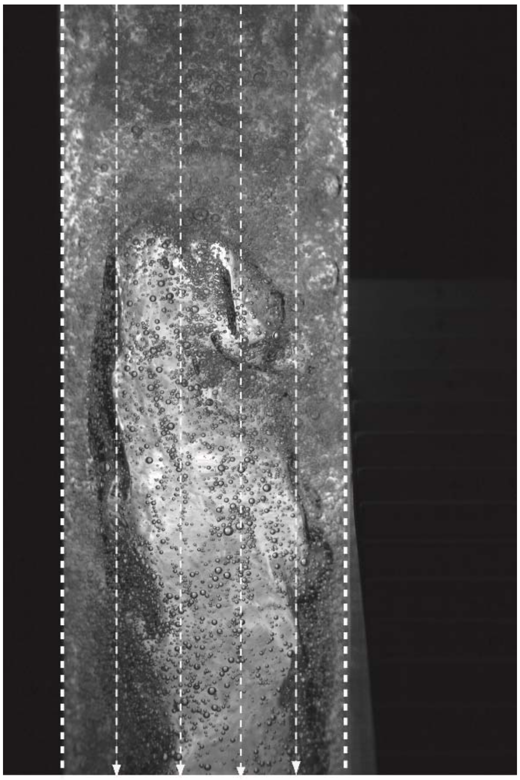

Figure 4: Typical expulsion phase with traced lines indicating cropping limits and profile lines extracted.

2.5. Self-organizing Maps (SOM)

The Self-Organizing Maps (SOM), initially inspired on human cerebral cortex, activate their neurons proportionally to the increasing distance from initial activation [14].

SOM is a neural network that produces high-dimensional visual maps which preserve topology distribution over input and output data space. These algorithms can be used to analyze and explore multidimensional structures and patterns. It has been considered a non-supervised neural network as it does not need to have a target vector to be trained. Most of its application is clustering data problems [15] like feature extraction, image and acoustic patterns classification, robots adaptive control, equalization, and others.

Basic functioning is supported by competitive learning, where neurons compete among themselves in order to better adapt to established goal, such as representing data distribution over input space. The winner-takes-it-all strategy was broadened to include a neighborhood influence during training phase.

SOM neurons are distributed and ordered in lattice bi-dimensional graphics preserving proximity between similar prototype vectors. Each neuron has its prototype vector that was trained to best represent corresponding variables on input data. This topographic map localizations are indications of implicit statistical characteristics contained on input data patterns. They can be also considered as a non-linear generalization of principal component analysis heuristic [16].

The basic algorithm is constituted of three main stages: competitive, cooperative and adaptive. In first one, the Best Matching Unit (BMU) is searched by net training. The criteria used to choose the best correspondence between input vector and neural network weight vector (neuron prototype) is the shorter distance (usually Euclidean), and is represented by:

$$i(x) = min\|x - w_j\|, for\ j = 1,2, \dots, n, \tag{1}$$

where i(x) is the general criteria for correspondence, x is the input vector, and w_j the weight vector.

Among the different distance types the most used is the Euclidean distance which can be stated as:

$$D_F = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \tag{2}$$

where x_n are input coordinates and yn are prototype-weight vectors. Other metrics are used to measure distance as Minkowski, Manhattan and others [15].

During the second training stage, Cooperative phase, the BMU neighborhood weight vectors are trained using pre-determined parameters as learning rate dependent upon distance, optimizing net neurons distance. And finally, after convergence criteria are satisfied, the resulting map can be evaluated through quality parameters, as quantization error and topographic error. Quantization error averages the distance between each data vector and its BMU. Topographic error measures the topology preservation by measuring map resolution by making a proportion of all data vectors for which first and second BMUs are not adjacent units on final map. The SOM algorithm was implemented using Som Toolbox 2.0 [17].

3. PRELIMINARY RESULTS

The SOM is being trained using one or two grayscale profiles as input. Typical obtained prototypes by the neural network are presented on Figure 5. The corresponding SOM map with Best Match Units and its corresponding subtype's classification are presented on Figure 6. This map corresponds to a 8x6 map trained with a 50% of all database, 5000 iterations (initial radius of 4) for initial training phase and 3750 iterations (initial radius of 2) for fine-tune training phase.

The initial classification results are unstable, depending on SOM initial parameters, although promising Incubation and Refill subtypes classification rates are good. Quantization Error (Qe) was 874 and Topographic Error (Te) was 0.21 for this case example where the right classification rates were: Incubation (87.5%), Refill (100%), Expulsion (31.25%), and Global Rate (72.92%).

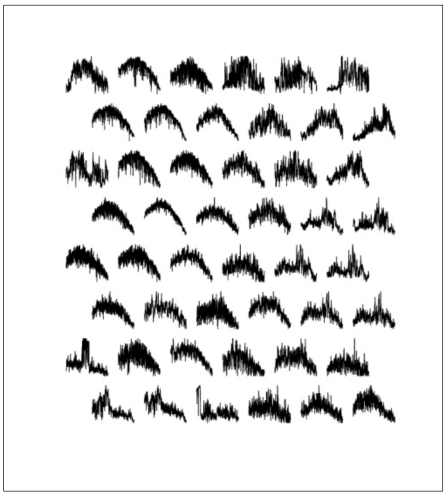

Figure 5: Typical SOM prototype map obtained using one vertical grayscale profile as input.

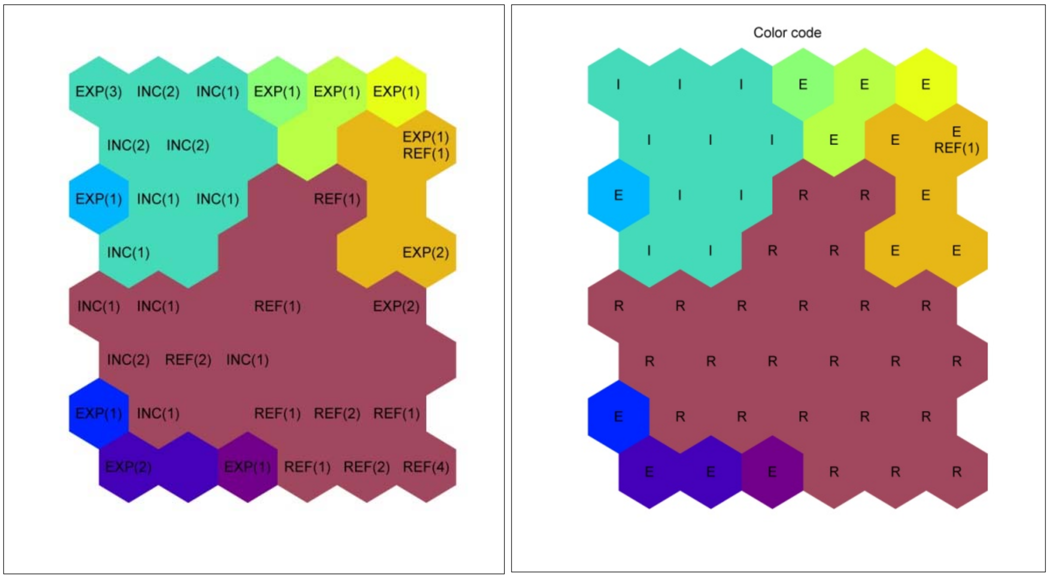

Figure 6: Typical SOM maps with Best Match Units and its corresponding subtype's classification.

4. CONCLUSIONS

The proposed classification system presents satisfactory results for this pattern classification problem. Further experiments using other features as inputs to SOM neural networks are being implemented to improve Expulsion subtype classification.

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