International Communications in Heat and Mass Transfer 71 (2016) 254–264

Contents lists available at ScienceDirect

International Communications in Heat and Mass Transfer

journal homepage: www.elsevier.com/locate/ichmt

Flow pattern identification of horizontal two-phase refrigerant flow using neural networks☆

Abdeel J. Roman [a], Paul J. Kreitzer [b], Jamie S. Ervin [c,*], Michael S. Hanchak [c], Larry W. Byrd [a]

[a] Air Force Research Laboratory, Wright-Patterson AFB, OH 45433, USA
[b] UES Inc., Dayton, OH 45432, USA
[c] University of Dayton Research Institute, Dayton, OH 45469-0044, USA

ARTICLE INFO

Available online 31 December 2015

Keywords:
Electrical capacitance tomography
Neural network
Refrigerant

ABSTRACT

In this work, electrical capacitance tomography (ECT) and neural networks were used to automatically identify two-phase flow patterns for refrigerant R-134a flowing in a horizontal tube. In laboratory experiments, high-speed images were recorded for human classification of liquid–vapor flow patterns. The corresponding permittivity data obtained from tomograms was then used to train feedforward neural networks to recognize flow patterns. An objective was to determine which subsets of data derived from tomograms could be used as input data by a neural network to classify nine liquid–vapor flow patterns. Another objective was to determine which subsets of input data provide high identification success when analyzed by a neural network. Transitional flow patterns associated with common horizontal flow patterns were considered. A unique feature of the current work was the use of the vertical center of mass coordinate in pattern classification. The highest classification success rates occurred using neural network input which included the probability density functions (in time) for both spatially averaged permittivity and center of mass location in addition to the four statistical moments (in time) for spatially averaged permittivity data. The combination of these input data resulted in an average success rate of 98.1% for nine flow patterns. In addition, 99% of the experimental runs were either correctly classified or misclassified by only one flow pattern.

1. Introduction

Understanding the two-phase flow behavior of refrigerants is important for the design of advanced aircraft cooling systems. Specifically, the classification of liquid–vapor structures into flow patterns is useful for predicting heat transfer rates and, ultimately, system performance. Most flow and heat transfer correlations require a priori knowledge of the two-phase flow pattern and are based on steady-state conditions [1,2]. Although flow pattern identification can be performed using high-speed imaging, this method generally relies on the visual interpretation of liquid–vapor patterns. Unfortunately, visual interpretation can be highly subjective [2]. As a consequence, numerous flow pattern classifications have been defined in the past [3–7]. In contrast to visual observation, which is often impractical, non-visual sensor signals can be analyzed to provide more objective classifications. Moreover, sensor signals are desired as inputs to real-time modeling and control.

Capacitance techniques are non-invasive and rely on differences in electrical permittivity to distinguish between liquid and vapor phases [2,8–9]. Capacitance measurements acquired simultaneously with high-speed videos of air-water flows have been used to identify two-phase flow patterns [2]. In addition, encouraging results involving the identification of two-phase flow patterns of refrigerants have been obtained using a capacitance probe that produced void fraction signals [10]. However, a single capacitance probe (as in [2,10]) may not fully characterize the liquid–vapor spatial distribution within a flow passage. This could lead to incorrect assumptions about the actual flow behavior. In contrast, electrical capacitance tomography (ECT) can provide a nearly instantaneous view of the liquid–vapor distribution within the system without optical access. Tomography may be used to derive the permittivity distribution from capacitance data [8,9]. The permittivity distribution, in turn, can provide the spatial distribution of the liquid and vapor phases. Many past research efforts involving ECT have focused on industrial applications where qualitative results were sufficient [8]. The use of ECT in detailed studies of liquid and vapor in horizontal flow has been limited, much less with the use of dielectric refrigerants which are of interest here [8,10,11].

Artificial neural networks are used for pattern recognition and trend prediction involving complex processes. In an artificial neural network, the neurons (often called nodes) receive input signals, and each node calculates an individual output using a weighted sum and nonlinear activation function. Learning is achieved by the adjustment of these weights [12]. Past studies suggest that there is potential for using a

☆ Communicated by W.J. Minkowycz.
* Corresponding author.
E-mail address: jervin1@udayton.edu (J.S. Ervin).

http://dx.doi.org/10.1016/j.icheatmasstransfer.2015.12.033
0735-1933/

Nomenclature

A_i	Individual pixel area [m^2]
A_T	Sum of all pixel areas [m^2]
D	Tube diameter [m]
D_b	Bubble diameter [m]
ECT	Electrical capacitance tomography
L	Length [m]
PDF	Probability density function
t	Time [s]
$y_c(t)$	Center of mass vertical coordinate normalized by the tube diameter
$y_c(t)_{PDF}$	Probability density function for center of mass (normalized) vertical coordinate
y_i	Vertical coordinate normalized by the tube diameter for the ith pixel
$\varepsilon(\tilde{x}, t)$	Permittivity determined by tomography [F/m]
ε_f	Liquid permittivity [F/m]
ε_g	Vapor permittivity [F/m]
$\varepsilon^*(\tilde{x}, t)$	Normalized permittivity
$\overline{\varepsilon^*}(t)$	Spatial average of normalized permittivity
$\overline{\varepsilon^*}(t)_{PDF}$	Probability density function of $\overline{\varepsilon^*}(t)$
$\varepsilon_i^*(\tilde{x}, t)$	Normalized permittivity for an individual pixel
$\langle\overline{\varepsilon^*}(t)\rangle$	Time averaged $\overline{\varepsilon^*}(t)$
$\langle\overline{\varepsilon^*}(t)\rangle_{KURT}$	Kurtosis of time averaged $\overline{\varepsilon^*}(t)$
$\langle\overline{\varepsilon^*}(t)\rangle_{SKEW}$	Skewness of time averaged $\overline{\varepsilon^*}(t)$
$\overline{\varepsilon^*}(t)_{VAR}$	Variance of time averaged $\overline{\varepsilon^*}(t)$
$\tilde{x}$	Spatial locations, x and y [m]

neural network to objectively classify liquid–vapor distribution data [13–15]. These studies have used measured or simulated impedance (conductance) signals rather than input from ECT [13–16]. In addition, nearly all previous flow identification studies that have used neural networks were performed for vertical flows.

In this paper, the use of ECT together with neural networks to identify liquid–vapor flow patterns is explored. For this purpose, experiments involving the horizontal flow of refrigerant R-134a through a tube of small diameter (7 mm) were conducted. A horizontal-two phase flow can be categorized into one of several flow patterns which may include bubbly, plug, slug, stratified-wavy, and annular flows [17]. Here, previous work is extended by including additional transitional flow patterns corresponding to four of the above flow patterns for horizontal flow. The names of the transitional flow patterns are derived from these four flow patterns and are given here as the bubbly-transitional, plug-transitional, slug-transitional, and stratified-wavy-transitional patterns. In the current work, high-speed images of the flow patterns were recorded for purposes of initial human classification and final training verification. Processed permittivity data obtained from two-dimensional tomograms was used to train neural networks. A goal was to classify nine horizontal two-phase flow patterns with reasonable speed using neural networks as a predictive tool. Input information for the neural networks included the spatially averaged permittivity, center of mass location, and their probability density functions (in time). It also included four statistical moments (in time) for spatially averaged permittivity data. Another objective was to determine which subsets of input data provide high identification success for the flow patterns when analyzed by a neural network.

2. Experimental setup

To explore the use of ECT in the identification of two-phase flow patterns, laboratory experiments were performed in which liquid–vapor flow patterns were generated for flow in a horizontal tube. Fig. 1 shows a schematic of the experimental arrangement in which liquid R-134a was pumped through a heater to produce two-phase flow. To obtain different liquid–vapor flow patterns, the volumetric flow rates were adjusted in the range 0.1 to 0.5 L/min, while varying the heater power between 0 and 500 W. Downstream from the heated section, the two-phase flow entered a fused quartz observation section (tube with 7 mm ID). The observation section permitted imaging using a high speed video camera (Phantom V4.2) and had thermocouples and pressure transducers located at 1.2 m increments along its length. The high speed camera was used to compare actual images of liquid–vapor flow with ECT characterization. R-134a passed through the cylindrical ECT sensor (ITS, 0690). Fig. 1 shows one flow path for R-134a and another for cooling water which was used to condense R-134a vapor in the condenser (Lytron, LL510G02). The water was cooled by a chiller (PolyScience, 4260 T).

Table 1 lists the measurement uncertainties associated with the thermocouples, pressure transducers (Omega PX-409), and flow meter (McMillan) shown in Fig. 1. Experiments were performed with the refrigerant saturation conditions at the ambient temperature of 20 °C. Relatively small temperature differences (~1 °C) between the ambient and refrigerant in the observation section of tubing provided reasonable grounds to neglect the heat transfer between them.

The ECT system consists of a multi-electrode sensor, electronics for capacitance determination, and data acquisition components [18]. The

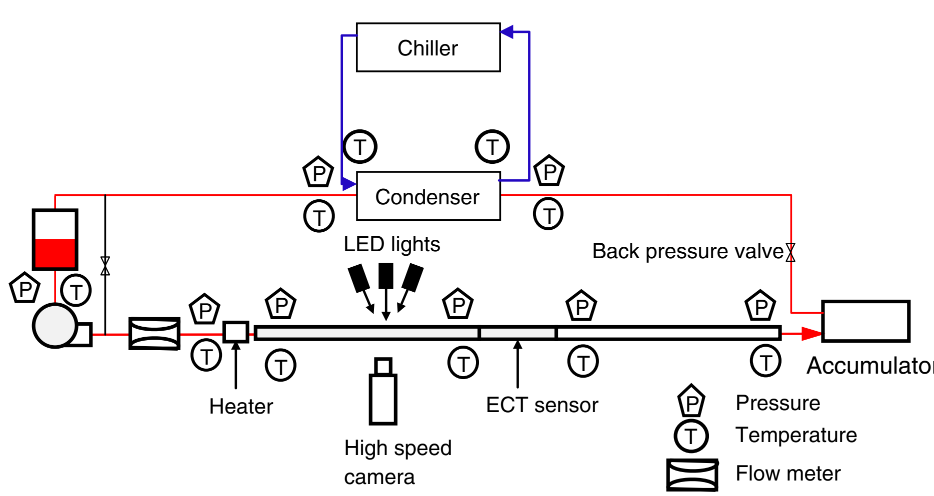

Fig. 1. Schematic of two phase flow system. Red represents the refrigerant, and blue represents chilled water.