Jurnal Teknologi, 55 (Sains & Kej.) Keluaran Khas (2), Ogos 2011: 75–85

CAPACITANCE-BASED TOMOGRAPHY FLOW PATTERN CLASSIFICATION USING INTELLIGENT CLASSIFIERS WITH VOTING TECHNIQUE

JUNITA MOHAMAD-SALEH[1*], ROSLIN JAMALUDIN[2]
& HAFIZAH TALIB[3]

Abstract. This paper presents a method for Electrical Capacitance Tomography (ECT) flow classification using voting technique, employing Multilayer Perceptrons (MLPs) as the intelligent pattern classifiers. MLP classifiers were trained with a set of simulated ECT data associated to various flow patterns and was tested with untrained data to verify their performances. MLP classifiers which gave high percentage of correct classification were integrated into a voting system and tested over a distinct set of ECT data. The performances of the individually selected classifiers were compared with the voting system. The results showed superiority of the voting system over individual classifiers.

Keywords: Electrical capacitance tomography; multilayer perceptron; voting; pattern classification; ensemble neural network

1.0 INTRODUCTION

Classification of gas-liquid flow patterns is one the most important activities especially in the industrial field. It is essential in order to know the content of process equipment to determine process flow parameters such as density, flow phase, velocity and mass flow rate (Warsito and Fan, 2001). Pattern classification refers to a technique used for automatic assignment of patterns to their classes based on input pattern vectors. Prior to classification, significant attributes of pattern data are extracted and separated from irrelevant details. Then, classification is accomplished using a pattern classifier system which employs certain classification techniques with an objective of minimizing misclassification error.

[1-3] School of Electrical and Electronic Engineering, Universiti Sains Malaysia, Engineering Campus, 14300 Nibong Tebal, Seberang Perai Selatan, Pulau Pinang, Malaysia
* Corresponding author: jms@eng.usm.my

Artificial Neural Network (ANN) systems have been commonly employed as flow pattern classifiers (Kuwahara *et al.*, 2008; Hernández *et al.*, 2007; Yan *et al.*, 2004; Xia and Yang, 2000; Jingbo and Xiatie, 2000). It is a variant of an intelligent system, which solves a problem based on the experience gained in a learning process. It accomplishes its objective by executing and generalizing the experiences.

ANN is a system consisting of a number of neurons as processing units, which are properly arranged to produce a useful ANN architecture capable of solving various tasks. Given inputs and sample outputs associated to a task, each ANN processing unit does a simple computation in the quest of learning. ANNs have been used to classify gas-oil flow patterns based on Electrical Capacitance Tomography (ECT) data (Xia and Yang, 2000; Jingbo and Xiatie, 2000; Yan *et al.*, 2004). However, the previous works have only focused upon classification results of a single ANN classifier. Such conventional intelligent classifiers are normally unstable in their classification capability (Cunningham *et al.*, 2000). Thus classification outputs may not be accurate and some patterns may be misclassified. This is of particular concern for ECT data which is so greatly flow regime dependent that a single intelligent classifier may not be efficient enough to cater for the instability problem.

Therefore, in this research, more than one intelligent pattern classifier is integrated into a system, and the best classification result for each set of ECT data is obtained based on a voting technique (Dietrich, 2002; Rao *et al.*, 2007). An integrated pattern classifier is a kind of ensemble system and has shown to be more robust than individual classifier at solving various classification applications (Bhattacharya and Chaudhuri 2002; Valdovinos and Sanchez, 2006; Pasti and Canuto *et al.*, 2007; Mackin *et al.*, 2007; Castro, 2009).

2.0 APPROACH AND METHODS

The combination of integrated pattern classifiers and voting technique is referred to as a voting system in this paper. In gas-oil flow, each flow pattern is associated to a certain type called flow regime. There are six flow regimes that are commonly recognized in oil-gas flows namely, annulus, stratified, bubble, full (i.e. full of oil), empty (i.e. full of gas) and core. For this work, the voting system is used to classify the gas-oil flow patterns into their appropriate flow regimes based on simulated ECT data. The work carried out to accomplish the objective is divided into three main tasks. The first task is the preparation of flow pattern ECT data. The second task is the development of the neural network for learning process and the third task is the implementation of the voting system, which constitutes the main objective of this work.

2.1 Preparation of Flow Pattern ECT Data

An ECT simulator (Spink, 1996) is used to generate ECT data. For this work, a total of 3672 raw ECT datasets of various flow regimes are generated using the simulator. This number should be sufficient for an ANN to learn. The ECT sensor used in this work consists of 12 electrodes, which is commonly used in industry. Based on $n(n\text{-}1)/2$ where n is the number of electrodes, each flow pattern is represented by 66 capacitance values. The generated raw data are then normalized based on,

$$\lambda_{i,j} = \frac{C_{i,j} - C_{i,j(empty)}}{C_{i,j(full)} - C_{i,j(empty)}} \tag{1}$$

where $\lambda_{i,j}$ is the normalized ECT value, $C_{i,j}$ is the raw ECT value, $C_{i,j\ (empty)}$ is the raw ECT value of an empty flow regime and $C_{i,j\ (full)}$ is the raw ECT value of a full flow regime for ECT value j of flow pattern i. The normalized ECT data are randomly divided into 3 datasets; training set, validation set and test set in the ratio of 45:10:45, respectively.

2.2 MLP Learning Process

In this work, a Multilayer-Perceptron (MLP) which is the simplest non-linear ANN architecture (Negnevitsky, 2005) is used as the intelligent pattern classifier. The Levenberg-Marquardt learning algorithm (Hagan and Manhaj, 1994) is used to train the MLP to be intelligent at flow regime classification. Essentially, an MLP has three layers of neurons; input, hidden and output layers. Basically, it learns the salient features in the ECT data in order to carry out the classification task. MLP learning is a process of determining an optimal number of hidden neurons and obtaining optimum neuronal connection weights (i.e. experience) for the optimal structure. The number of input neurons for an MLP is the number of input features and the number of output neurons equals the number of classes. Hence, for this work, an MLP has 66 input neurons and 6 output neurons.

The MLP learning process involves 3 main stages; training, validation and testing. The training data are used for MLP learning. The validation data are used to stop the training process when the MLP is optimally matured and the test data are used to assess the generalization performance of the trained MLP. The learning process operates based on the network growing whereby the number of hidden neurons in the MLP structure is gradually increased (starting from one) until an optimum size is achieved. For this work, training of MLP for each number of hidden neuron is repeated 30 times. Repetitions are carried out to ensure that the MLP reaches the global minimum. Each repetition produces one best-trained pattern classifier (PC). A trained MLP performance is assessed based upon the correct classification percentage given by,

$$Correctclassification = \frac{No\ of\ correctly\ classified\ data}{Total\ data} \times 100\% \qquad (2)$$

Table 1 illustrates an example calculation of correct classification percentage. Based on Table 1, the percentage of correct classification given by the ANN output is 66.67%, obtained by dividing the total data (i.e. 3) by the number of correctly classified data (i.e. 2) and multiplied by 100%.

Table 1 Example calculation of correct classification which equals 67.77%

ANN Output						**Target Output**						**Correctness**
0	0	0	0	1	0	0	0	0	0	1	0	1
0	0	1	1	0	1	0	0	1	0	0	0	0
1	0	0	0	0	0	1	0	0	0	0	0	1
Total of Correctness												2

The average and maximum correct classification percentages for training, validation and testing for each hidden neuron are recorded.

2.3 Development of Voting System

As explained, a voting system involves classification and voting stages. The classification stage consists of all best-trained MLP PCs whose classification outputs are passed to the voting stage which will select (based on voting technique) the best output as the final classification result.

The selection of best-trained PCs is done after the learning processes based on various number of hidden neurons. PCs which give best percentage of correct classification for each training, validation and testing sets are chosen and placed together in a voting system. If there is more than one best PCs for the same number of hidden neuron, their weights are first compared. If two or more PCs have the same weights, only one PC is selected. This is because PCs with the same weights have the same stability and capability. If however, they have different weights, then all of them are integrated into the voting system. Figure 2 shows a schematic diagram of the proposed voting system.

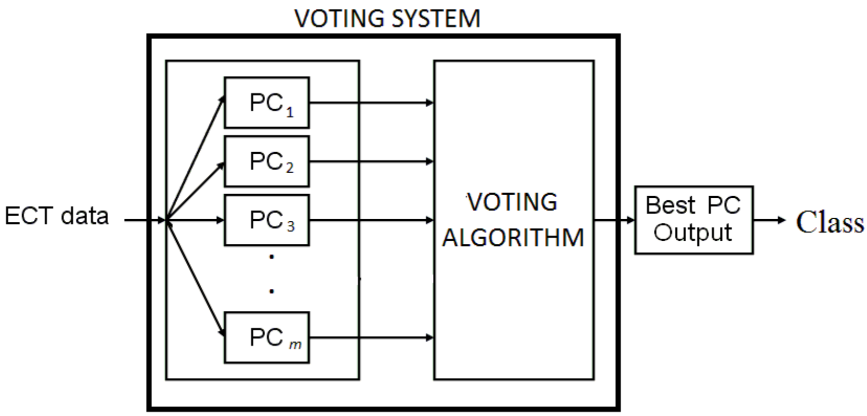

Figure 2 Block diagram of pattern classifier voting system

Once the best-trained PCs have been selected, a voting strategy is implemented. The technique employed is based on voting by calculating the confidence level of a PC's output. Simple mathematical formula is used to calculate the confidence level of outputs from each PC. It is given by (Kumar *et. al.*, 2000),

$$\textit{Confidence level} = \textit{Largest output} - 2^{nd} \textit{ largest output} \qquad (3)$$

The confidence level for each PC is determined by subtracting the second highest MLP output value (which may be a possible error) from the highest MLP output value (which is the possible class representation). This means that a PC with high confidence level is one which gives the highest difference between its largest and second largest outputs. This denotes that the PC is very confident in its classification output.

The performance of the proposed voting system is assessed by comparing its correct classification percentage with all individual PCs based upon 1292 sets of verification data comprising ECT data that are different from the training, validation and test data. It has to be noted that the verification ECT data are simulated based on a different ECT sensor design. Hence, the PCs performance verification involves an extremely difficult classification task due to different input features from what they have been trained previously.

3.0 RESULTS AND DISCUSSION

Figures 3 to 5 show the results these values for training, validation and test datasets, respectively. All the three plots have similar shape, where the percentage of maximum correct classification increases with the addition of the number of hidden neuron. For 1 hidden neuron, the percentage of maximum correct classification for training, validation and test data have the smallest value compared to more hidden neurons. This is because the MLP with one hidden neuron is not powerful enough to achieve complete "intelligence" because the system has not reached an optimum structure. Later, it can be observed from each of the figures that the average correct classification percentage starts to decrease after 8 hidden neurons. Hence, MLP learning process is stopped at 12 hidden neurons.

For training (Figure 3) and validation (Figure 4), the percentage of maximum correct classification reaches 100% starting at the 3rd hidden. It can be seen that the percentage correct classification values increase with the increase in the number of hidden neuron. This is evident from 1 hidden neuron until 5 hidden neurons. From 6 to 12 hidden neurons, the plot fluctuates. For the test data (Figure 5), 100% correct classification is achieved starting from the 7th hidden neurons until the 12th, except at the 11th hidden neurons when the correct classification drops to 99.94%. This situation shows that the ANN has started to undergo saturation, which most probably leads to the problem of over-fitting, making the ANN incapable of generalizing the input pattern.

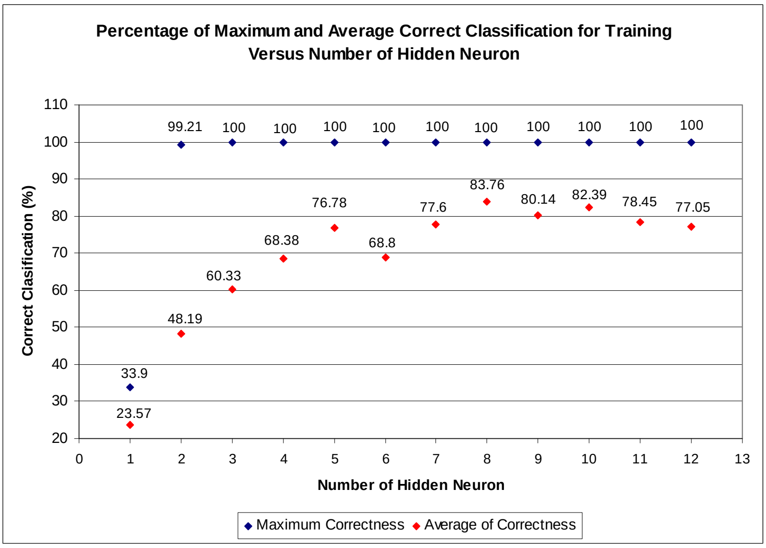

Figure 3 Graph of correct classification based on training data

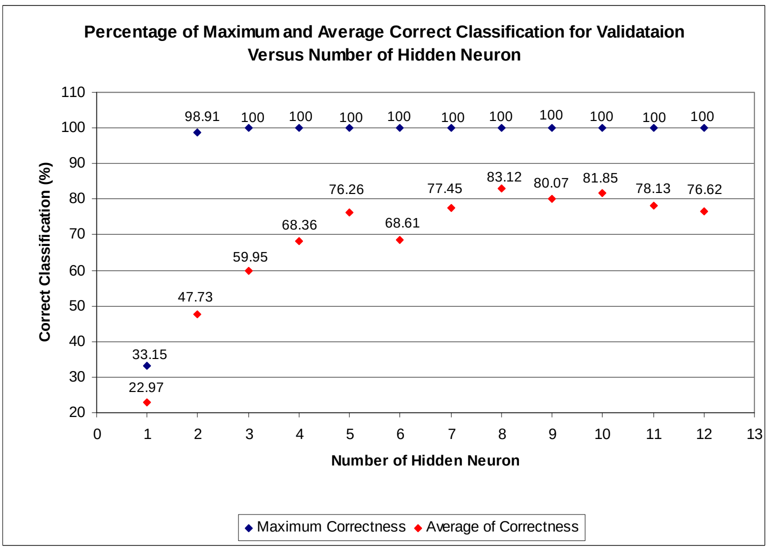

Figure 4 Graph of correct classification based on validation data

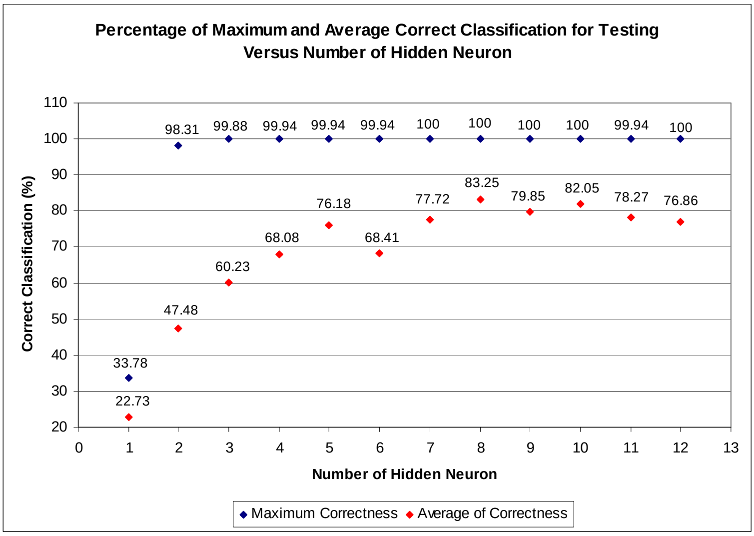

Figure 5 Graph of correct classification based on test data

The best-trained PCs are selected based on 100% correct classification results of training, validation and test data. Table 2 lists all the selected PCs. Each of the selected PCs is given a representation name as in the table. The MLP PC with 11 hidden neurons is not selected because its correct classification of test data is not 100%. The MLP PC with 12 hidden neurons is also not selected because it is the outcome of an over-fitted classifier. Hence only MLP PCs with 7, 8, 9 and 10 hidden neurons are selected as the best-trained PCs.

Prior to integration in the voting system, the performances of the selected PCs are first verified with the verification dataset for the task of gas-oil flow pattern classification. Then all of them are gathered into a single voting system and its performance is verified using the verification dataset.

Table 2 List of best-trained PCs. The PCs with 7 and 9 hidden neurons have different weight values

No. of Hidden Neurons	Representation
7	Net1
7	Net2
8	Net3
9	Net4
9	Net5

10	Net6

Figure 6 shows the performance comparison between all individual best-trained PCs and the voting system. It has to be reminded that low correct classification percentages obtained are due to ECT data of different ECT sensor design for the verification sets. The difference should test for the robustness of the PC systems.

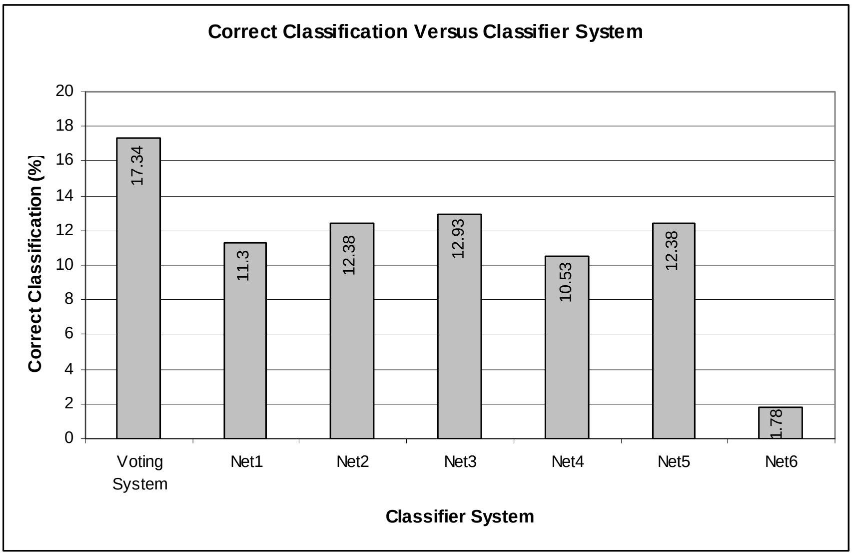

Figure 6 Performance comparison among the proposed voting system and individual PCs for classification of gas-oil flow regimes

The bar graph shows that the voting system gives the highest correct classification of 17.34%, compared to the other individual good PCs. This is followed by Net3 with 12.93% correct classification. The results demonstrate that a voting system is superior to individual intelligent PCs. Net6 corresponding to PC with 10 hidden neurons produces the lowest correct classification of only 1.78%. This shows that 10 hidden neurons creates a PC which is too large (i.e. not optimal) leading to over-fitting of data and hence, degrade the generalization capability.

4.0 CONCLUSION

The paper aims to study the performance of integrated intelligent pattern classifiers with voting technique. The proposed system, referred to a voting system involves two stages; classification and voting of output class. Its performance is compared with individual pattern classifiers towards gas-oil flow classification based on ECT data. The voting system of MLP ensemble has been found to have a superior classification performance compared to the individual intelligent pattern classifiers. This demonstrates the added benefits of using a voting system for classification, particularly for flow regime classification based on ECT data.

ACKNOWLEDGEMENT

The authors would like to acknowledge the financial support from MOHE Fundamental Research Grant Scheme (FRGS), No: 203/PELECT/6071165.

REFERENCES

[1] Bhattacharya, U. and Chaudhuri, B. B. 2003. A Majority Voting Scheme for Multi Resolution Recognition of Hand Printed Numerals. *Proceeding of the 7th IEEE International Conference on Document Analysis and Recognition*. 16-20.

[2] Canuto, A. M. P, Abreu, M. C. C., Oliveira, L. D. M., Xavier, Jr. J. C. and Santos, A. D. M. 2007. Investigating the Influence of the Choice of the Ensemble Members in Accuracy and Diversity of Selection-based and Fusion Methods for Ensemble. *Pattern Recognition Letters*. 28(4):472-486.

[3] Cunningham, P., Carney, J. and Jacob, S. 2000. Stability Problem with Artificial Neural Networks and the Ensemble Solution. *Artificial Intelligence in Medicine*. 20(3): 217-215.

[4] Dietrich, T. G. 2002. Ensemble Learning. *The Handbook of Brain Theory and Neural Networks*. 2nd Edition. Cambridge:MIT Press.

[5] Hagan, M.T. and Menhaj, M.B. 1994. Training Feedforward Networks with the Marquardt Algorithm. *IEEE Transactions on Neural Networks*. 5(6):989-993.

[6] Hernández, L., Jose, J. E., Chiva, S., Sidharth, P. and Mamoru, I. 2007. Two-phase Flow Regime Identification Combining Conductivity Probe Signals and Artificial Neural Network. AIP Conf. Proc. 914:307-312.

[7] Jingbo, X. and Xiatie, Y. 2000. Flow Pattern Identification based on Fuzzy Neural Network Using Multi-Electrode Capacitance Sensor. *Proc. of the 15th World Conference on Non Destructive Testing, Rome.15 21 Oct.*

[8] Kumar, A. S., Chowdhury, S. and Majumder, K. L. 2000. Schemes for Integrating Multiple Neural Networks for Multispectral Data Classification. *Indian Conference on Computer Vision, Graphic and Image Processing, Bangalore, India, 20 22 Dec.*

[9] Kuwahara, T., Vuyst, D. and Yamaguchi, H. 2008. Flow Regime Classification in Air–magnetic Fluid Two-phase Flow. *Journal of Physics: Condensed Matter*. 20(20):204141.

[10] Mackin, K. J., Yamaguchi, T., Nunohiro, E., Jong Geol Park, Hara, K., Matsushita, K., Ohshiro, M. and Yamasaki, K. 2007. Ensemble of Artificial Neural Network Based Land Cover Classifiers using Satellite Data. *IEEE International Conference on Systems, Man and Cybernetics, Montrüal, Canada, 7 10 Oct*. 1653 – 1657.

[11] Negnevitsky, M. 2005. *Artificial Intelligence: A Guide to Intelligent Systems*. 2nd Edition. New Jersey:Addison Wesley.

[12] Pasti, R. and Castro, L. N. D. 2009. Bio-Inspired and Gradient-Based Algorithms to Train MLPs: The Influence of Diversity. *Information Sciences.* 179:1441-1453.

[13] Rao, K.V. G., Chand, P. P. and Murthy, M.V. R. 2007. Soft Computing-Neural Networks Ensembles. *Journal of Theoretical and Applied Information Technology*. 3(4):45-50.

[14] Spink, D.M., 1996. Direct Finite Element Solution for the Capacitance, Conductance or Inductance and Force in Linear Electrostatic and Magnetostatic Problems. *The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*. 15(3):70-84.

[15] Valdovinos, R. M. and Sanchez, J. S. 2006. Ensemble of Multilayer Perceptron and Modular Neural Networks for Fast and Accurate Learning. *5th Mexican International Conference on Artificial Intelligence (MICAI'06). 13 17 Nov*. 229-236.

[16] Warsito, W. and Fan, L. S. 2001. Measurement of Real-Time Flow Structures in Gas-Liquid and Gas-Liquid-Solid Flow Systems Using Electrical Capacitance Tomography (ECT). *Chemical Engineering Science*. 56:6455-6462.

[17] Xia, J. and Yang, X. 2000. Flow Pattern Identification Based on Fuzzy Neural Network using Multi-Electrode Capacitance Sensor. *Proceeding of 15th World Conference on Non Destructive Testing, Rome, 15 21 Oct.*

[18] Yan, H., Liu, Y. H. and Liu, C. T. 2004. Identification of Flow Regimes Using Back-Propagation Networks Trained on Simulated Data Based on a Capacitance Tomography Sensor. *Measurement Science and Technology*. 15:432-436.