Digital Neural Processing Unit for Electronic Nose

Hoda S. Abdel-Aty-Zohdy and Mahmoud Al-Nsour
Microelectronics System Design Lab
Department of Electrical and Systems Engineering
Oakland University, Rochester MI, 48309-4401, USA
zohdyhsa@oakland.edu

Abstract

In a biological nose, the environment usually suggests a number of common odors. The classification process checks sensed information against existing knowledge. This similarity with Reinforcement Learning neural networks suggests challenging implementation problems.
A VLSIC digital design and implementation of a Reinforcement Artificial Neural Network (RANN) for chemical classification, in an electronic nose is presented. The chip is designed to classify chemical gases among four possible volatile organic compounds. The system consists of four neurons and twelve synapses [1]. A neuron has been implemented on a tiny chip, using 2.0μm *n-well CMOS technology, at Orbit Semiconductors, through the MOSIS facilities. Simulation results demonstrated proper operation. Stand alone experiments are satisfactory, with off-chip weight storage and weight update. Electronic nose system testing is currently under way.*[1].

1. Introduction

Electronic nose implementations are needed for many industrial and environmental applications including; automated manufacturing, environmental engineering, health care, space stations, military environments, and quality assurance of food products [1]-[4]. Towards designing an integrated electronic nose, a specialized Reinforcement artificial Neural Network (RNN) approach has been considered by the author [1], [2]. A digital VLSIC design, implementation, and evaluation is presented in this paper. The objective is to discriminate among chemical gasses. The system design recognize four specific Volatile Organic Compounds (VOCs): Acetone, Benzene, Methanol, and Chloroform.

[1]This work is supported by a Grant from Michigan Space Grant Consortium, 1997-98, and Research Excellence Fund from The State Of Michigan, 1997-98.

2. RNN Electronic Nose

In contrast to supervised ANN, RANN is most suitable in situations where there is not enough detailed model information available to the network. Models of the features, for chemical gases, are usually difficult or not available with current chemical sensors. For example, the resistance of a conducting polymer (polyaniline and poly-pyrole) chemical sensor, does not have an accurate model for its variation with each of the features: temperature, saturation level, and sensor exposure time to the analyte mixture. The features composition for each chemical are presented to the RANN as a training vector. The RANN system consists of an input layer with four neurons. Each input is evaluated by the network in the light of a distribution of reward or penalty signals to accomplish classification of the chemical. The synaptic weights iteratively converge in order to reflect the inherent characteristics in features. The implemented system block diagrams are depicted in Fig. 1, and Fig. 2.

3. Digital Chip Design

The implemented chip comprises neurons that accept three feature inputs from sensors via synapses. Sensors output is assumed to range from -1.75 to 1.75V. Each feature is represented by three bits and a sign bit. In order to optimize silicon area utilization, two synchronized multiplexers are employed. A feature and its weight are latched and multiplied. Multiplication result is then converted into 2's complement and stored in the accumulator.
Each NPU consists of an accumulator and a nonlinear sigmoid circuit, which is a second order approximation

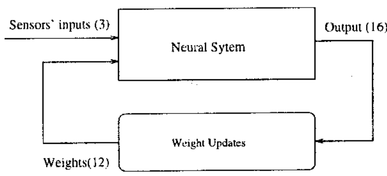

Figure 1. Block representation of the RANN system with 4-input neurons (units) and 4-neurons in the output layer

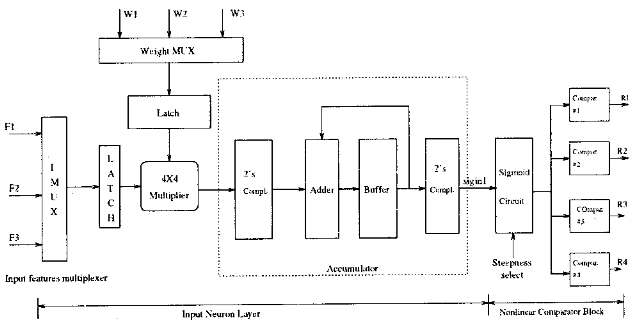

Figure 2. Digital neural processing unit (NPU).

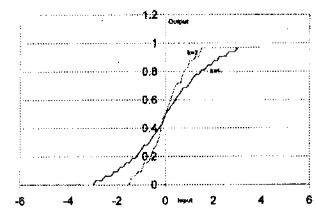

Figure 3. Programmable Sigmoid function simulation with $k = 1$ and 2

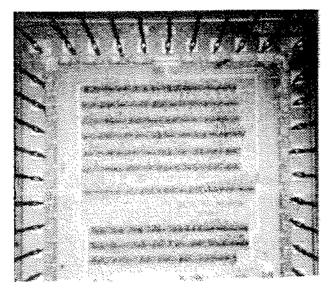

Figure 4. Microphotograph of the Neural processing unit, on a tiny chip

of the function: $f(x) = 1/(1 + e^{-kx})$, Where k is the steepness parameter, Fig. 3. The accumulator, Fig. 2, takes only three cycles to have all weighted inputs added and stored in the buffer. The fourth cycle is divided into two halves. During the first half the sum is passed to the sigmoid circuit. In second half cycle a control circuit is used to reset the accumulator and start a new cycle. The circuit accepts inputs in the range $\pm 3.875V$ and the output is binary (0 or 1). Six bits and a sign bit are needed from the accumulator. The three least significant bits are ignored since they do not contribute much to the calculations. To classify a chemical out of four, four-comparators are used. Each neuron output is connected to all four comparators. The sigmoid circuit has a steepness selector bit which normalize the input range. When the synapse output is within $\pm 2V$, the selector is "1", otherwise it is "0".

4. Test Results and Conclusions

RANN digital system is designed, simulated, implemented, and tested. A system test is under way for recognizing methanol, acetone, benzene, and chloroform chemicals. The design may be altered for programmability to recognize other chemicals. Also, added features may be included. The accumulator part of the NPU has a matrix of three features and three weights. Chip testing shows that the steeper the sigmoid function, the faster it is to trigger the comparators outputs. It also shows that the approximation used to implement this circuit is acceptable with a maximum absolute error of 0.045. Prototype simulation results are encouraging. Test and evaluation results were as expected.

Learning via reward and penalty is effective for chemicals classification. Supervised learning requires accurate models, while unsupervised learning give conservative results.

References

[1] H. S. Abdel-Aty-Zohdy, "Artificial Neural Network Electronic Nose For Volatile Organic Compounds," *IEEE GLSVLSI98 Proceedings*, pp.122-125, February 1998.

[2] H. S. Abdel-Aty-Zohdy, "Reinforcement Neural Learning with Application to Gas Sensors," *IEEE MWSCAS97 Proceedings*, pp. 1269-1273, August 1997.

[3] H. T. Nagle, S. Schiffman, and R. Gutierrez-OsUna, "The how and why of electronic noses," *IEEE Spectrum*, vol. 35, pp. 22-31, September 1998.

[4] N. Najafi, K. D. Wise and J. W. Schwank, "A Micromachined Ultra-Thin-Film Gas Detector," *IEEE Transaction on Electron Devices*, vol. 41, No. 10, pp. 1770-1777, Oct. 1994.