FPGA Implementation of a Bio inspired olfactory system for odor Identification and Classification using ANN Algorithm

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Abstract— This paper presents Electronic nose system is an artificial neural network system used to detect or classify odour of a specimen and it finds wide application in all commercial industries. To identify a new sample and then to estimate its concentration, use to both spike timing dependent plasticity learning techniques and the least square regression principle. In the first one is aimed at teaching the system how to discriminate among different gases, while the second one uses the least squares regression approach to predict the concentration of each type of samples. During the experiment, the odor data are sampled by a commercial electronic nose and are normalized before training and testing to ensure that the classification result is only caused by learning. The SNN has either a high or low output response for a given input odor, making it easy to determine whether the circuit has made the correct decision. The system aims at reducing the area overhead by incorporating a transposable SRAM array that share learning circuits which grows with the number of neurons also the system is trained for usage in chemical industry by coupling a chemo sensor array. All the component subsystem implemented on neuromorphic chip has been successfully tested in FPGA.

Keywords—Electronic Nose, Field programmable gate array, neuromorphic circuits, olfaction, Spike time dependent plasticity

I. INTRODUCTION

Currently the biggest market for Electronic Nose (EN) system used for all type of industries including Agriculture, Biomedical, Chemicals, Cosmetics, Environmental, Food, Manufacturing, Military and various research fields. In the electronic Nose system learning and classification algorithms plays an important roles [4].

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Nowadays, electronic nose are used for quality control application in the food industry, chemical industry and cosmetics industries and also improve the product purity. Currently it includes detection of odors specific to diseases for medical diagnosis and detection of pollutions and gas leakage for environmental protection. Electronic nose was developed in order to mimic human olfaction that functions as a non separative mechanism. That is odour and flavor preserved as a global finger print.

Spike time based training algorithm calculates the weight updates based on the temporal distribution of the pre synaptic spike or post synaptic spikes. This phenomenon is known as spike timing dependent plasticity (STDP) [1]. During the training, weight of the synapse is modified according to the timing difference between the pre-synaptic spike and the post-synaptic spike. When the post-synaptic spike occurs immediately after the pre-synaptic spike, the synaptic weight is increased. This type of synaptic is called the long-term potentiation (LTP).when, the synaptic weight is decreased, and this synaptic is called the long-term depression (LTD).

Recently the synaptic weight plasticity depends on not only the action potential timing but also on the post-synaptic depolarization. The LTP dominates at high firing frequencies. This mechanism can be used for two steady states (potentiated or depressed) and is widely implemented in the spike-based neuromorphic learning system. This work provides the integrated sensor technology and systems using spike time based neuromorphic models to implement an olfactory system in FPGA. The use of FPGA allows for low power operation, and reduces the silicon area. Most importantly, a neuromorphic Implementation detect the complex odor, in particularly odor segmentation and odor object identification in varying chemical environments to be solved with classical approaches Thus, the system has possible convenient sensing applications there is a requirement for the bias against a wide variation in background of odor signals.

In an olfactory bulb, the onset latency of the action potential decreases but the inter spike intervals remain constant as the odor concentration increases. As a result, onset latency could be a better way of representing odor concentrations in olfactory systems. The use of this characteristic determines the latency of a spike. A possible solution may be adding into the network a sub threshold oscillation, a phenomenon measured in biological neurons in which the voltage of the soma oscillates even without input stimuli. The latency can be defined as the timing difference between the start of the oscillation period and the first spike. In this work, the oscillation is not only treated as the time reference but also as an important characteristic for improving the classification performance.

In this paper, we present the Electronic nose system used to classify the different sample of odors and its represent the concentrations. The proposed spiking neural network takes advantages of sub threshold oscillation and onset latency

representation to reduce power consumption and chip area, providing a more distinct output for each odour input. The rest of this paper contained as follows: In Section II, introduces the circuit blocks. Section III presents the results and discussion. Finally, Section IV offers the conclusion.

II. CIRCUIT IMPLEMENTATION

Fig.1. Shows the system diagram. Olfactory network provides scalable olfactory system interconnecting the multiple chips. The olfactory sensors implemented in a resistive chemo sensor array employing carbon black (CB) sensing materials with signal processing circuitry. The sensor interface circuitry includes a dc cancellation circuit to sense the chemical odor molecules range. A spiking neural network forms the signal processing stage of the olfactory model. Learning circuit is dynamically adapting the weights for odor detection and classification. Learning is crucial for the design of an odor sensing system.

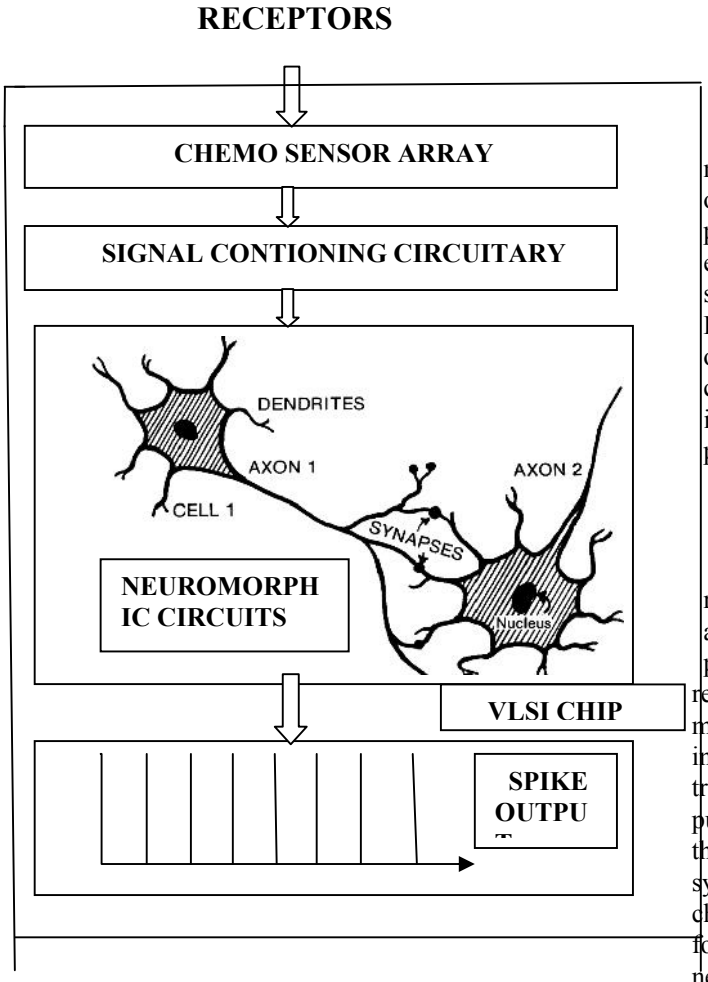

Fig.1.Sytem diagram .In this paper, receptors cells are realized by chemo gas sensors, where as signal conditioning circuitry receives the sensory signals from chemo sensors e array are digitally stored using analog to digital converter. neuromorphic circuits are integrated into a single chip.

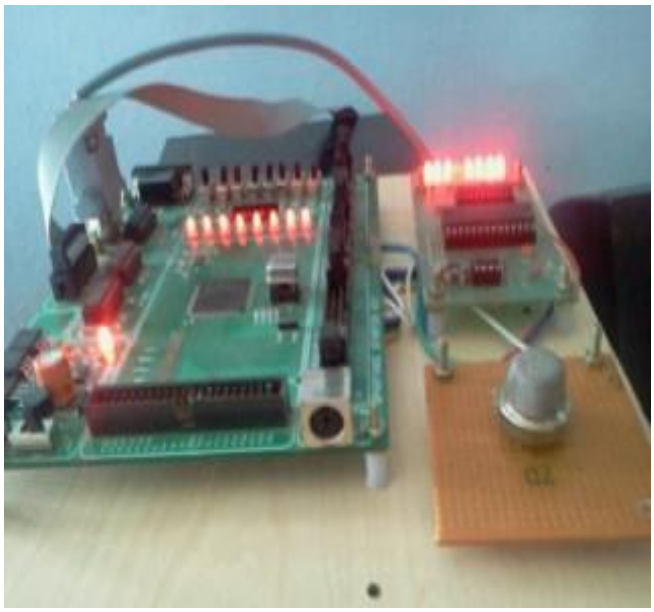

Fig 2. FPGA implementation of olfactory system kit.

A.Receptors

Olfactory receptor neurons represent the front end of the mammalian olfactory system. Receptor cells respond to odorant molecules, and send the signal in to the glomeruli for preprocessing and encoding. Experimental data indicates that each glomerrulus receives axon from receptor cells. Mainly synapse onto the dendrites, act as a principal neurons (PNs). PN sends dendrite to a single glomerulus. Inhibitory neurons of the olfactory bulb make many principle neurons, forming a complex network represent the first stage of olfactory information processing. The output of PNs performs further processing.

B. Chemo sensor Array

The chemo sensor array consists of different sensor types respond to different chemical compounds. Such a various array potential has to increase the selectivity in the olfactory pattern
recognition task while mimicking the function of the mammalian olfactory system. Chemosensory are transformed into spike trains by olfactory receptor models. These spike trains directly drive synaptic currents and summed for the purposes of signal enhancement. This summed signal provides the excitatory drive to PNs, provides the main output of the system. Lateral inhibitory neurons are used to both the output characteristics of the system. The sensor signals are fed in to forward through neural elements to principle neurons the network forms a distinct modular structure, of the glomerular organization for biological olfactory bulb model.
We are implementing, each sensor cell contains a programmable current source, a sensor, and neuromorphic circuit. Each sensor has a dedicated set of circuitry, each of them biased and amplified optimally.

C .Signal Conditioning Circuitry

The neuromorphic network receives sensory signals from an array of chemo sensors which transform the molecular chemical information of an odorant into electrical signals suitable for processing in analog circuitry. The large variation of baseline signals for a chemo sensor array are caused by the poisoning effect during post-processing and different optimal operating

An adaptive neuromorphic olfaction device consisting of on-chip chemo sensor array, on-chip sensors interface circuitry and neuromorphic olfactory current specifications for different sensor types. The large variation in baseline dc signals among the sensors may result in saturation of the subsequent signal conditioning amplifier stages thereby most important is loss of measurement range. Baseline signals of all sensors in the array are digitally stored using analog to digital converter. The output from the digital to analog converter provides the initial analog offset signal which is canceled using a difference amplifier. The output sensor interface circuit is maintained in analog continuous time domain and feeds into the subsequent neuromorphic circuit stage implemented on chip.

D .Synapse

Most of the researchers have proposed different circuits to implement the function of the synapses. The circuits integrate pre-synaptic spikes to a voltage and produce the EPSC according to this voltage. Due to the large number of synapses, occupied by the capacitor is very large. Biologically realistic neuron model is used, the input of the neuromorphic chip is provided by the non-biological sensor when the neuromorphic chip is integrated into an E-Nose. When the firing rate of the pre-synaptic neuron is constant and large enough, and the integrated current in the synapses is equal to the leakage current. Because the output of the pre synaptic neuron, adjust the current according to the synaptic weight. This modification reduces the circuit complexity, the chip area, and the power consumption.

To change the synaptic weight, the pre-synaptic spike and the post-synaptic spike should occur within a specific period, which is called the STDP window. This paper changes the STDP window according to the firing rate of the post-synaptic neuron to achieve a similar performance in learning with an improved training speed. The weight updates frequently (minimal frequency, 100 Hz) in the training phase, and the resolution of the weight is extremely low. Consequently, no refresh is required during training.

II. RESULT AND DISCUSSION

A. Chip information

circuits with on-chip STDP learning has been fabricated on a single chip using CMOS technology. Scalable olfactory system can be constructed by interconnecting multiple chips. Each sensor cell has an associated sensor interface circuit for dc cancellation, amplification and filtering. The outputs of sensor interface circuits feed to the inputs of the neuromorphic circuits. The sensor response and performance of the interface circuitry were characterized by delivering target vapors in the air. In the chip contained 3 spiking neural network arrays with each array having receptor neurons, synapses and principle neuron. The purpose of this chip was to test the circuit blocks implementing the neuromorphic systems. The learning in this chip was performed by off-chip.

B. Performance of the Olfactory system

The odor data were sampled by a commercial E-Nose product, the resistance of each sensor results was saved in the computer. The device samples the resistance of the sensor every 0.5–0.6 s. The device resamples the resistance baseline of the sensor when the gas experiments are performed to reduce the effect of background odor. The E-Nose ends a gas experiment by inhaling clean air (background air) for a short period to clean the sensors. The odor data were pre-processed and normalized by a self-written Lab View program and categorized into a training part and a testing part. The training part is fed into the neuromorphic chip by FPGA kit to perform the training. After the training procedure is completed, the testing part is fed into the chip and the classification result is shown by the computer.

In the electronic nose system are using chemo gas sensors. When using this type of sensor provides meaningful information and it's calculated by the percentage of the resistance change before and after the sensor interacts with the odor molecule. When the reaction of the sensor to a particular odor is stronger, the resistance change is larger. The data have been preprocessed and normalized. The input voltage ranges from 0.35 V to about 1 V. The data need to be converted into threshold voltage format before fed into the chip. To make certain classification result is only caused by learning; the data need to be normalized before training and testing by fixing the total strength of the input stimuli. The self-written Lab View program extracts the percentage of the resistance change of each sensor, converting the data from a percentage change to the threshold voltage and normalizing it. The normalization procedure is as follows.

The information from the receptors is expressed as R1after ▫ Rn after and R1before ▫ Rn before. Rn after represents the resistance of the nth sensor after responding to the odor, and subscripted "before" represents the resistance before responding to the odor. The glomeruli implemented in the computer perform the following functions. Given n dimension data x which represents the percentage of reaction x = [x1…xn]

$$X1 = \frac{R1after - R1before}{R1before}$$

Step 1 (Inverting Data): The threshold voltage is smaller when the sensor response is larger xn_invert = max (xn) − xni.

Step 2 (Fixing Total Stimulation Strength): When the data in different categories have levels of stimulation strength, the output of the neuromorphic network varies, even though the synaptic weights are all equal to a constant.

xni_fix = xni_invert / Σ xni_invert

Step 3 (Adding Offset): After the second step, the minimal value in xn is zero. When the threshold is set to zero, the soma voltage of this neuron is never lower than the threshold level. xni_new = xni_fix + x0. xn_new = [x1_new…xn new] is the actual input to the neuromorphic chip.

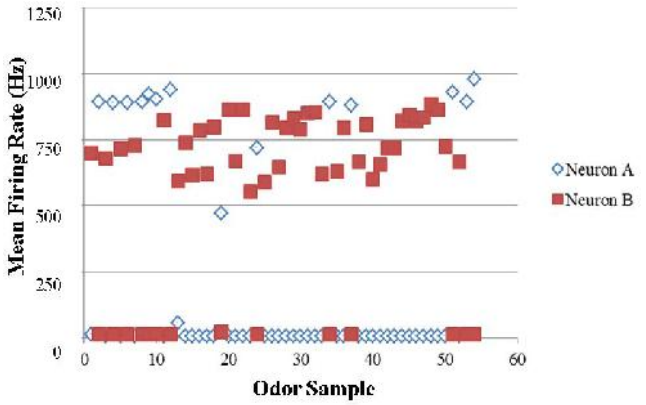

Fig.2. Mean firing rate of Neuron A and Neuron B

Mean firing rate of each odor sample can be represented in the graph. For Neuron A odor sample of Ethanol although, the firing rate of neuron B is varied when different samples come in, It is larger than the firing rate of neuron A in most cases. In this experiment, the geometric mean is used to measure the total classification performance from each testing odor set.

C. *Neuromorphic Circuits Results*

The neuromorphic circuits are presented in this section. A synapse circuit is tested by exciting spike input. The response for the synapse programmed with a weight input and time constant. Since the weight is negative with respect to the baseline, the synapse exhibits an inhibitory response. The output response of the on-chip STDP circuit over a two different pre synaptic and postsynaptic input spike. Initially, the synaptic weight is negative causing the synapse to generate an inhibitory response. The weight increment (decrement) is smaller if the pre synaptic spike follows the postsynaptic spike by a larger time interval. When a receptor neuron is connected to PN through a synapse. The input of receptor neuron firings at a rate of approximately 25 ms. the repeated receptor neuron firing and synapsing on to the PN eventually causes the PN to fire. The summation of exponentially decaying synaptic currents for multiple receptor neuron spikes. Importantly, this test result demonstrates the functional signal path through the entire neuromorphic circuit. The performance of the neuromorphic olfaction chip components are summarized in Table I.

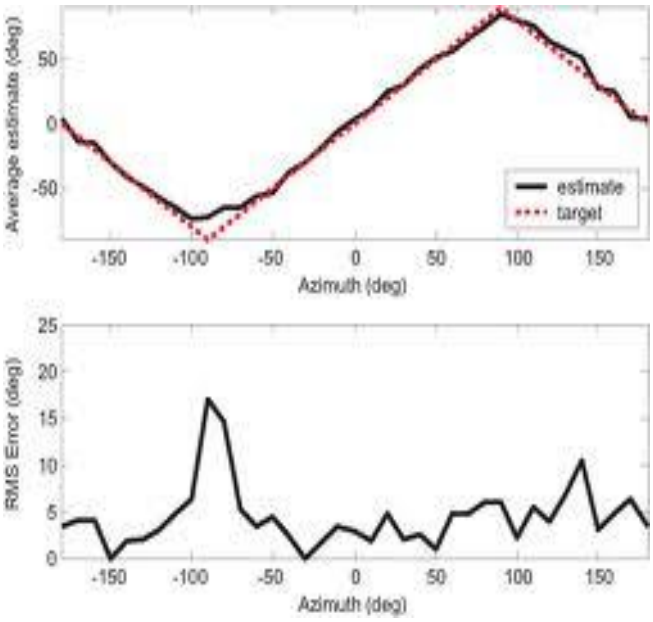

Fig 3.Finger print graph of Ethanol

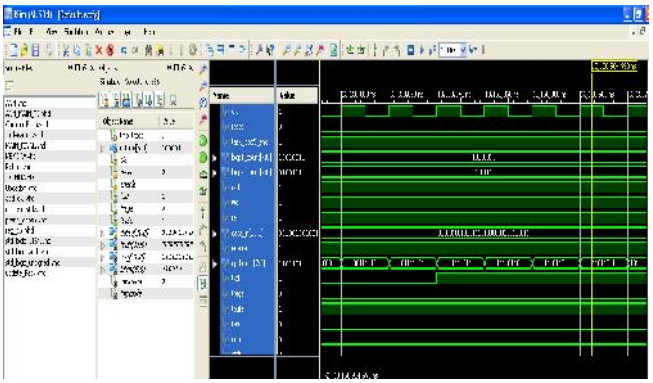

fig 4. ANN Simulation output

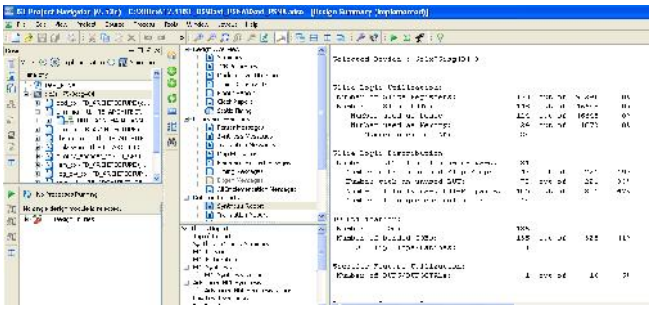

Fig 5. Area Usage

Table I.

PERFORMANCE SUMMARY OF THE ADAPTIVE NEUROMORPHIC OLFACTION CHIP

Parameter	Values
Technology	0.18µm
Supply voltage	5v
Chip area	1.78mm²
Sensor resistance	10kΩ to 200kΩ
Sensor driving current	1µA, 10µA, 100µA
Sensor bandwidth	<1Hz
Synaptic time constant	10 ms to 300ms
Weight range	± 1V
Neuron spike width	10µs- 1ms
Neuron refractory time period	10 ms – 300ms

All receptor neurons have a time constant of 200ms. The threshold voltages of all the RN's are set at 70% of the peak sensor signal amplitude. To initiate learning in the network, the threshold voltages of PNs are chosen such that they spike on the arrival of first few correlated RN spikes. The refractory period of the RNs and the PNs are 60 and 120 ms, respectively. The STDP window function is set at ± 50ms. The circuits of the individual building blocks used in this network have been validated in the chip results. The proposed neuromorphic chip consumes less power and this is suitable for electronic nose system to classify the odour recognition and classification.

IV. CONCLUSION

This paper proposed Field Programmable Gate Array based adaptive neuromorphic circuits were inspired by the mammalian olfactory system. In this neuromorphic chip composed of chemo sensor arrays and STDP synapses, utilizes sub threshold oscillation to represent the strength of the stimuli resulting in lower power consumption, smaller chip area, and more distinct output for each odor input. The neuromorphic chip has been fabricated by CMOS process. The chip can be trained to classify odor categories at the same time combining two or more neuromorphic chips, the classification task can be performed by the electronic nose system. For the testing odor data set, provides the better classification performance and accuracy. As a result, the proposed neuromorphic chip is suitable for application in an E-Nose system for odor recognition and classification.

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