Electronic Olfaction System on a Chip

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ABSTRACT

Olfaction today has many applications not only for an individual's life but also for the industries. Applications include food product quality control, safety and security, environmental monitoring, indoor air quality, health care, medical diagnosis, pharmaceutical purposes, and military applications. In these applications human olfaction is still the primary instrument. This is a costly process since trained experts are required who can only work for relatively short periods of time, not mentioning fatigue, mental state, subjectivity, and the danger being exposed to hazardous chemicals. Therefore using machine olfaction to perform the task would be a significant advance. Many researchers have investigated electronic noses, but currently only relatively large "instrument" electronic noses have been built. We have designed, simulated, fabricated and tested an integrated electronic nose on a single silicon chip. This electronic nose chip is able to learn and distinguish eight different odors. We suggest that the chip performance can be improved by adding more different sensors and processing more odor data.

Keywords: Electronic nose, Olfaction sensing, Nose chip, Electronic olfaction system.

INTRODUCTION

Olfaction, the sense of smell, is the main sensory system in humans that contributes to the sensation of flavor. Together with other sensations, such as vision and audition, olfaction makes one's life more colorful. Imagine walking in a garden full of beautiful flowers without enjoying their wonderful fragrance, or eating delicious New York steak without smelling it, one can easily conclude that olfaction is so important to our daily life. But it is more than that. There are many applications of olfaction not only for an individual's life but also for the industries. Applications include food product quality control[1, 2], safety and security, environmental monitoring[3, 4], indoor air quality, health care, medical diagnosis[5, 6, 7], pharmaceutical purposes, and military applications.

These applications of olfaction raise a demand to find a "nose" that meets the needs. The biological nose is the first thing that comes to mind. In fact, today the human nose is still the primary "instrument" used to assess the smell or flavor of various industrial products. But there are many drawbacks, such as individual variability, fatigue, infections, mental state, subjectivity, exposure to hazardous compounds, etc. Moreover, it is not a good process economically because of the cost to train experts who can only work for relatively short period of time. Thus an alternative "nose" that can imitate the function of the biological nose is needed.

Perhaps the earliest work on odor sensing can be traced back to Moncrieff in 1961[8]. It was actually a mechanical nose. The concepts of early electronic noses were reported by Wilkens and Hatman back in 1964[9], Buck[10] in 1965, and Dravnieks[11] in 1965, but the concept of an electronic nose as an intelligent chemical sensor array system for odor classification was introduced 20 years later by Persaud at Warwick University in UK[12] in 1982 and Ikegami at Hitachi in Japan in 1985 and 1987[13, 14]. The term "electronic nose" appeared around the late 1980s as it was used at a conference in 1987[15]. In 1989, during a session at a NATO Advanced Workshop on Chemosensory Information Processing, artificial olfaction was discussed and the design of an artificial olfactory system was further established[16]. The first conference dedicated to the topic of electronic noses was held in 1990[17].

Since 1990, many researches on a sensor array system for odor classification have been done. Several kinds of electronic nose sensors have been investigated. They fall into five main categories: conductivity sensors (metal oxide[18, 19, 20, 21] and conducting polymer[22, 23, 24, 35]), piezoelectric sensors (quartz crystal microbalance (QCM)[25, 26] and surface acoustic-wave (SAW) devices[27, 28]), MOSFETs[29], optical sensors[30, 31], and spectrometry-based sensing methods (Gas chromatography, mass spectrometry, and light spectrum). Several manufacturers have already commercialized different "electronic nose" instruments with the ability to mimic the biological nose to some extent. They are either in size of desktop or laptop, with very few companies researching on palmtop size electronic nose. These electronic nose instruments require very high cost and operating power. Therefore, innovative methods have been investigated to build up a low cost, low power, small size, and versatile sensing platform, such as a "electronic nose chip". There have been some efforts designing nose-on-a-chip by several people[29, 33, 34], but a real electronic nose chip has yet been made. We have investigated, designed, simulated, and tested an electronic nose chip that is capable of learning and distinguishing eight different odors. Chip design and experimental results are discussed in this paper.

CHIP DESIGN

The electronic nose chip is composed of four different stages: Sensor stage, Signal Processing stage, Database stage, and Classifier stage.

The sensor stage, as its name suggests, deals with the sensor directly. The sensor we use is a carbon black-organic polymer whose relative resistance change is proportional to the given odor concentration[35]. The function of the sensor stage is to adapt this resistive sensor to a preset baseline value, take the AC signal voltage, then output a current proportional to the signal voltage. So the sensor stage outputs a signal current which contains information about the odor concentration. An adaptive electronics stage, a peak detector, and a transconductance amplifier are designed to complete the sensor stage. Adaptive electronics are implemented to adapt the sensor to be within a proper working range of the circuit while tuning out the environment background. Adaption is done by constructing an adjustable current source. After adaption is done, the bias current value is held, so the sensor voltage at this time contains two different types of information: baseline value and signal value. The peak detector traces the input signal to its maximum value, then holds the value for further signal processing. This is needed because the signal voltage is defined as the difference between the maximum sensor voltage and the baseline sensor voltage. The transconductance amplifier converts voltage to current linearly while functioning as high pass filter. The output current is equal to the difference between the two input voltages multiplied by some gain (called transconductance). The output of the peak detector, the maximum sensor voltage, is used as the non-inverting input, while the baseline sensor voltage is used as the inverting input. By the differential input characteristic of the transconductance amplifier, the baseline information is cancelled, and only the signal information remains. Thus, the output current from the transconductance amplifier contains the signal information, i.e., odor concentration.

The signal processing stage performs two important tasks for further signal processing. First, normalization throughout the signal array is realized. Then the Euclidean distance between the signal vector and the data vector is calculated. A normalizer using city-blocks distance is designed and an Euclidean distance calculation circuit is built. A normalization circuit using city-blocks distance is implemented to generate a normalized signal vector. This normalized signal vector is stored in a SRAM through an A/D in the LEARNING State. On the other hand, in the CLASSIFYING state, Euclidean distance between the normalized signal vector and the data vector is calculated. Euclidean distance circuit is implemented to calculate the Euclidean distance between signal vector and data vector. The Euclidean distance is output in the form of a current. This distance measure is utilized for classification.

The database stage stores the signal vector in the data storage device (LEARNING state) or outputs the data vector from the data storage device (CLASSIFYING state). This stage also takes care of the interface between the electronic nose chip and the outside world. A central control unit is designed to generate all the control signals and arrange the time sequence. Eight-bit Static Random-Access Memory (SRAM) is used for data storage. A/D converter is used to convert the signal vector into a digital word. This happens during the LEARNING process. A D/A converter is used to convert the data from SRAM into the data vector. This happens during the CLASSIFYING process. A current copier cell is designed to maintain the value of the data current. Several current copier cells are used to form a data vector. The central control unit is designed to generate all the control signals needed and their time sequence.

The classifier stage receives all the Euclidean distances between signal vector and data vectors, and generates the output corresponding to the shortest Euclidean distance, while inhibiting all the other outputs. The generated output is denoted as the answer to the pattern recognition problem. The current copier cell in the database stage is used to maintain the value of the Euclidean distance current. Several current copier cells are used to generate inputs for the LTA circuit. The Loser-Take-All (LTA) is used for parallel classification. Global inhibition can be done by using an LTA circuit.

A complete floorplan is shown in figure 6 at the end of this paper. Three different polymer sensors are used at the front end, so three sensor stages are constructed. Thus a three-dimensional signal vector is generated from the sensor stages, and the data vector is three dimensional as well. For this reason three current copier cells (CC) are implemented in the database stage. Eight different odor data are stored in the database, so eight current copier cells are used in the classifier stage. All the four stages are shown in the floorplan.

Figure 1 shows the actual chip layout for the electronic nose chip. Four stages: sensor stage, signal processing

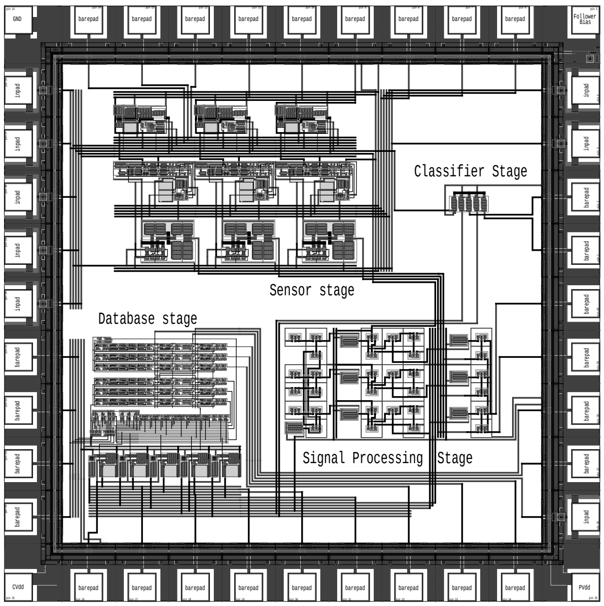

Figure 1: electronic nose chip Layout

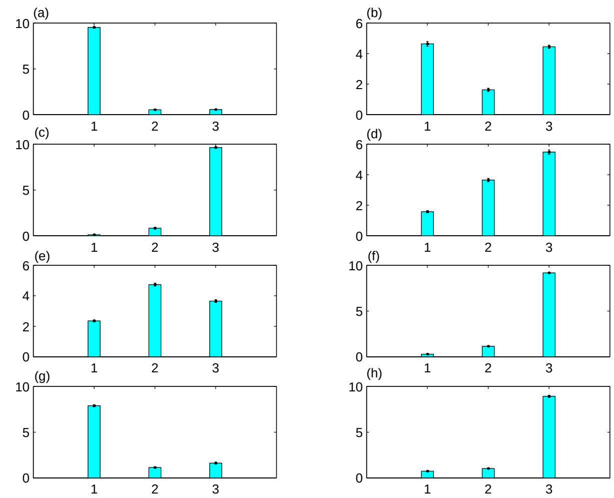

Figure 2: Normalized data patterns (a)methanol(D_1), (b)2-propanol(D_2), (c)hexane(D_3), (d)ethyl acetate(D_4), (e)acetone(D_5), (f)toluene(D_6), (g)ethanol(D_7), (h)chloroform(D_8)

stage, database stage, and classifier stage are labelled, as shown in the figure. The chip is fabricated by 1.2μm 2-poly 2-metal process at MOSIS. The size of the chip is 2117μm$\times$2117μm.

EXPERIMENTAL RESULTS

Longitudinal tests for the ability of the electronic nose chip to learn and classify different odors is performed. To test the chip, three different kinds of polymers, poly(N-vinylpyrrolidone), poly(styrene), and poly(ethylene-co-vinyl acetate), are chosen for the polymer sensors for the chip. The signals generated from these three sensors construct the three dimensions for the odor vector. The poly(N-vinylpyrrolidone) sensor denotes x-dimension, the poly(styrene) sensor denotes y-dimension, and the poly(ethylene-co-vinyl acetate) sensor denotes z-dimension. The data patterns from eight different chemicals: methanol(D_1), 2-propanol(D_2), hexane(D_3), ethyl acetate(D_4), acetone(D_5), toluene(D_6), ethanol(D_7), chloroform(D_8), are stored as data vectors in SRAM. Six chemicals: methanol(T_1), 2-propanol(T_2), hexane(T_3), ethyl acetate(T_4), acetone(T_5), benzene(T_6) are used to test the classifying ability of the electronic nose chip. Notice that $T_1 \ldots T_5$ are known odor to the chip, while T_6 is a new odor. Therefore, $T_1 \ldots T_5$ are used to test if the chip really "learns" the odor, and T_6 is used to test the ability of the chip to distinguish a new odor.

Ten exposures for each odor ($D_1 \ldots D_8$) have been measured during a five-day span. Data patterns were taken twice a day, including one time in the morning and the other in the evening. So there are ten un-normalized data patterns for each odor after five days. All the data vectors were normalized in the signal processing stage of the chip. Figure 2 shows the eight normalized data patterns.

The classifying ability of the electronic nose chip is tested by running six different chemicals through the chip separately. Six signal vectors ($T_1 \ldots T_6$) are generated by the sensor stages, and six normalized signal vectors ($T_{n1} \ldots T_{n6}$) are generated in the signal processing stage. Figure 3 shows the six normalized test patterns.

The test chemicals $T_1 \ldots T_5$, since they are already known odors for the electronic nose chip, can be easily classified into correct groups by the LTA circuit that raises the output cell with the shortest input Euclidean distance. But for benzene (T_6), because it is an unknown chemical to the chip, the chip would classify it to the class which is closest, toluene. One way to improve the chip could be to set up a threshold Euclidean distance D_t. If the shortest Euclidean distance is smaller than D_t, the test odor is classified to the class with the shortest distance. Otherwise, a new class is formed and the normalized test vector is stored as the data vector of the new class. In our experiment the threshold Euclidean distance current can be set at 0.25μA.

The classifying power can be enhanced even more. First notice the high similarity between data patterns of hexane(D_3), toluene(D_6), and chloroform(D_8). Because of the high similarity between these three patterns, it is very possible for the electronic nose chip to make a wrong decision due to noise from temperature, humidity, etc. An intuitive way to solve this problem is to add more differ-

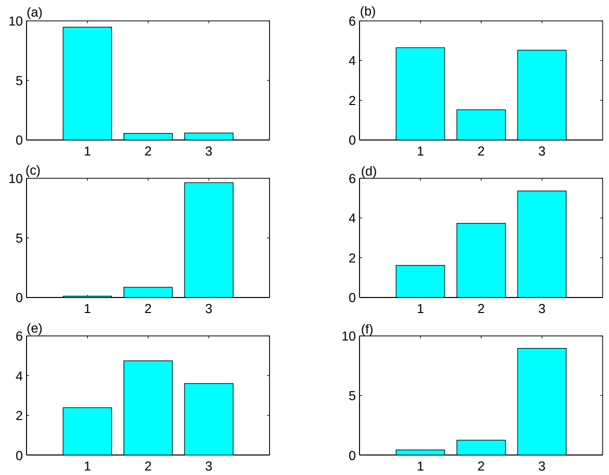

Figure 3: Normalized test patterns: (a)methanol(T_1), (b)2-propanol(T_2), (c)hexane(T_3), (d)ethyl acetate(T_4), (e)acetone(T_5), (f)benzene(T_6)

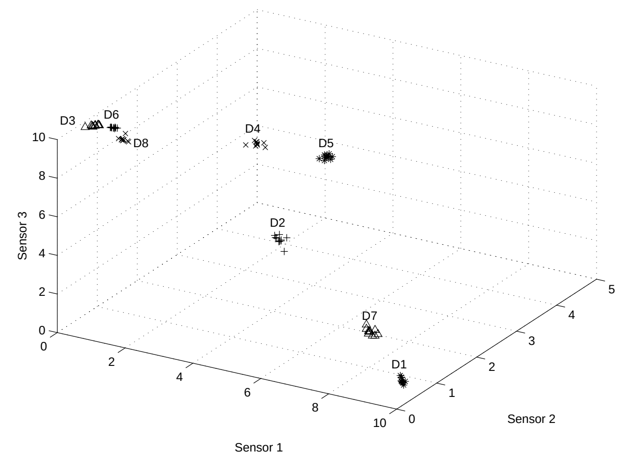

Figure 4: 3-D plot of the eight different normalized data patterns

ent polymer sensors to explore the odor space more thoroughly and reduce the similarity between data patterns. In addition to increasing the number of different sensors, the performance of the electronic nose chip can be further improved by processing more sample odor patterns for the chip to learn. By learning more samples, the odor database is increased, and more known odors are stored in the nose's memory.

Figure 4 is a three dimensional plot for the eight different normalized data vectors ($D_{n1} \ldots D_{n8}$). The three different carbon black-organic polymer sensors form the three dimensions of the plot. From the figure we can see that the data patterns are very well separated except D_3, D_6, and D_8. The six normalized test vectors ($T_{n1} \ldots T_{n6}$) together with the normalized data vectors are shown in another three dimensional plot in figure 5. We can see from the figure that $T_{n1} \ldots T_{n5}$ can be classified correctly to $D_{n1} \ldots D_{n5}$. For test vector T_{n6}, although it is close to some data patterns (D_{n3}, D_{n6}, D_{n8}), the result is not as good as the other test odors.

CONCLUSION

This paper introduces a novel electronic nose chip having the ability to distinguish eight different odors by using three different carbon black-organic polymer sensors. Four stages in order to construct the chip are discussed, and experimental results for testing the classifying ability of the chip are presented. We conclude that the processing ability of the chip to classify more odors can be enhanced by giving more sample odor patterns to learn and adding more different sensors. By processing more sample odors the database is increased and more known odors are stored in the nose's memory. On the other hand, adding more different polymer sensors enables the nose chip to explore the odor space more thoroughly.

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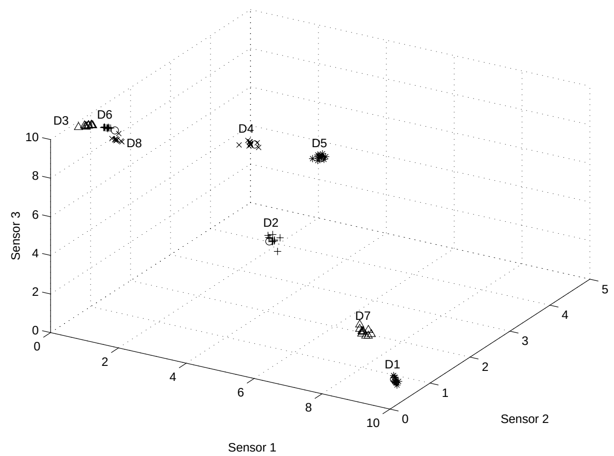

Figure 5: 3-D plot of the six normalized test patterns and the eight normalized data patterns. The test points are shown in circles 'o'. From the figure we can see the first five test odor can be classified easily to the correct class, while the 6th test odor still needs some further processing.

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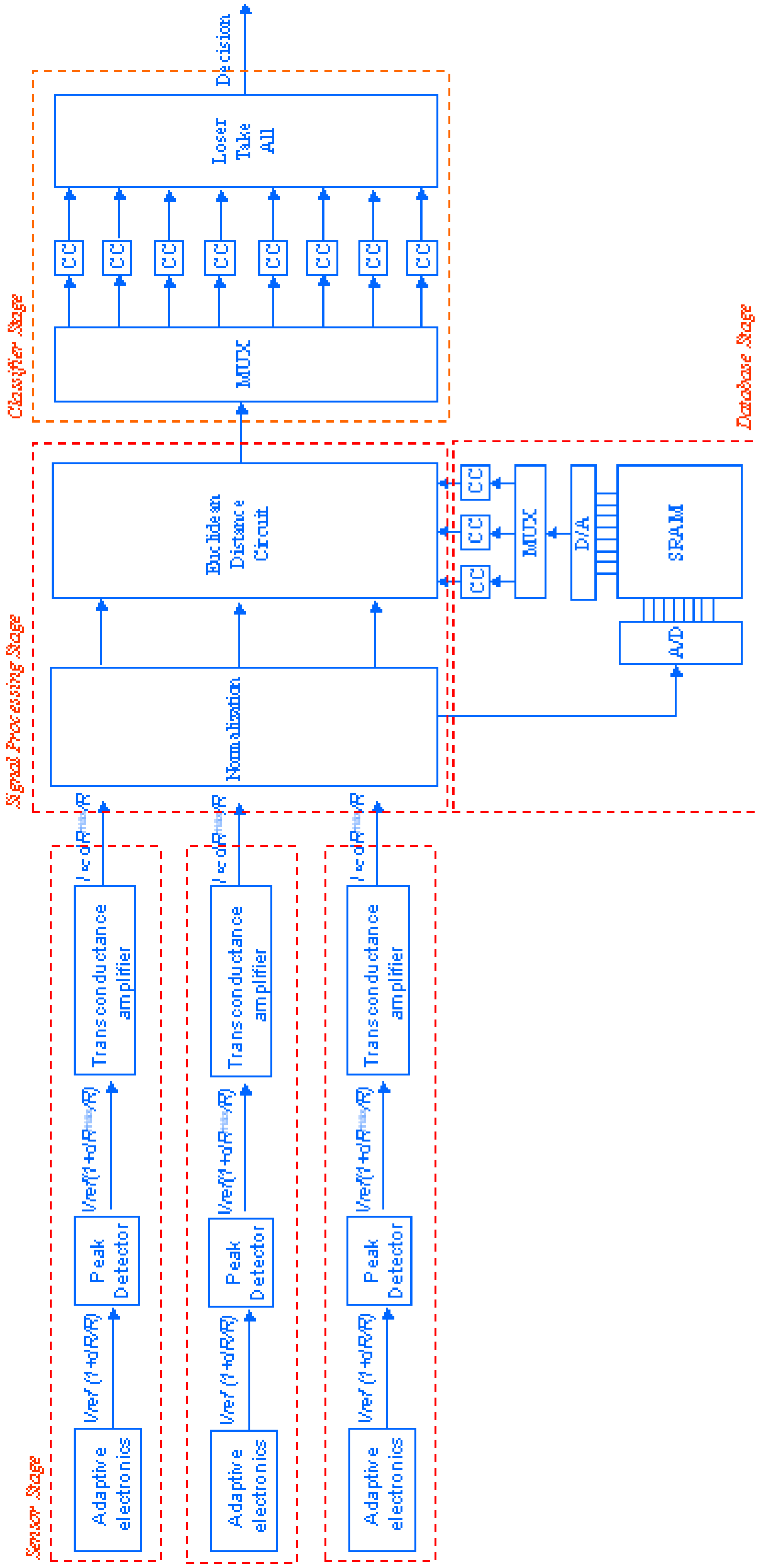

Figure 6: Chip floorplan for electronic nose chip