Energy-Efficient Gas Recognition System with Event-Driven Power Control

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Abstract—For energy-limited applications of electronic nose, an application-specific architecture is essential to realize a low-energy gas recognition system. In this paper, a pseudo-zero-leakage gas recognition system is proposed to recognize different gases using event-driven power control. Additionally, this gas recognition system can recognize four different gases with concentration information by drift-insensitive on-line training, achieving 100% recognition accuracy for gas type and 89.4% accuracy for concentration analysis. For further reducing the overall energy consumption, both near-threshold SRAM and low-voltage embedded ReRAM are integrated into the proposed system, respectively. Based on TSMC 65nm LP CMOS process, the total energy of the gas recognition systems with SRAM and ReRAM are only 8.62μJ and 2.04μJ in a sensing period, respectively. Hence, an energy-efficient gas recognition system can be realized by a pseudo-zero-leakage event-driven structure with ReRAM.

Keywords—gas recognition, event-driven, zero-leakage, ReRAM

I. INTRODUCTION

Gas identification has raised extensive attention in the past twenty years. Gas detection can monitor and precisely measure leakage of combustible and explosive gases [1]. Moreover, miniaturized and energy-efficient Metal-oxide (MOX) gas sensors are utilized for electrical noses by constructing a gas sensor array, permitting to improve the selectivity of gases and the ability to classify different odors [2]. Accordingly, a pattern recognition system for gas sensors is required to selectively detect and determine various kinds of gases.

The recognition accuracy can be improved by extracting the specific emphasized features using vector angle approximation, and spike sequence extraction. Additionally, the total gas information can be further reduced by classifying and filtering the demanded features from the sensing row data. Therefore, several flexible pattern recognition algorithms have been proposed to classify the chemical sensor data based on class-conditional density estimation or the discriminant functions [3-9]. K-nearest neighbors (KNN) classifiers [3], probabilistic principal component analysis (PPCA) [4, 5] and Gaussian mixture models (GMMs) [3] were adopted based on the class-conditional density estimations. Accordingly, multi-layer perceptrons (MLPs), radial basic functions (RBFs) and self-organizing maps (SOMs) [6] were exploited according to the discriminant functions. Moreover, a gas recognition method was proposed to decrease the overall power consumption and hardware complexity through spike pattern comparison [7]. The spike patterns are observed by the changing of the detected resistances. In a MOX gas sensor array, unfortunately, the variation to the detected spike patterns would be increased by the cross-sensor interferences, sensor drifts and gas concentrations.

For electrical-nose applications, a robust energy-efficient gas recognition system is required to be tolerant to these variations. In this paper, a pseudo-zero-leakage gas recognition system is presented by exploring energy-efficient algorithm-architecture co-design and event-driven power control for a MOX gas sensor array. This system can identify four different gases with high recognition accuracy and concentration analysis through drift-insensitive 2-D spike signatures. The reference library of spike signatures is updated by an on-line training process. To further achieve energy-efficiency, low-voltage embedded ReRAM is utilized for the reference library to realize a pseudo-zero-leakage datapath in the recognition system. The rest of this paper is organized as follow. Section II presents the response gas signal model of a MOX gas sensor array. Section III describes the signature construction of 2-D gas recognition patterns. Section IV describes the proposed gas recognition with concentration analysis by exploring the algorithm-architecture co-design. Section V elucidates the design and analyses of the proposed pseudo-zero-leakage event-driven recognition system. Finally, conclusions are given in Section VI.

II. MODELING FOR MOX GAS SENSOR ARRAY

For identifying the original gas information, the characteristics and cross-coupled model of gas signals received from the multi-gas sensors in a MOX gas sensor array should be established first. A MOX gas sensor array is implemented by a
metal-oxide semiconducting film, mainly tin-dioxide (SnO$_2$), and heated at an adequate temperature for gas detecting. Hence, the target gas will introduce a chemical reaction in MOX sensors, and the gas information is captured by measuring the relative resistance across the two electrodes. The equivalent resistance is increased with the increasing concentration of the target gas. The process during 1 detection period can be split into four stages: idle, growth stage, steady stage and recovery-stage [7]. For modeling the response signal of each gas sensor in a MOX gas sensor array, this process can be represented by a cross-sensitivity matrix. The mixed multi-gas signals are nearly linearly mixed according to the cross-sensitivity matrix.

$$X_{ij} = \sum_{p=1}^{R} c^p a^p_{ij} + d^j + z^j_i$$  \hspace{1cm} (1)

The specifications of MOX gas sensors are determined by the catalysts and dopants. Therefore, the signal model for a MOX gas sensor array is constructed based on the specifics of a 4x4 SnO$_2$ gas sensor array [9]. Each row of the array is different from the other, and the sensor array is designed to detect 4 different gases with 20-200ppm concentration range in 30 seconds. The gas signal reflects a short response time for low concentrations. Whenever the concentration of these gases raises, human bodies would be damaged. The relationship between the resistance and the concentration of gas follows the power law as Eq. (2), where $\alpha$ and $\gamma$ are the constants depending on the gas and sensor material. The sensitivity factor, $x$, is the extracted feature by the latency coding. With a given sensor $i$ of the gas sensor array, this factor is exposed to a certain gas $j$. To avoid confusion, the gas concentration in the sensitivity formula is represented by $C$, instead of $\zeta$ in the power law.

$$R_i = \alpha_j \zeta^{-\gamma_j} \cdot x_{ij} = \left( \frac{R_i}{R_0} \right)_{air} \approx \alpha_{ij} C^{\gamma_j}$$ \hspace{1cm} (2)

$$t_{ij} = t_0 \cdot \frac{\ln x_{ij}}{y_{ij}} = t_0 \cdot \frac{\ln a_{ij}}{y_{ij}} = t_0 \cdot \ln C$$ \hspace{1cm} (3)

The sensitivity can be converted into a spike fired at time $t_{ij}$ with a constant across a group of sensors $i_0$ as Eq. (3). The spike firing order only depends on the gas types. The concentration-invariant order can be used to construct robust recognition patterns for reliable gas identification.

The patterns of each gas are established independently with different gas concentration ratios by the pattern parameter extraction technique [9]. The gas sensor array can be exposed to different gas concentration levels, and the sensor array is designed to detect different gases with 20-200ppm concentration range in 30 seconds. The gas signal reflects a short response time for low concentration.

### III. 2-D GAS RECOGNITION PATTERN CONSTRUCTION

The target gases are carbon monoxide (CO), Ethanol (C$_2$H$_5$OH), Propane (C$_3$H$_8$), Hydrogen (H$_2$), which are compounds of carbon, hydrogen and oxygen common in mines. Whenever the concentration of these gases raises, human bodies would be damaged. The relationship between the resistance and the concentration of gas follows the power law as Eq. (2), where $\alpha$ and $\gamma$ are the constants depending on the gas and sensor material. The sensitivity factor, $x$, is the extracted feature by the latency coding. With a given sensor $i$ of the gas sensor array, this factor is exposed to a certain gas $j$. To avoid confusion, the gas concentration in the sensitivity formula is represented by $C$, instead of $\zeta$ in the power law.

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The concentration ratio is not concerned, the parameters are more reliable and not interfered by the experiment environment. The 2-D spike patterns and the corresponding matrix format of the target gases are as shown in Fig. 3. Each row shows a group of sensors with the same catalyst, and the number on top of spikes is their corresponding dopant. (1 for P, 2 for B, 3 for H, and 4 for N.D.) The pattern of each gas is unique and independent to concentration variations and sensor drifts.

IV. ALGORITHM-ARCHITECTURE CO-DESIGN FOR GAS RECOGNITION WITH CONCENTRATION ANALYSIS

The gas recognition method is designed and implemented by energy-efficient algorithm-architecture co-design considering the trade-offs among power, delay and accuracy of extracted signals for multi-gas sensor applications. The structure of the gas recognition method with spike patterns is described in this section. Furthermore, the concentration analysis is inserted to the recognition process, and the gas identification also focuses on the scalability of gas types, developing the potential for electronic-nose applications. Fig. 4 illustrates the proposed gas recognition method consisting of five parts: sensing stage, readout stage, processing stage, recognition stage, and feedback stage.

The drift of sensors is one of the critical challenges for gas recognition. To overcome this problem, the sensing stage relies on a 4x4 metal oxide sensor array and each row of sensors represents a “group” of sensor exhibiting similar drift behavior [7]. The following stages are designed according to the groups of sensors to build a robust recognition method. When the target gas is detected, the readout circuitry generates a specific pattern and extracts the resistance of each gas from the sensor response of the gas sensor array. The spike pattern used for the gas-type recognition is generated from the groups of sensors, decreasing the influence by the sensor drifts. Also, the resistances of sensors exploited in the concentration analysis block are extracted at the same time. Therefore, an address allocation is required to construct the gas patterns as shown in Fig. 5. When all the spikes are recorded, the gas patterns for recognition is translated from spikes into a 2-D signature which is drift-insensitive and concentration-independent. The row of the matrix represents the group of sensors, and the column of the matrix represents the address of a sensor in the specific group.

A. Gas-Type Recognition

The specific 2-D signature constructed in the processing stage is compared to the gas signatures in the reference library. Fig. 6 presents the comparison flow, and the sample gas, GASk, is stored in four 8-bit flip-flops as Gk0 - Gk3. Each 8-bit information represents a spike sequence of a group in the sensor array. Therefore, four reference gas signatures are stored in the memory. Accordingly, each referred gas signature is also represented in four 8-bit storage units, Gij, with the gas type i and the group index j of that gas. The structure of this storage provides a good scalability of the number of recognition gas types. Additionally, the referred signature can be extracted easily through changing the index of the storage unit.

To decide whether the sample gas is similar to the reference gas, the spike sequences in all groups of the specific gas have to be compared by 4 cycles. Therefore, 4n cycles are required for n different gas types. For 4 gas types, the average latency of this method is around 10 cycles. According to the regularity of the reference library, the comparisons of the gas signatures is based on the sensor groups for reducing the searching time. Thus, the comparison is started from group0 sequence between the sample gas and the reference gas. If the spike sequences of group0 are different from the reference library, the worst case will take n+3 cycles to achieve the recognition. Hence, the average latency of this method is 5.5 cycles. To further decrease the latency, the previous gas information is utilized to select the comparison sequence, and the comparison starts from the type of the previous gas. The average latency is decreased to 4.9 cycles. When the number of target gases increases, the average latency can be reduced significantly.
The difference between the resistances in the baseline and steady-state varies with the gas concentration that can be utilized for the concentration analysis. The concentration analysis block is implemented by a concentration look-up table (LUT), a binary searching engine and a comparator as shown in Fig. 6. The concentration table stores the $\Delta R$ in 8 steps for each gas, and these 8 steps is sorted in the sequence from 25ppm to 200ppm with 25ppm per step. Therefore, the concentration distribution can be divided into ten regions, <25ppm, around 25ppm... around 200ppm and >200ppm. Additionally, the binary searching process is utilized using the two distances, Dist1 and Dist2, for the concentration analysis. Dist1 and Dist2 represents the differences between the sampled $\Delta R$ and the upper/lower $\Delta R$ in the selected region, respectively.

C. On-Line Training Block

For increasing the accuracy of concentration analysis, the concentration table is updated in the training block with on-line K-means clustering as shown in Fig. 7. At the beginning, the initial data of the concentration tables and 2-D signatures of gases are off-line loaded in the reference library. In the training block, the extracted-resistances are used for the sensor selection at the first time to define the target sensors. The target sensors are highly sensitive to the target gas inducing the largest variation on $\Delta R$ within different concentrations. After the target sensors are defined, the concentration tables are updated by the on-line K-means clustering based on $\Delta R$ of target sensors.

The selection of the target sensors affects the concentration accuracy of each gas significantly. In general, the sensors detect both larger $\Delta R$ variation and faster response time for the target sensor. Additionally, the concentration analysis is less sensitive to the drift phenomenon when the variation on $\Delta R$ between different concentrations is large. Therefore, the sensor selection process focuses on the first two fast response sensors in each group and searches the largest $\Delta R$ variation between these sensors. Fig. 8 shows the process of the sensor selection. After capturing $\Delta R_s$ by the resistance extraction process, the relation between this $\Delta R_s$ and the previous $\Delta R_{s-1}$ should be checked. When the difference between $\Delta R_s$ and $\Delta R_{s-1}$ is larger than a threshold, the differences of sensors is transferred to the maximum comparator to find out the larger $\Delta R$ variation, defining the target sensor. The threshold is set to the minimum $\Delta R$ of sensors, 300$\Omega$. After all $\Delta R$s pass through the maximum comparator, the sensors with the largest variation are defined automatically.

The concept of on-line K-means clustering [10] is similar to K-means clustering, including centroid selection, distance calculation and convergence determination. The difference is the updating-rule of new centroids (mean of clusters). For on-line K-means clustering, the centroid is updated with a new data point to reduce the requirement of storage. To further reduce the computation complexity and area, a simplified on-line K-means clustering is used based on a discounted updating rule as shown in Fig. 9. First, cluster centroids are initialized in order of 8 concentration steps. A new $\Delta R$ is sorted easily by the binary searching engine, and the minimum distance between the sampled $\Delta R$ and the cluster centers is also calculated. Second, the sample to a cluster with the minimum distance is assigned. Thus, the centroid can be updated with the discounted updating rule. The final clusters can be obtained until the clusters converge. Additionally, the updating rule can be implemented by an addition, a subtraction, and a shifter instead of a multiplication through 4-cycle training, 8-cycle training, and 16-cycle training. Fig. 10 shows the maximum error and the average error of three gases under different training cycles.
D. Error Detection

The error detection is designed to examine whether the sensor in the gas sensor array is broken based on the recognition results in the feedback stage. In general, a broken sensor would always be saturated or not reacted to any target gases that induces large $\Delta R$. If a broken sensor is detected, the reference library has to be modified for the other survival sensors through the error messages based on $\Delta R$. For each gas type, two concentration tables are implemented to maintain the reliability of the recognition system. Therefore, the concentration analysis has to discard the patterns of the broken sensor in the other concentration table, and the spike generated by corresponding sensors will be ignored.

V. PSEUDO-ZERO-LEAKAGE EVENT-DRIVEN GAS RECOGNITION SYSTEM

For energy-limited applications of electronic noses, the event-driven power control technique is utilized to reduce the overall energy for the gas recognition system. The execution time of the gas recognition procedure is much smaller than the interval period between two gas samples. Therefore, the gas recognition system is almost in the idle mode, and the overall power consumption is occupied by the leakage power up to 95%. In view of this, the leakage current should be cut-off in the idle mode using a pseudo-zero-leakage event-triggered structure. For cutting-off leakage current paths, the event-driven power control is proposed to shut down the gas recognition circuitry by an event-triggered wake-up controller (ETWC). However, the data in the reference library cannot be destroyed. In view of this, this reference library is implemented by near-threshold SRAM [11] and nonvolatile ReRAM [12] in two gas recognition systems, respectively.

The recognition system with near-threshold SRAM is as shown in Fig. 11, consisting of a gas recognition block, ETWC, a power management unit, and 1kb near-threshold SRAM. The ETWC is always turned on for receiving the events from the gas sensor array. While receiving the events, the ETWC will turn on the power for the gas recognition system through the power management unit. Thus, the power management unit is designed to control the power supplies for different power domains by three states, including the idle state, data-retention state and execution state. For decreasing the energy of memory, the overall gas recognition system is operated at 0.5V in the execution mode. Furthermore, the near-threshold SRAM is operated at 0.3V to reduce the leakage power in the data-retention state. However, a fully-integrated on-chip voltage regulator (VR) is required to generate 0.3V. Therefore, a digital linear VR [13] is utilized for different power domains.

For further achieving leakage current reduction, a CMOS-compatible low voltage embedded ReRAM is also adopted for the reference library in the gas recognition system as shown in Fig. 12. The ReRAM is turned on when accessing data only. However, a boosted voltage is required for the write operation of the embedded ReRAM, and the latencies of read/write operations in ReRAM are much larger than those in SRAM. Fortunately, the required speed of the gas recognition is quite slow, and the reference library is updated unfrequently. Thus, the embedded ReRAM would not cause any speed penalty in this gas recognition system. Thus, the pseudo-zero-leakage structure can be implemented for the event-driven gas recognition system by the nonvolatile ReRAM.

These two energy-efficient gas recognition systems are simulated and implemented by TSMC 65nm low power (LP)
process. The supply voltage and the frequency of the system clock are 0.5V and 50k Hz, respectively. Fig. 13 presents the energy breakdowns for the standby energy and active energy in the same period, respectively. The power management unit and ETWC should be turned on all the time to ensure the data retention and wake up the whole system. Based on the event-triggered power control, the recognition block can be turned off during the data-retention state and idle state for reducing the energy significantly. For the near-threshold SRAM, the leakage current can be further reduced in the data-retention mode if the voltage is decreased from 0.5V to 0.3V. To apply dual voltages for the SRAM, however, the energy overhead of the VR dominates the overall standby power in the data-retention state. Although the quiescent current of the VR used in this system is only 2.7μA, the energy overhead of the VR cannot cover the energy reduction of the small SRAM. In the system with the low-voltage embedded ReRAM, all blocks except ETWC is powered-off in the data-retention and idle states. The average energy of the near-threshold SRAM is only 5.82pJ for each read or write access, and the leakage current of this SRAM is also small compared to other SRAM designs. Compared to this near-threshold SRAM, the read/write power of ReRAM is much larger. Especially, when the supply voltage decreases, the write energy of ReRAM increases significantly. However, the reference library is seldom updated. Thus, the active energy of ReRAM is also lower than that of SRAM.

The overall energy consumption in a sample period is also analyzed as shown in Fig. 14. During a sample period, the gas recognition system is only operated in the execution state within a short time. In view of this, the leakage currents induce great amount of energy consumption. The energy consumption of the system with dual-supply SRAM is largest because the overhead of the on-chip integrated VR. Without this on-chip VR, even though the leakage current of SRAM increases, the energy decreases significantly. The energy of the system with ReRAM is 4.2x lower than that with SRAM because the zero leakage of nonvolatile ReRAM. Therefore, a pseudo-zero-leakage gas recognition system can be realized by the event-driven power control with the embedded ReRAM.

VI. CONCLUSIONS

An event-driven pseudo-zero-leakage recognition system is presented in this paper by the latency coding and on-line training techniques. Based on the energy-efficient algorithm-architecture co-design considering the trade-offs among power, delay and accuracy, this gas recognition system can achieve 100% recognition accuracy. Additionally, this gas recognition system can also recognize four different gases with concentration information by drift-insensitive on-line training, achieving 89.4% accuracy on the concentration analysis. For further reducing the overall energy consumption, both near-threshold SRAM and low-voltage embedded ReRAM are integrated into the proposed system with the event-driven power control, respectively. Based on TSMC 65nm LP CMOS process, the total energy of the gas recognition systems with SRAM and ReRAM are only 8.62μJ and 2.04μJ in a sensing period, respectively. The energy of the system with ReRAM is 4.2x lower than that with SRAM because the zero leakage of nonvolatile ReRAM. Hence, a pseudo-zero-leakage gas recognition system can be realized by the event-driven power control with the embedded ReRAM.

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