Proceeding Paper

CMOS-MEMS Gas Sensor Dubbed GMOS for Selective Analysis of Gases with Tiny Edge Machine Learning [†]

Adir Krayden, Maayan Schohet, Oz Shmueli, Dima Shlenkevitch, Tanya Blank, Sara Stolyarova and Yael Nemirovsky *

Electrical Engineering Department, Technion—Israel Institute of Technology, Haifa 3200003, Israel; adir-krayden@campus.technion.ac.il (A.K.); maayan-s@campus.technion.ac.il (M.S.); shmueli@ee.technion.ac.il (O.S.); dima@todos-technologies.com (D.S.); tblank@technion.ac.il (T.B.); ssstolya@technion.ac.il (S.S.)

* Correspondence: nemirov@ee.technion.ac.il

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Abstract: Embedded machine learning, TinyML, is a relatively new and fast-growing field of ML, enabling on-device sensor data analytics at low power requirements. This paper presents possible improvements to GMOS, a gas sensor, using TinyML technology. GMOS is a low-cost catalytic gas sensor, fabricated with the standard CMOS-SOI process, based on a suspended thermal transistor MOS (TMOS). Exothermic combustion reactions lead to temperature increases, which modify the suspended transistor's (used as the sensing element) current-voltage characteristics. We were able to use GMOS measurements for gas classification (both for gas types, as well as concentration), resulting in high–proficiency gas detection at a low cost. Our preliminary results show great successes in the detection of ethanol and acetone gases. Moreover, we believe the method could be generalized to more gas types, concentrations, and gas mixes in future research.

Keywords: TinyML; MEMS; gas sensor; SOI; MOS; data analytics; classification; machine learning; Edge Impulse; Arduino

1. Introduction

Since the 1980s, CMOS has remained the dominant microelectronics technology, for well-established advantages. CMOS technology maintains the essential advantages of low power consumption, high noise tolerance, wide operating voltage, and operating temperature range. Furthermore, it has rapidly and continuously improves the integration degree and intrinsic speed. Therefore, CMOS technology has become the most important technology in VLSI [1,2].

CMOS MEMS are micro-machined systems in which MEMS devices are integrated with CMOS circuitry on a single chip to enable miniaturization and performance improvement. With advancement of both CMOS and micromachining technologies, CMOS MEMS have also evolved tremendously in recent years [3–5].

In recent years, the need for mobile, low cost and low power gas sensors, has increased dramatically. Such gas sensors are needed for safety at homes and cars, monitoring air quality, well-being of people as well as industrial process control and precision agriculture.

The need to achieve digital scent technology, namely a technology to sense, transmit and receive scent-enabled digital media (such as motion pictures, video games, virtual reality, extended reality, and music) has been recognized as highly challenging.

This challenge has motivated the authors to focus on CMOS-MEMS technologies and the result is a new pellistor-like sensor dubbed GMOS. Since the first report in 2018, several papers describing the GMOS have been reported by the same group [6–8].

The main uniqueness of the GMOS is its ability to detect selectively different gases. Selectivity is achieved by measuring a fundamental physical property- heat of exothermic reaction and ignition temperature; Instead of measuring relative changes of resistance, as in Metal Oxide Semiconductor gas sensors. Thus, enabling selectivity (see also Section 2).

In real-life applications, there is even a more challenging task: to measure selectively mixtures of gases. This study focuses on adding tiny edge machine learning to enable better analysis of gas mixtures.

The focus of this paper are the improvements we are adding to GMOS using TinyML technology for gas detection.

This paper is outlined as follows: Section 2 briefly describes the GMOS design and operation principles. Section 3 describes the tiny edge revolution, which makes the GMOS smarter by applying ML techniques based on the TinyML [9,10]. This paper presents the full system we built and describes our preliminary classification task. Section 4 provides our preliminary results, and last but not the least Section 5 states our conclusions, based on our results.

2. GMOS Design and Operation Principles

GMOS is a tiny combustion-type gas sensor, based on CMOS-SOI technology. The sensing element, a suspended MOFSET transistor, operates at subthreshold, and therefore requires low power consumption. In contrast to MOX sensors where the sensing element directly interacts with the gas, in GMOS the sensing element (the transistor) does not. Therefore, the sensor has potential for long-term stability.

Due to chemical reaction of gas combustion on a catalytic layer, the temperature change modifies I–V characteristics of the sensing element (transistor). GMOS is operated at the transition temperature between surface-controlled and diffusion-controlled transport, defined by the inflection point T^*. Since the temperature region of the steep increase (transition region) is characteristic for a specific combustible gas and a certain catalyst (e.g., Pd, Pt), selectivity may be achieved. For different gases and the same catalyst, the transition region can be observed at different temperatures. Furthermore, an array of pixels with different catalytic layers, each operated in its T^* temperature tailored for specific gases, allows specific detection of mixtures of gases [6–8].
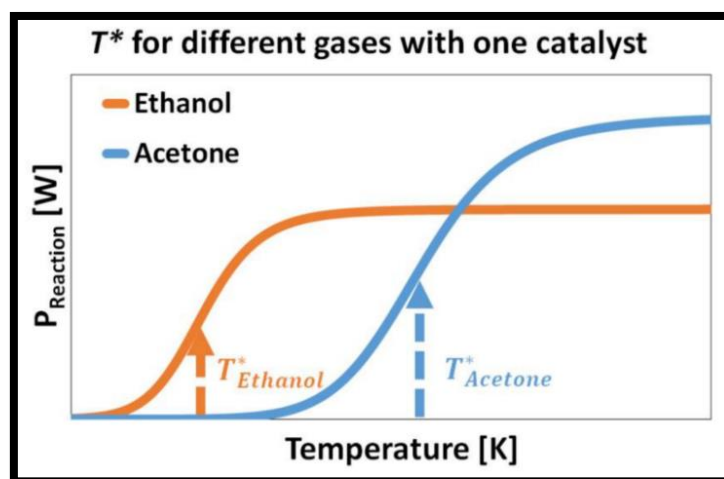
Figure 1. Comparison between Ethanol and Acetone gases. For the same catalyst, different T^* are obtained.

3. TinyML for Gases Analysis

3.1. TinyML Presentation

Tiny Machine Learning (TinyML) is a relatively new and fast-growing field of research (due to modern hardware capabilities), which combines embedded systems and machine learning. The field integrates, reduces and optimizes machine learning applications that require "full-stack" (hardware, system, software, and applications) solutions, including machine learning architectures, techniques, tools, and it approaches capability of performing on-device analytics at the very edge of the cloud [10]. Such technology enables ML applications on devices, which are power and resource constrained, and cheap—there is no need to send data to the cloud which would add latency to the system.

3.2. Gas Detection Using GMOS and TinyML

We built a full system comprising a GMOS sensor, an Arduino-nano controller, and LED bulbs. The system operates on the GMOS output, and analyzes it using a pre-trained neural network written to the Arduino controller. Finally, the neural network outputs a classification of the detected gas, and the verdict is displayed using the LED bulbs.
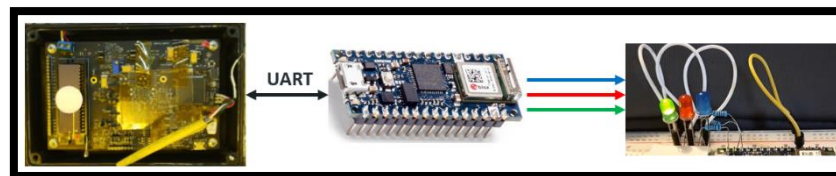
Figure 2. A schematic depiction of the full system: An Arduino controller requesting samples from GMOS over UART and lights a LED bulb according to its gas classification.

We focus on voltage measurements, where the sensing element's voltage changes due to the chemical reaction. Contrary to the assumption that the difference between varied gases is the heat of exothermic reaction and ignition temperature, we did not look at the voltage graph of the GMOS output while igniting the gas. Rather, we looked at the voltage graph after it had stabilized. As a result, we could make use of additional information received by the sensor, which had not previously been used.
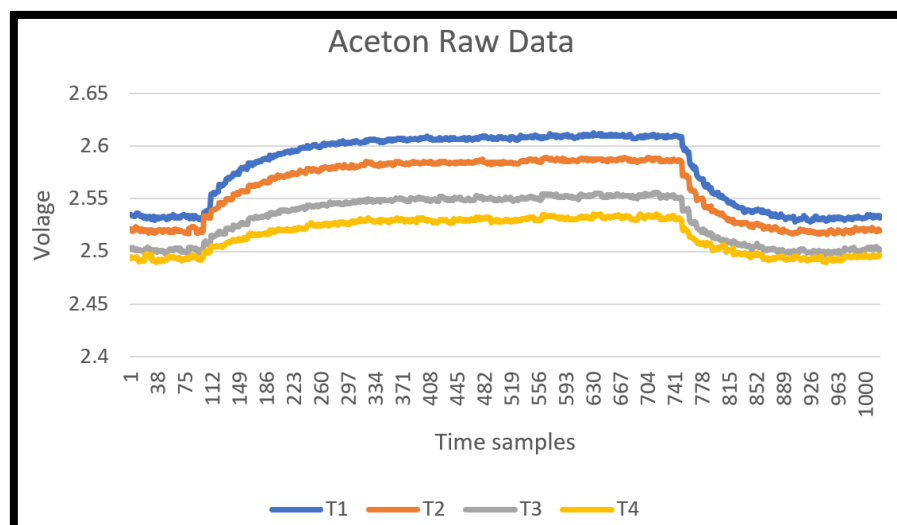
Figure 3. A GMOS reaction in the presence of 100 PPM Acetone, sampled.

We should note that GMOS's output is always relative to its initial output voltage (the reference voltage, the voltage before adding the gas to the sensor environment) so the

actual value of the voltage is probably of minor importance. Our samples were acquired with different reference voltages and hence we started by pre-processing the raw data so all samples would start from an initial voltage of 2.5V.

In order to train the system, we had used the Edge Impulse interface. We uploaded the data, after it was pre-processed, to the Edge Impulse application. We tried different features and network architectures to get good separation between the classes we had defined.

The communication between the GMOS and the controller is carried out over a UART (Universal Asynchronous Receiver Transmitter) channel. The written code on the controller includes 4 main modules:

- Controller requests data from GMOS sensor.
- Raw data preprocessor.
- Feature extraction and inferencing (created using Edge Impulse tools).
- Output display.

The controller sends a request to the GMOS sensor to sample data. The current data size used as an input into the TinyML system is 1 × 24. When 24 samples are collected into the controller, the data is pre-processed by the controller in the same manner that samples were pre-processed during system training. Then, features are extracted from the raw data, and transmitted as an input to the neural network.

The output vector size of the neural network is 1 × 3, where each value represents the probability of fitting to a corresponding class.
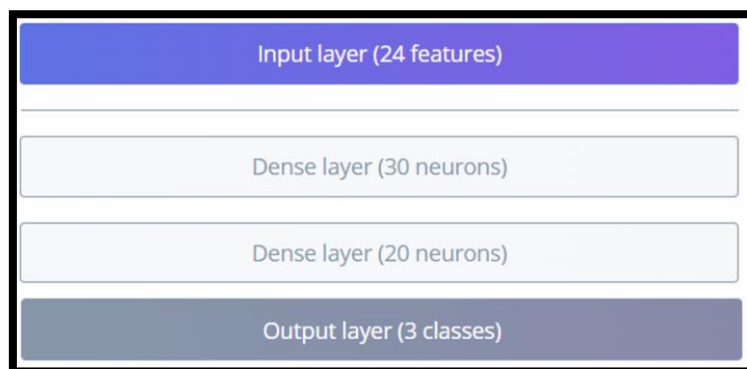
Figure 4. The fully connected neural network architecture: includes an input layer (1 × 24), two hidden layers (30, 20 neurons) with ReLU activation functions, and an output layer (1 × 3) with a Softmax activation function.

The training algorithm includes 80 epochs (number of training cycles) and the learning rate is 0.005.

We currently support two ways of displaying the classification results. We can display the output on a screen (using the Arduino platform). Additionally, to fit the full system in a tiny size, we also used LED bulbs, where each LED that lights up indicates a different classification identified by the system.

3.3. Proof of Concept Using Preliminary Classes

Our preliminary work focuses on Acetone and Ethanol gases. Our first objective was to classify into one of the following classes:

- Ethanol—100 PPM
- Acetone—100 PPM
- None of above (no gas was inserted)

The features that were chosen for this classification task allowed us to achieve a good linear separation between the classes.

One of those features, for example, was the standard deviation across time within the same temperature. As shown in Figure 4, the three classes may be separated.
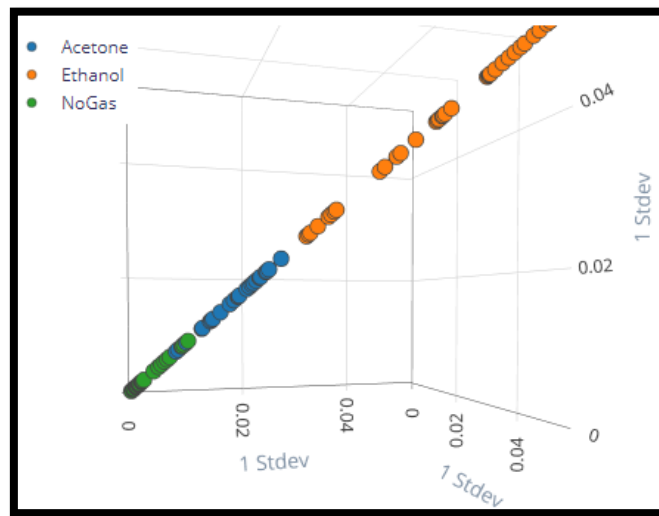
Figure 5. Standard deviation feature on a minibatch. Good separation was achieved (little overlap between Acetone and 'No Gas' classes).

4. Experiment and Results

The samples were taken from GMOS. They were divided into three subsets, which are the training, validation, and testing data sets. The raw data was preprocessed, and then features were extracted. We have checked the system performance on our test set, after training on our training and validation sets.

	ACETONE	ETHANOL	NOGAS
ACETONE	100%	0%	0%
ETHANOL	0%	100%	0%
NOGAS	0%	0%	100%
F1 SCORE	1.00	1.00	1.00

Figure 6. The confusion matrix. 100% success was achieved on the test set.

We can see that the samples were perfectly classified. Additionally, the computational cost is quite low, as required, due to our current shallow neural network. The RAM usage is 1.7 K, the Flash usage is 19.8 K and the added latency to the system is 1 ms.

5. Conclusions

This paper demonstrated the possible improvements for GMOS using TinyML technology. We have built a full system which enables sampling data from GMOS as input, and outputting gas detection at the other end. A preliminary classification model was created from GMOS measurements with high score on our test set. We believe that this proof of concept shows that this system may help and improve the GMOS sensor. Future work may use more samples from a variety of gases and concentrations, as well as gases mixtures, in order to solve more complex classification tasks, hence make the GMOS sensor smarter with TinyML.

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