TruffleBot: Low Cost Multi-Parametric Machine Olfaction

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Abstract*— This paper presents a low-cost, open-source platform for enhanced electronic olfaction designed to expand on traditional chemical sensing and odor discrimination techniques. The *'TruffleBot'* contains an array of chemical, pressure, and temperature sensors and interfaces with a microprocessor to facilitate data acquisition. By combining this sensor board with a temporally-modulated vapor transmitter and then simultaneously pumping chemical vapor through four chemically selective columns, we acquire spatial and temporal information that significantly enhances classification of odor. Using only chemical information, we demonstrate 91% cross-validated odor classification accuracy for nine analytes. With the addition of time series features from pressure and temperature data, the *TruffleBot* classification accuracy increased to 95.8%. TruffleBot italicized in abstract, but nowhere else - should be consistent I think.

***Keywords*— electronic nose, artificial olfaction, odor classification, flow modulation**

I. Introduction

A sense of smell is one of the most fundamental ways that animals interact with the world. Chemical molecules in the air come in contact with the olfactory receptors in the nose, generating signals which the brain decodes in order to identify the odor. Yet modern neuroscience has recognized that the brain takes advantage of many types of non-chemical information when analyzing an odor, including temporal, spatial, mechanical, hedonic, and contextual correlations [ref]. Conversely, engineered chemical sensors may not take full advantage of this ancillary information. Electronic noses (e-noses), for example, often specifically correct for the influence of humidity and temperature, which removes contextual information from the chemical classification [ref].

Most implementations of e-noses comprise an array of chemical sensors which are analyzed in parallel at discrete points in time to determine chemical presence or absence. E-noses are widely employed across military, industrial, food processing, chemical, medical, and environmental sciences [**?**]. There exists a wide range of potential applications for devices exhibiting increased sensitivity and/or accuracy. These applications range from explosives, threat and disease detection to environmental monitoring (e.g. harmful benzenes or carbon monoxide). Advances are being sought out and many experiments are being performed using gas chromatography, optical sensors, and spectrometry [ref], but this avenue of pursuit has little to do with modeling the biology and mechanics of olfaction.

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In this paper, we describe the design and functionality of the TruffleBot. The TruffleBot consists of both chemical and mechanical sensors to improve the sensitivity of a chemical sensing system over that of traditional e-noses by extracting additional features from the vapor plumes. We show that these multidimensional signals are dependent on numerous chemical and physical properties that are unique to particular chemical vapors. Using spatio-temporal signatures will increase the performance and accuracy of chemical sensing while reducing overall costs.

II. System Architecture and Design

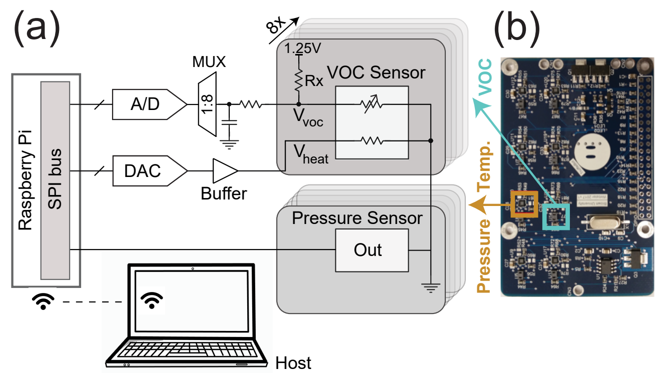

Fig. 1. (a) Schematic of Chemical Sensing Circuit. Analog VOC sensors are sampled via a multichannel A/D converter. DAC output controls the heater voltage in the VOC. Pressure sensors are digital. (b) Topview of the TruffleBot. Individual pressure sensors (brown) and VOC sensors (cyan) are adjacent to one another and are arranged in 2×4 columns.'Temp.' in b, but not a is confusing

The TruffleBot is designed to be a versatile, remotely deployable sensor board and as such has a small footprint of just 55 cm x 85 cm — the same size as a Raspberry Pi. Figure 1 depicts the salient components of the board along with key components in the system setup. An array of eight sensor dyads are arranged in two rows of four with each dyad containing one Volatile Organic Compound (VOC) sensor and one pressure sensor. The pressure sensors are digital and communicate with the microcontroller via Serial Peripheral Interface (SPI) lines. The analog VOC sensor outputs are filtered and routed to the ADC on individual inputs. They share a common reference on the ADC for measurements. The ADC in turn is connected to the microcontroller over the same SPI bus. The microcontroller supplies 5V and 3.3V to the TruffleBot eliminating the need for an additional external power source. A 2.5 V reference diode generates the differential reference for the ADC and a resistor divider along with an op-amp used as a buffer produces the 1.25 V for VOC sensor reference. The TruffleBot can generate transmission patterns by switching 5 V lab devices such as air pumps or solenoids via its on-board programmable transistors or can similarly control devices via the USB ports on the microcontroller (the VISA protocol is supported currently by the host application).

The VOC sensors are AMS CCS801 VOCs - metal-oxide sensors (MOX) with integrated variable heaters. The heaters inside all of the VOC sensors are fed from a common buffered DAC output which can be varied to adjust the responsiveness of the sensors. The ADC supports sampling the complete array of VOC sensors at a maximum rate of 4374 Hz. The pressure sensors are ST LPS22HB MEMS sensors. The LPS22HB is a digital sensor which measures absolute pressure with a maximum sample rate of 75 Hz and contains an on-board temperature sensor. Each pressure sensor shares the common SPI bus but utilizes its own chip select line.

For each cycle when sampling, the client program selects the ADC, and has it cycle through each of its eight inputs to record all of the VOC sensor outputs. Next, it selects each pressure sensor in turn and records their pressure and temperature values. In practice the sampling rate of the TruffleBot is limited by the SPI access times of the microcontroller and software and we found the maximum rate to be 54 Hz.

The host computer communicates with the clients over a local area network which may be wired or wireless depending on the feature set of the chosen microcontrollers implemented as clients. Each client is assigned a static IP address and can be designated as either a data collector, signal transmitter, or both via the host's configuration file. The host program initiates the experiment by broadcasting to all clients a *begin* command for data collection and/or signal transmission. When the experiment is concluded, the host downloads each client's dataset and compiles them all into a single HDF5 file for processing and analysis via MATLAB.

III. Results

A. Sensor Performance

The sensors were individually tested by emitting analyte vapor for a brief period of time in a continuous stream of pressurized air directly over the sensors. Fig.2 shows the sensor response to a 5 second emission of beer (5% ethanol). The effects of vapor emission are evident in all sensor signals. As VOCs are detected, the differential voltage across the VOC sensor decreases changing the output voltage from the sensor. The output of the VOC sensor is scaled with respect to the VOC reference voltage (1.25 V in our case) and a positive output in VOC sensor [awkward term, but I'm not sure what would be better] indicates that a volatile organic compound is present. Pressure and temperature sensors are mechanical sensors that show signal variation based on physical properties of the vapor such as vapor pressure, density, and molecular weight. Release of beer composites decreases the overall pressure and increases the temperature. However, these changes vary in scale and magnitude depending on the physical properties of the analyte composites (see Section III). Sensor readings steadily

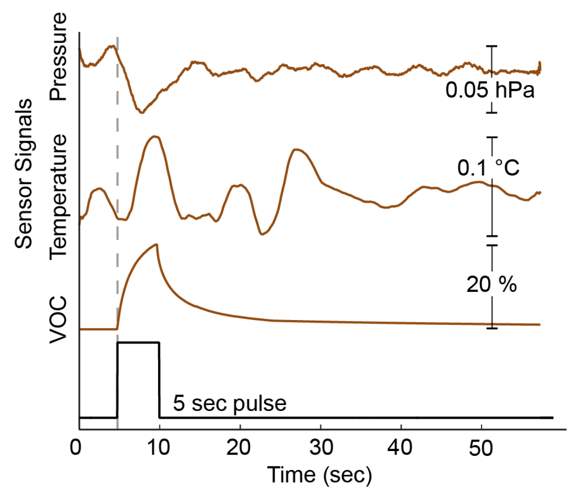

Fig. 2. Sensor response for a single sensor node to beer (5% vol). Low bit in the pulse (black) represents a constant flow of clean air at 850 sccm. A digital high forces ethanol vapor along with compressed air over the sensor node for 5 seconds. VOC sensor signal has a better signal-to-noise ratio and has a positive output only when VOCs are detected. It is expressed as the ratio of change in voltage with respect to sensor reference voltage. Average temperature and pressure were 25°C and 1018 hPa when the vapor transmitter was off. Output of the pressure and temperature sensors are dependent on the physical properties of the analyte vapor.

return to atmospheric values when emission ends. Since ambient conditions like temperature, pressure, and humidity are not strictly controlled, pressure and temperature readings show significant background deviations and drifts over time.

B. Response to different chemicals

Experiments were performed in the test bench shown in Fig.3. A three-way solenoid valve (Takasago CTV-3-1/4UKG-S) uses a binary data stream to toggle the flow of chemical vapor in the system, with bit 1 pumping chemical vapor to the sensor board. Using a pseudorandom binary sequence, we then introduced a temporal structure into the vapor flow. The analytes used in these experiments were apple cider vinegar, lime juice, beer (5% vol), vodka (40% vol), wine (chardonnay, 13% vol), pure ethanol, pure isopropanol, and acetone. A manifold splits the fluid flow through four different polyvinyl columns with various obstacles before reaching the sensors array. These obstacles are analogous to the concept of using multiple columns with different polymer composites [ref]. The flow rate was controlled using a variable area flow regulator. The setup allowed us to change parameters including the overall airflow, temporal structure, test analyte, and columnar arrangement. The analytes were

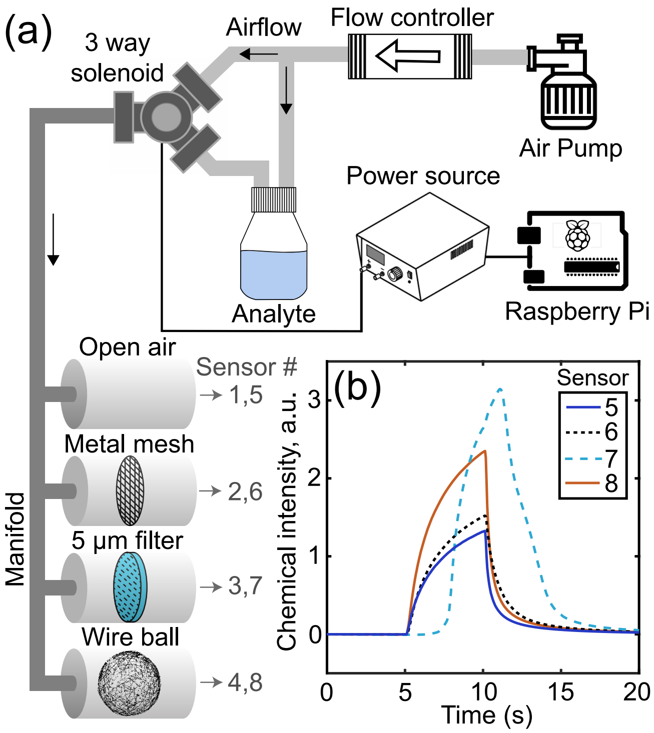

Fig. 3. (a) Experimental setup for modulated release of chemical vapor. The solenoid output is digitally controlled and switches between clean air and analyte vapor. Output flow is then divided across four columns with different barriers as indicated. (b) Discrete shapes and porosity of barriers alter flow in each column resulting in different VOC sensor signals.column order is reversed. will fix

chosen based on differences in their physical properties and composition. Figure 4 shows a comparison of sensor responses to modulated release of ambient air, vodka and pure acetone for a period of 20 seconds. Since net flow rate is controlled, ambient air readings (red) represent average background fluctuations and are not associated with transmission pattern. Background fluctuations are mainly caused by noise and uncontrolled parameters like environment temperature, humidity and pressure. Assuming a lossless system with fixed volumetric flow, total pressure in each column head can be represented as

$$P_{OFF} = P_{ATM} + P_{Pump} \tag{1}$$

$$P_{ON} = P_{ATM} + P_{Pump} + P_{Analyte} \tag{2}$$

where P_{ON} is the total pressure when the chemical transmission is on, P_{Pump} is the regulated pressure from the air pump, and P_{ATM} and $P_{Analyte}$ are the partial pressures exerted by atmospheric air (mostly nitrogen) and analyte vapor respectively. According to the Darcy-Weisbach equation, Newtonian fluid flowing through a cylindrical tube experiences pressure drop given by

$$\Delta p = \frac{\rho f L v^2}{2D} \tag{3}$$

where ρ is the fluid density, v is the fluid velocity and f, L, D are friction coefficient, length and diameter of the tube respectively. Since the volumetric flow is controlled and tube properties do not change, Δp is only depends on ρ. Thus an analyte with vapor density greater than air (1 g/cm^3) would incur more pressure loss in the tube resulting in decrease of average air pressure. For example, as seen in figure 2 and figure 4, aggregate pressure readings decreases during release of beer (ρ= 1.05g/cm^3) but increases for vodka (ρ= 0.95g/cm^3).

Similarly, these pressure changes along with other vapor specific properties the heat capacity causes fluctuations in temperature readings at different scales. This result is coherent to the idea that non-chemical sensor signals could contain features that improve chemical classification.

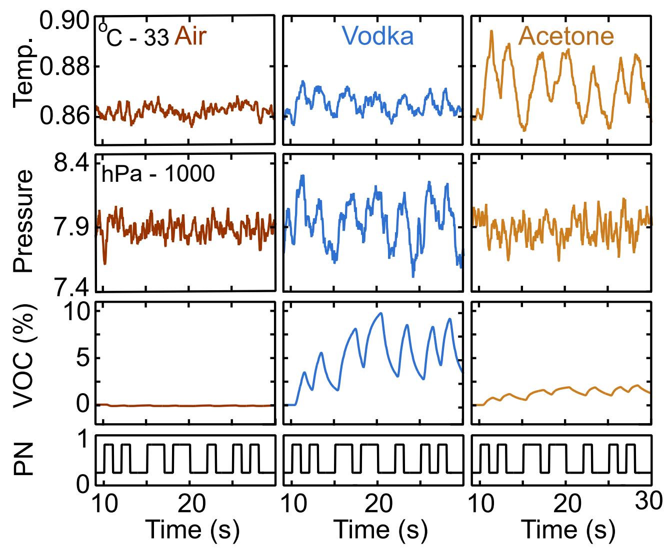

Fig. 4. Sensor readings for ambient air, vodka and acetone in presence of modulated chemical release. Temperature sensors record on-chip temperature values, which are usually higher than atmospheric temperature. Readings for air represent the ambient conditions. For vodka and acetone fluctuations in sensor readings correlate to the PN sequence used to transmit chemical vapor. However, temporal properties of the reading vary across analytes.

C. Analyte Classification

The layout of the sensor board and experimental setup supports extraction of temporal and spatial features. As seen in figure 4, signals from same set of sensors for two different chemicals show different temporal behavior. Using the setup in figure 3, a sequence of 40 pseudorandom binary bits was transmitted at 1 bit/second to collect sensor data for 9 different analytes. Figure 5 illustrates sensor data for individual analytes over 40 seconds. The first 8 rows (row 1 to 8) represent VOC sensor readings, followed by 8 rows of pressure readings and 8 rows of temperature readings. Depending on the chemical composition, distinct sensor types show signal variations that are correlated with the transmission pattern. Air readings provide a baseline by representing ambient conditions. Presence of non-VOC impurities in air correspond to constant VOC readings but show temporal fluctuations in mechanical sensors, perhaps due to aromatic compounds present in the mixture. For ethanol-based beverages and pure VOCs, change in MOX sensor readings is most evident. The VOC sensors are more sensitive to pure ethanol. So the contrast between VOC sensor readings in the three alcoholic beverages (beer, wine and vodka) mostly indicate the difference in ethanol concentrations.

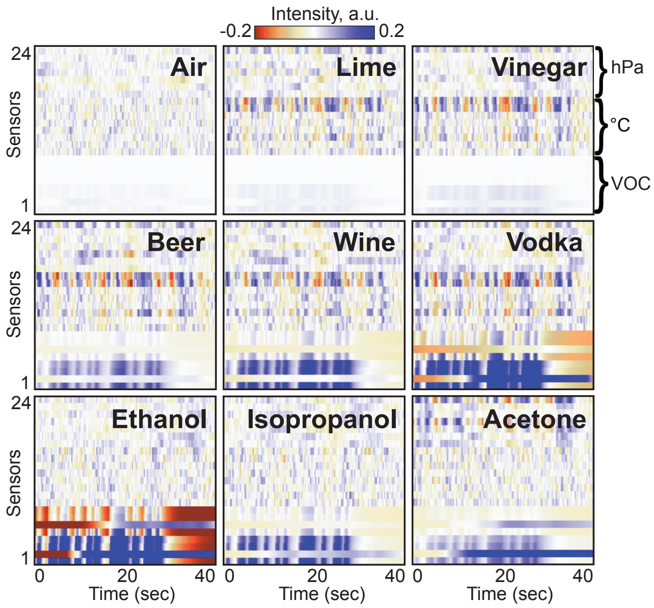

Fig. 5. Sensor readings to compare two analytes with ambient air (note: reading is intensity shift to intensity)

The experiment was repeated twenty times for each analyte. The time traces contained features unique to each analyte vapor. The feature vectors chosen for further analysis were 0.5 second windowed measurements of the mean, slope and standard deviation for each of 24 sensor time series. We performed principal-component analysis (PCA) on these features for the combined sensor data of all 9 analytes (Fig. 6). Even with a comparison of only the first two principle components, distinct, tightly grouped clusters emerged for each analyte. We then performed k = 2-fold cross-validation of our results using a simple k-means algorithm over 1000 iterations.

A cross validation accuracy of 90.9% was achieved using temporal signals from just MOX sensors and improved to 95.8% with addition of temporal features from temperature and pressure sensors. Addition of mechanical sensor readings reduced the error rates by a factor of two. The confusion matrix in figure 7 shows that false classification of lime as vinegar produces maxium error. This was expected from the overlaid PCA clusters for lime and vinegar (figure 6). Repeating the analyte classification without trials for lime gives a cross validation accuracy of 98.5%. Since significant error is caused by misclassification of a single analyte, results suggest that classification accuracy can largely improve with appropriate choices of analyte. The first principal component puts larger weights on VOC sensor signals resulting in higher

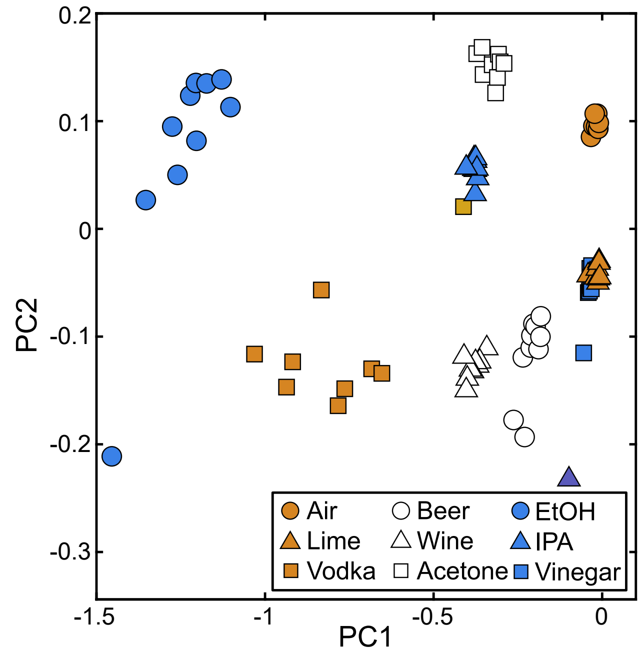

Fig. 6. First and second principle components of the sensor data for 9 analyte types

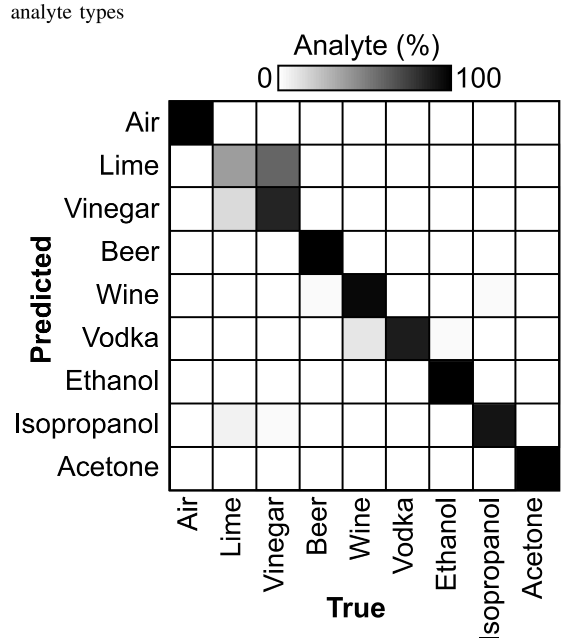

Fig. 7. Confusion matrix of the true analyte vs. predicted analyte percentage classification. Lime and vinegar are frequently conflated, but all other analytes show only minimal errors.

errors for analyte vapors that have similar time series for VOC sensor unless their physical properties are evidently different like clean air and vinegar.

Recent researches have designed multisensor arrays with varying sensor types and array sizes for odor discrimination. While non-selective chemoresistive sensors like metal oxides (MOX) are preferred for low-cost chemical sensing [ref], their performance as odor discrimination devices suffers compared to large-array carbon-nanotube field-effect transistors (CNFETs) and discrete electrochemical sensors [ref]. Using time series from only 8 sensor nodes comprised of

TABLE I

SENSOR ARRAY FOR CHEMICAL CLASSIFICATION

ref	Sensor Type	#Var	#Sens	#Class	Method	Acc
-	MOX & Mechanical	3	8	9	PCA	96%
[?]	MOX	1	12	5	PNN	88%
[?]	Chemoresistive	1	900	4	PNN	85%
[?]	Electrochemical	7	1	8	SVM	100%
[?]	CNFET	1	2048	7	PCA	100%

Jason, Please fix the reference numbers once they're done

MOX sensors and relatively cheap pressure and temperature sensors, we were able to extract multiple features over time and demonstrate a classification success rate that is comparable to other studies (Table I).

IV. CONCLUSION

We have presented a multi-parametric sensing platform for reliable chemical vapor discrimination. We have also shown that pressure and temperature changes are important parameters for analyte classification. By combining chemoresistive sensors with mechanical sensors in a multiple separation columns, this platform closely represents the mechanics of animal olfaction. Additionally, we use flow modulation to assert temporal characteristics to sensor data thus scaling the number of features that can be used for classification techniques by several factors. As a result, despite using a smaller sensor array, we have demonstrated better classification between chemical vapors.