Electronic nose for ambient detection and monitoring

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ABSTRACT

Our ambient air carries hundreds of volatile organic compounds that can provide information about the toxicity and hygiene of our immediate environment. This paper presents prototype electronic nose designs that integrate array of chemical sensors into the embedded system to detect volatile organic compounds in the ambient air. Two specific applications for the electronic nose of detecting food spoilage and identifying sources of indoor air pollutants are discussed. A system with three chemical sensors was tested with various food items at varying stages of spoilage. The presented results show that food spoilage can be detected with a high degree of accuracy. A second system with eleven sensors was tested with various household items that emit compounds known to have adverse effect to human health. The results show that with the considered sensor array, the tested sources can be identified with a high degree of accuracy. The presented designs are being further improved to achieve higher accuracies, further expand the compounds that can be identified for a broader range of applications, and to build a miniaturized hand-held electronic nose device. The system development, testing methodologies, and results analysis are presented and discussed.

Keywords: Smart sensing system, indoor air quality, electronic nose, ambient detection, sensor data analysis, embedded system

1. INTRODUCTION

Air borne compounds in our surroundings have been studied widely for applications ranging from health, defense, and household[1-3]. Volatile organic compounds emanated from our body and those from the headspace of samples have reported to have correlations with various diseases, and attempts have been made to utilize those compounds to diagnose diseases[4,5]. Volatile organic compounds in our ambient air that come from sources including household items, fungi, mold, and bacteria have been linked to various health related issues[6-9]. Prolonged exposure to these compounds can cause serious adverse effect to our health. Studies aiming at correlating these compounds with specific health conditions, including, diseases, have been reported in the literature[6-10]. In addition, volatile organic compounds emanated from food items have been studied for food spoilage detection[10,11].

This paper presents smart electronic noise designs aimed at identifying the sources of various indoor air pollutants and detect food spoilage to provide feedback to the user if the food is safe to consume. Current electronic noses consist of hundreds of non-specific sensors, and are bulky, costly, and not suitable for personal and household applications. The presented work aims to overcome those shortcomings by developing miniaturized hand-held electronic nose devices.

1.1 Electronic Nose

An electronic nose is an embedded system-based device with an array of highly sensitive chemical sensors and capabilities to collect, analyze, and interpret sensor data[1,-3,12,13]. The information is then communicated to the user, either on a display on the device or via other smart devices. Figure 1 shows a high-level block diagram of a smart sensing system electronic nose. One of the key aspects of a smart sensing system design is the selection of the sensors. The sensors need to be highly sensitive toward the target agents, while cross-selectivity is the key feature to consider [1-3,14]. The difference in the sensing properties of the sensors provides more information. The key goal is, to have sensors that respond differently to the target as well as artifact components, such that the presence, absence, or change in the components of interest can be differentiated from the artifacts. Adding more sensors provides more information for this differentiation. However, increasing the number of sensors increases computational resource needs, footprint, power consumption, and cost. Thus, an efficient design should consider using least number of sensors possible and selecting sensitive, cross-selective, low-power, and lower-cost sensors.

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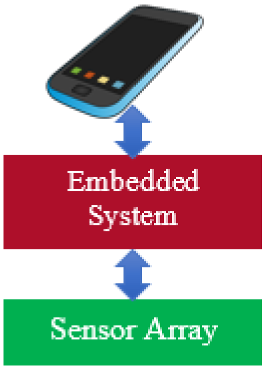

Figure 1. High-level block diagram of a smart sensing system electronic nose.

In many application scenarios, the system depends on battery power. In such cases, reducing power need at the sensor levels becomes one of the important design consideration. As many of the higher sensitivity metal oxide based sensors require heaters, this could quickly increase the power requirements. Two of the applications presented in the paper aim may not have strict power restriction when utilized as stationary monitoring device. However, in case of handheld and portable device application, power consumption needs to be considered carefully. Power efficient sensors were considered for the presented study.

This paper presents two specific application examples of the smart sensing system in development: Food Spoilage Detection and Identifying Sources of Indoor Air Pollutants. The background for these two applications consideration are introduced below.

1.2 Food Spoilage Detection

According to a recent study, 30-40% of all food in the United States is wasted[15]. In 2014 alone, 38 million tons food was wasted in the US. A major portion of the wastage includes food that is perfectly fine to consume. These foods end up in the waste because consumers are unsure if the food is safe to consume. This happens for several reasons, one of which is confusing food labels. As the cost of seeking medical treatment is much higher than the price of the food, many consumers opt to throw the food away.

1.3 Identifying Sources of Indoor Air Pollutants

Air quality issues are generally discussed with focus on outdoor air, however, studies have discovered that the air contaminants are in fact present at higher concentration in indoor air. There are various contaminants found in indoor air, and VOCs are common components. VOCs are organic chemicals that have higher vapor pressure under normal ambient conditions. There are numerous classifications of VOCs, which include both natural chemical compounds and synthetic products. In a study conducted by the United States Environmental Protection Agency (EPA) involving 650 subjects in four states, 20-25 different VOCs were found in the air, drinking water, and in the breath[6-8]. The study found that the VOCs levels in indoor settings were about 2 to 5 times higher than the outdoor settings. Some of these compounds are harmful to human health and have been linked to several types of cancers and other health problems such as allergic skin reaction, nose and throat irritation, headache, nausea, fatigue, dizziness, damage to liver, kidney, and nervous system, and others. These harmful VOCs can originate from several indoor sources, including household products such as paints, paint strippers and solvents, wood preservative, cleaners and disinfectants, insect repellent and controls, aerosol sprays, and pesticides. The presented work aims to identify some of the sources of these indoor air pollutants for future indoor air quality monitoring and improvement applications.

2. HARDWARE AND TEST PROCEDURE

2.1 Hardware

The sensors used in this work were obtained from commercial sources. The sensors were selected based on their ability to detect volatile organic compounds, ammonia, hydrogen sulfide, alcohol, solvent vapors, methane, propane, butane, and other compounds. Although the results are not shown here, a temperature sensor and a separate humidity sensor were used to measure ambient temperature and humidity. For food spoilage detection, three sensors were used. An Arduino Mega[16] was used for collecting data for tea versus coffee and spoiled versus fresh food. Mega was used because of existing setup for testing and data acquisition. Figure 2 shows a schematic of an electronic nose for differentiating between fresh and spoiled food. The circuit consists of a display to communicate the result to the user and a Bluetooth module to send the information to a smart phone for data logging and further analysis. However, system testing results are not included in the paper. For indoor air quality monitoring, the sensors were connected to an Arduino Micro[17]. Initially, four sensors were used and the system was tested with five components. Later, seven sensors were added and the system was tested with seven different components.

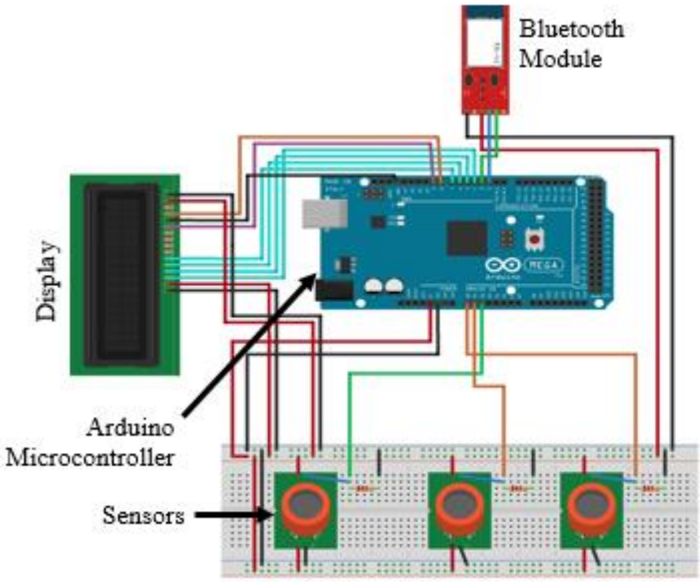

Figure 2. Schematic diagram showing various components of the electronic nose design for spoilage detection (drawn in Fritzing[18]).

2.2 Testing and Data Collection

The setup used for testing the sensors consisted of a container that enclosed the sensor array circuit and the test compounds. A representative schematic of the test set-up is shown in Figure 3. The sensor array was connected to an Arduino microcontroller, which in turn connected to a computer. The sensor data was recorded on the computer using a serial data acquisition tool, and was saved as text files. For food spoilage detection, test items were stored in airtight jars and the sensors were instead into the jars for testing. A separate jar was used for each of the items. The data was collected for two to three minutes, after which the sensors were removed and kept in the air for a time interval (resting-time) long-enough for the sensors to return to the initial state. The resting time varied between two to five minutes, however, this time duration was fixed for each type of experiment. For measuring indoor air pollutants, initially plastic bags were used as containers. The bags were discarded after each measurement. The testing with eleven sensors were carried with fixed containers, with a separate container for each component. Like the food spoilage testing, the sensors were introduced to the test components and the data was collected and saved on the computer for further analysis. For each test, the sensors were introduced to the test compounds for three to five minutes, followed by three to five minutes of resting-time. The measurement and the resting times were fixed for each experiment.

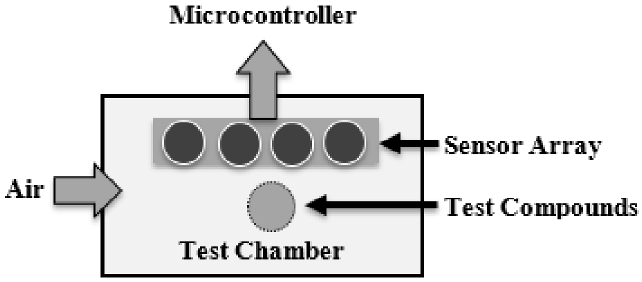

Figure 3. Schematic of the test set-up.

3. RESULTS AND DISCUSSION

The results for food spoilage detection and indoor air pollutant identification are presented and discussed in this section. Several data analysis techniques for sensor data were studied[19,20]. As the end goal of the work is to implement the developed analysis techniques in the embedded system-based device, the methods that are feasible to do so were selected for further considerations. The results presented in the paper uses principal component analysis (PCA) for initial analysis of all sensor data and for studying indoor air pollutants. However, other simpler methods such as the distance between training and testing data and the angle between the vectors represented by the data points were used for item identification and food spoilage detection.

3.1 Food Spoilage Detection

The developed sensors were tested for differentiating fresh versus spoiled food and to distinguish between food items. For food spoilage detection, the system with three sensors were tested for fresh and spoiled milk, strawberry, bread, and potato. These items were selected as representative for produce, fruits, bakery, and vegetables. However, a broader selection of food items is needed for better understanding of sensor responses for a widely applicable detection. Figure 4 shows the PCA analysis results with two principal components. The steady-state sensor values were used. The stars represent fresh food while the circles represent spoiled food. Each of the food items are indicated with a different color in the Figure. A relative separation of fresh food items from the spoiled is observed for milk, strawberry, and bread, however, they fresh and spoiled potato appears to be close to each other. It could be because potatoes take longer to spoil, and they may not have been spoilt well during this experiment. Results from a separate experiment were analyzed using the distance between the test values and the mean values for each fresh and spoiled item (known-data-set), taking three sensor values as three coordinates. The distance between the test vales and the known-data-set were calculated, and the result was associated with the item that is closest to the test item. The results are presented in Table 1. The first column shows the tested food items, and the following three columns show classification results for each test shown in abbreviation, as the food items were at various stages of spoilage. The accuracy of detecting each item and overall detection as the spoiled items are also shown. The data was also analyzed using the angle between the vectors created by the known-data-set and the test data. Results comparable to the previous method were obtained.

Results for differentiating between coffee and tea using three sensors data taken at steady-state are shown in Table 2. Four separate experiments were conducted and each data set was tested against the known-data-set. The result was associated with the item in the training data with the closest distance. This result was also analyzed using PCA and 100% accuracy in differentiating between coffee and tea was observed in each test case.

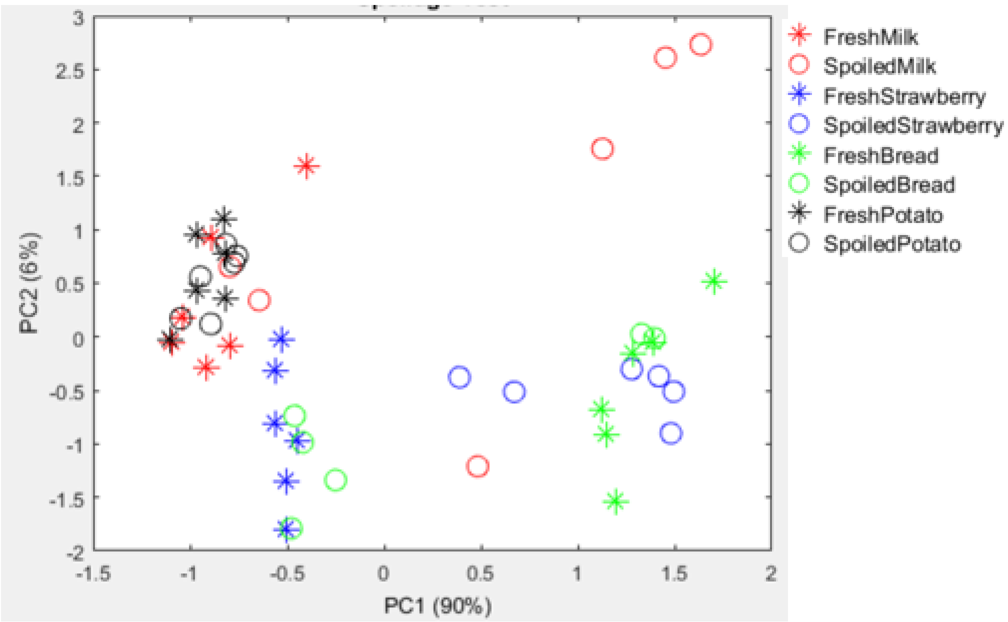

Figure 4. PCA analysis of milk, strawberry, bread, and potato tested over six days.

Table 1. Results for food spoilage classification results using the distance between the known-data-set and the test sensor values (FB: Fresh Bread).

Test/Classification (→) Test Substance (↓)	Day-2	Day-4	Day-7	Accuracy	Spoiled vs. Fresh
Spoiled Milk (SM)	SM	SM	SM	100%	100%
Spoiled Potato (SP)	SP	SP	SP	100%	100%
Spoiled Bread (SB)	FB	SB	SB	67%	67%
Spoiled Strawberry (SS)	SB	SB	SM	0%	100%

Table 2. Results for identifying coffee and tea using the distance between the known-data-set and the test sensor values.

Test/Classification (→) Test Substance (↓)	Test-1	Test-2	Test-3	Test-4	Accuracy
Coffee	Coffee	Coffee	Coffee	Coffee	100%
Tea	Tea	Tea	Tea	Tea	100%

3.2 Identifying Sources of Indoor Air Pollutants

As many of the indoor air pollutants stem from common household items such as cleaner and disinfectant, aerosols, paints, and bug and pest controls, the developed system was tested with representative household items. A system with four sensors was introduced to Air Freshener, Ant Control, Bug Repellent, Paint, Paint Stripper, and Wax Cubes. The PCA results showing first two principal components are presented in Figure 5. Each item is indicated with a different color while the blank is indicated with black circle. Each data point on the figure represents a separate test. Figure 5 shows that the first principle component carries 94% of the total variance. The results show separations between the tested items, however, more test would provide more definitive outcome. The distribution in Figure 5 overlaps for items such as Air Freshener, Paint Stripper, and Ant Control. For testing purpose, each data set was tested against a training set comprising of remaining of the data sets. The classification results and the calculated detection accuracies are shown in Table 5. The first column shows the test item, following four columns represent each separate test and the classification outcomes for each item shown with abbreviations. For example, "AF" represents Air Freshener. In the row for Air Freshener, an "AF" implies a correct classification, and any other item name indicate an incorrect classification. The results show that the detection accuracy for Bug Repellent is 100%, Paint and Wax Cubes are 75%, and 50% for the other items.

In later experiments, additional sensors were integrated to the system and was tested with Air Freshener, Ant Control, Bug Repellent, Cleaner, Lighter Fuel, Paint, and Paint Striper. The PCA results with first two principal components for ten experiments are shown in Figure 6. The tested items are indicated with different colors. Each star in the figure represent one experiment. The Blank is indicated by black circles. The sensor data was further tested for detection accuracy. Each test data was tested against a training data set comprising all sensor data except the one under test. The test results are presented in Table 6. As discussed previously, the first column shows the tested items and the following columns represent separate experiments with classification outcomes. In each row, if the outcome is same as the tested item, it represents a correct classification. The results show that the detection accuracy for Lighter Fuel, Bug Repellent, and Paint stripper are 90-100%. While the accuracy for Cleaner and Paint are only 30%. The low detection accuracy indicates that these items emit similar compounds. For example, the sensors appear to have confuse between Paint and Cleaner. If a test is conducted as Paint or Cleaner, the accuracy improves to 85%. This indicates that the detection accuracy can be improved by improving cross-selectivity of the sensor array. In addition, the detection accuracy can also be improved by improving the data analysis techniques, using different analysis methods, and by conducting additional experiments for more robust training sets.

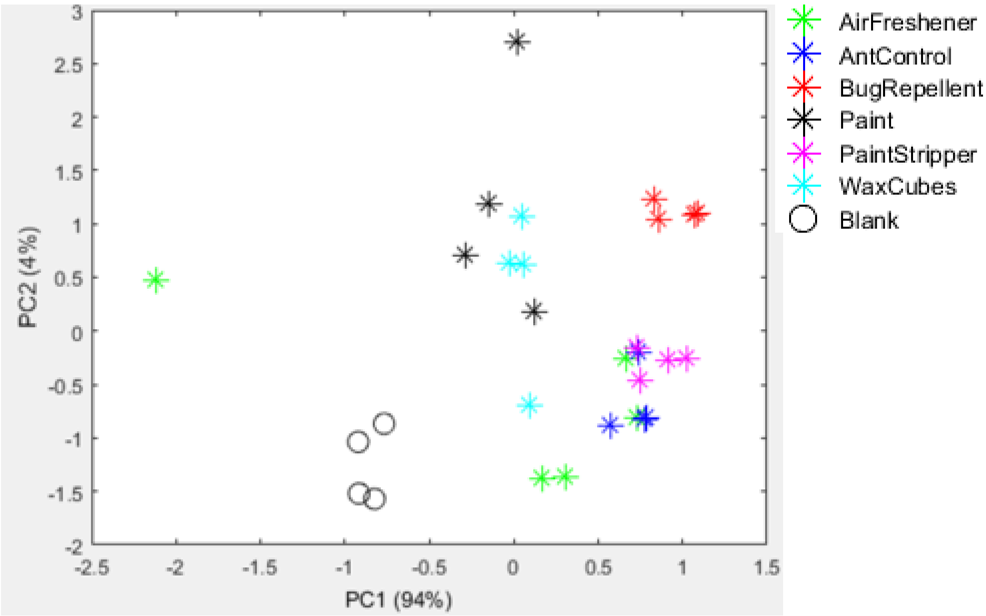

Figure 5. PCA analysis of four sensor responses tested for Air Freshener, Ant Control, Bug Repellent, Paint, Paint Stripper, and Wax Cubes.

Table 5. Results for item classification and detection accuracy from the sensor data collected with four sensors.

Test/ Classification (→) Test Substance (↓)	**1**	**2**	**3**	**4**	**Accuracy**
Air Freshener (AF)	AC	PA	AF	AF	50%
Ant Control (AC)	AC	AC	PA	AF	50%
Bug Repellant (BR)	BR	BR	BR	BR	100%
Paint (PA)	PA	WC	PA	PA	75%
Paint Striper (PS)	PS	PS	AC	AC	50%
Wax Cubes (WC)	AF	WC	WC	WC	75%

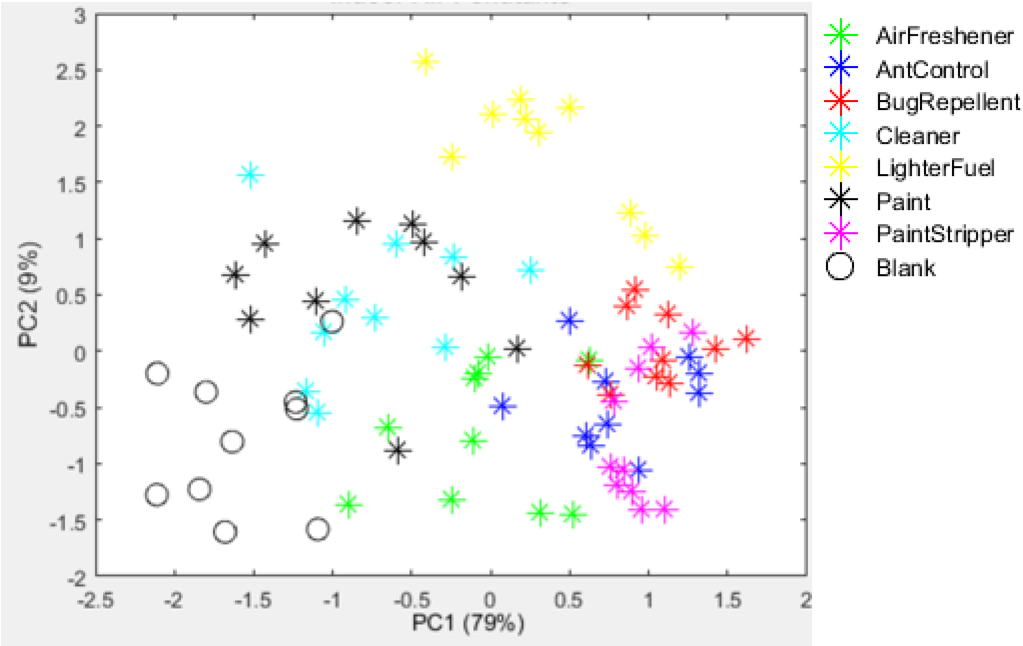

Figure 6. PCA analysis of eleven sensor responses tested for Air Freshener, Ant Control, Bug Repellent, Cleaner, Lighter Fuel, Paint, and Paint Stripper.

Table 6. Results for item classification and detection accuracy from the sensor data collected with eleven sensors.

Test/ Classification (→) Test Substance (↓)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Accuracy**
Air Freshener (AF)	AF	PA	AC	AC	PA	AF	AF	PA	AF	AF	50%
Ant Control (AC)	PS	AC	AC	AC	AC	AC	PS	AC	BR	PA	60%
Bug Repellant (BR)	BR	BR	BR	BR	BR	BR	BR	BR	BR	AC	90%
Cleaner (CL)	PA	CL	PA	PA	CL	PA	BA	PA	CL	PA	30%
Lighter Fuel (LF)	LF	LF	LF	LF	LF	LF	LF	LF	LF	LF	100%
Paint (PA)	CL	CL	AF	CL	AF	PA	CL	PA	PA	CL	30%
Paint Stripper (PS)	PS	PS	PS	PS	PS	PS	AC	PS	PS	PS	90%

4. CONCLUSIONS

Smart sensing system electronic noses for detecting food spoilage and identifying indoor air pollutants have been presented and discussed. The device for detecting food spoilage consisted of three chemical sensors designed around Arduino Mega embedded system. The device was introduced to four different fresh and spoiling foods over several days and the results were analyzed. It has been shown that each spoiled item as well as fresh versus spoiled food can be detected with high degree of accuracies. However, it has been identified that additional sensors, and further testing and analyses may be required to improve the accuracy as well as to detect a wider range of products. The device for identifying indoor air pollutants consisted of four to eleven sensors designed around Arduino Micro embedded system. The device was tested with seven common household products known to emit volatile organic compounds harmful to human health. The results show that the system could identify the items with high accuracies. The low accuracies for some of the items have been attributed to the fact that these items may have used common solvents and emit similar compounds. The accuracy can be improved by improving cross-selectivity of the sensor array, conducting additional tests for a more robust training data set, and improving data analysis techniques. The authors continue to work on improving these aspects of the presented systems, and the outcomes will be reported in the future.

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