Detection of Unwanted Odors using Unmasking Odor Algorithm (UOA)

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Abstract— A new approach to detection of the existence of unwanted odors after spraying the smart home and vehicular environment with perfumes is considered in the work. The approach is based on registering the response curve of an array of sensors to perfumes and to odors such as herbs, then using the proposed intersection algorithm to uncover the ability of the perfume to mask specific odors. Three odors (herbs) and three perfumes are tried and resulted in the ability of perfumes to mask two of the herbs, one deeper than the other. The response curve intersection technique (RCIT) provides the ability to unmask unwanted odor existence, thus forms the heart of the unmasking odor algorithms (UOA). Mathematical equations are used to prove the concept with digital logic is further used to support the presented algorithm. The research found that using the proposed technique, an odor masked by spraying of perfumes can be unmasked using the RCIT as the case in herb 3 presented in the work. The work also showed the unique curve shape for both perfumes and herbs and the fact that some herbs can be easily masked and hidden within the response of perfumes. In addition, it is shown that the perfumes response is much more complex compared to herbs.

Keywords— Odor Detection, Odor Classification, Chemical Sensors, Smart Vehicles, Smart Homes, E-Nose.

I. INTRODUCTION

SMELL is a common ability possessed by many organisms, which is very useful if replicated in artificial systems using sensing devices, by combining biologically based engineering elements, such as chemical and gas sensors. Thus, enabling applications in many areas such as medical, environmental, military, industrial, and recently automotive and smart city applications. The mammalian olfactory system, which is highly sophisticated, is the most sensitive odor detector. Due to the limitations of traditional instrumental techniques in the field of odors, odor measuring procedures now rely on artificial sensor-based detectors. [1], [2], [3], [4], [5].

The development of a smelling system that mimicked the mammalian biological system, in particular the human olfactory, was aided by the availability of materials with chemical-electronic properties. These sensor-based device can detect, extract, and distinguish between a wide range of basic and complicated scents. The used array of sensors response in a similar manner to olfactory receptors present in the human olfactory biological system, thus provide quality information regarding odors and their patterns with ability to classify them into categories [6], [7], [8], [9], [10].

In addition, data manipulation techniques are used to process incoming chemical-electronic signals, similar to how data is processed in biological systems. Association and correlation are used to achieve the goal of odor recognition. A wide range of competing sensor technologies with repeatable and reversible responses, ranging from polymers to metal oxide sensors are available for such applications.

Odors, and chemicals carry important information regarded as a fingerprint of each odor or chemical and its effect on the surroundings, other odors and chemicals. Such information should be extracted carefully and accurately using different sensors with good sensitivity, repeatability, selectivity, and accuracy. Such sensors are used are receptors that react to odor vapors, gases, and general chemicals in a process representing artificial olfaction or digital olfaction with the support of electronic sensors such as chemical resistors that gives the ability to classify odors, aromas, chemicals, gases and gas their mixtures.

There is a continuous interest in employing the mechanisms of the olfactory system in instruments capable of accurate and reliable odors detection and classification. Electronic Nose (E-nose) does provide such odor measuring system, which can mimic the human mechanism of smelling.

E-nose proved that it is capable of detecting smell effectively as it comprises chemical sensors(s), with applications in wide range of industries ranging from food, environment, biomedical, to cosmetics, transportation and military applications [11], [12], [13], [14].

E-nose is designed to recognize odors, gases, and aromas in a similar manner to human nose. Advantages of the E-nose are its capability to continuously sample odors without getting affected by human conditions and its ability to detect odorless chemicals and gases, by identifying a unique pattern or finger print for the detect substance. The E-Nose device built operates on the principles of voltage and electrical resistance change in response to detection of odor molecules. The signal produced as a result of voltage changes is processed through specific signal processing algorithms with pattern recognition capabilities. Examples of theses algorithms and techniques are: Genetic Algorithm, Neural Networks, Principal Component analysis, Linear Discrimination Analysis, Support Vector Machine, K-Nearest Neighbor Classifier, among others [15], [16], [17], [18], [19].

E-nose system comprises components for sensing and pattern recognition. The sensing system usually contains array of sensing elements, where they are subjected to odors and chemicals, which result in a specific response or signature that characterizes the detected components forming each element. Pattern recognition is needed to classify detected odors.

The main applications of artificial or digital olfaction are:

i. Quality of fresh and processed food, drinks and flavors, fruits and vegetables, meat and fish.

ii. Smart home applications with odor and aroma sensors placed round the house for air quality, food quality.

iii. Automotive applications, where Odor sensing technology in vehicles can assist in detecting bad smells inside the vehicle to helping in failure recognition through detecting odors for excess fuel, electrical wiring overheat, driver and passengers health problems among others.

Odor molecules are produced due to activity and energy variation, such as temperature, humidity, agitation. Each odor can be captured and detected by an array of odor, gas or chemical sensors. Most of the time people spray perfumes to mask odors, which interact with the present odor and produce a mixture of both.

In this paper, a new approach is proposed to extend odor sensing applications in the smart home environment and within the vehicular environment to enable identification of unwanted odors as a key to enable healthier living and cleaner vehicular environment irrespective of the existence of other odors that could modulate or mask the odor detection using a new approach of curve intersection to enable odor extraction from the surroundings, which is usually masked by the spray of perfumes. The method is tested on herbs and perfumes that are used to spray homes and vehicles.

The rest of this paper is divided as follows: Methodology, Results and Discussion, Conclusions, References.

II. Methodology

The main idea of this work is based on the hypothesis that to use the chemical sensor response curve in terms of shape functions and response times to in order to establish a process by which masking perfumes as a function of specific odors such as herbs can be determined through intersection of response curves.

An array of TGS sensors (TGS 822, TGS 813), are used in this work. The sensors are produced by Figaro and shown in Figure 1.

Figure 1. Sensing Devices by Figaro

The sensor array enables wider selectivity and more reliable odor feature extraction compared to a single sensor, with ability to pattern map more odors. The used TGS sensors uses Tim Oxide doped material ($SnO2$), where their conductivity changes dependent on the presence and type of odor, chemical, gas, or volatile compound there are subjected to. For stability and better detection, the sensors have printed heaters in their structure [20], [21].

TGS 822 is very sensitive to vapors of organic solvents and volatile compounds with ability to detect combustible gases, and operates reliably as a general purpose sensor. TGS 813 is very sensitive to methane, propane, butane in addition to combustible gases and works effectively as a general purpose sensor [22], [23].

The implemented RCIT in UOA algorithm is shown in Figure 2. The algorithm acquires odor and perfume responses and apply signal conditioning to the obtained signals. An intersection routine is applied to the sensors outputs and level of masking is deduced based on application of logical operators.

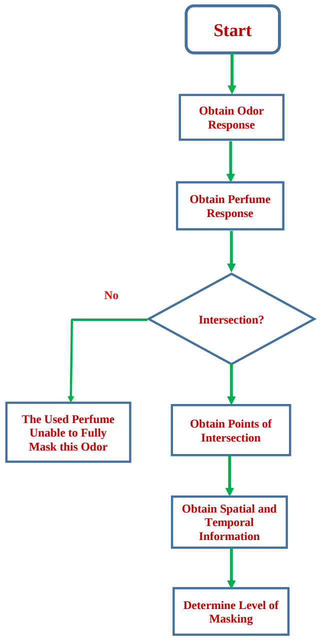

Figure 2. Algorithm used to determine effect of perfume masking on odors.

III. Results and Discussion

Tables I and II present initial results detecting herbs and perfumes where each value in the tables is a result of summation of 10 sampling points.

TABLE I
RESPONSE OF ODOR SENSING SYSTEM TO HERBS

	Sensing System Response (Volts)		
Exposure Time (Sec.)	Odor (1)	Odor (2)	Odor (3)
0.0	0.7	2.7	2.2
1.0	1.3	3.4	2.9
2.0	1.6	3.6	3.2
3.0	1.9	3.8	3.4
4.0	2.0	3.9	3.5
5.0	2.2	4.0	3.6
6.0	2.3	4.1	3.7
7.0	2.4	4.2	3.8
8.0	2.6	4.3	3.8
9.0	2.7	4.3	
10.0	2.7		

TABLE II
RESPONSE OF ODOR SENSING SYSTEM TO PERFUMES

	E-Nose Response (Volts)		
Exposure Time (Sec.)	Perfume (1)	Perfume (2)	Perfume (3)
0.0	1.8	2.0	1.5
1.0	2.3	2.8	2.5
2.0	3.3	4.0	3.0
3.0	5.8	7.0	5.5
4.0	7.0	7.2	6.7
5.0	7.0	7.2	6.7

Figures 3 to 8 present plots for the obtained data for herbs and perfumes. The slowdown in response for both herbs and perfumes and in general for any chemicals, gases, and odors, is a function of the sensitivity and rate of adsorption-desorption of odor molecules. In addition, such curve response rate is also dependent on the detection layer thickness (deposited film thickness), type and rate of extraction of odor smell out of the detection environment. In addition, equivalent circuit representation shows capacitive behavior, thus, speed of response and recovery is affected. When the response curve starts to reach steady-state, it indicates that saturation point is reached as the available surface area for chemical reaction gets smaller, until molecular extraction is carried out, then rate of response will increase again [24], [25], [26].

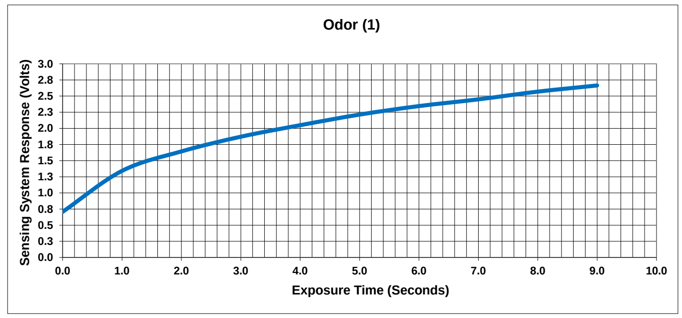

Figure 3. Sensing Systems Response to Herbs.

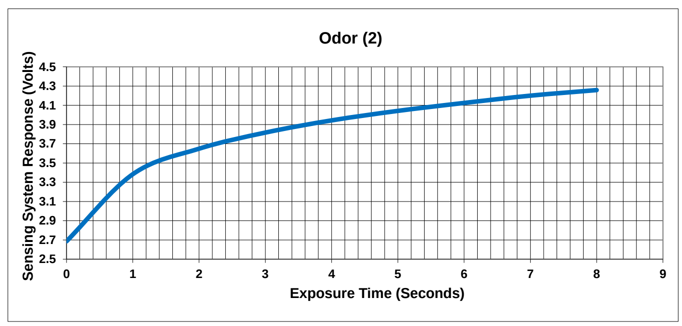

Figure 4. Sensing Systems Response to Herbs.

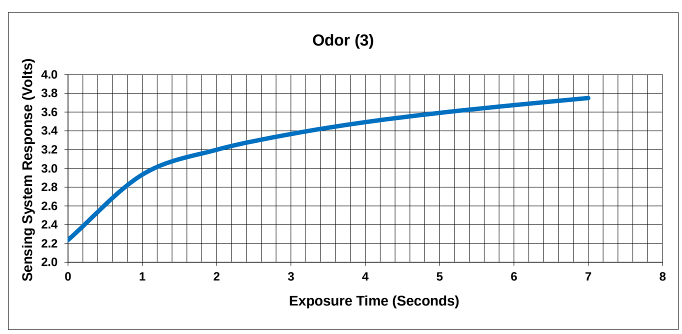

Figure 5. Sensing Systems Response to Herbs.

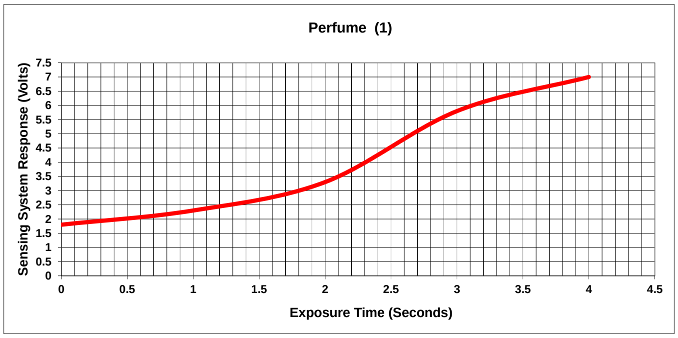

Figure 6. Sensing Systems Response to Perfumes.

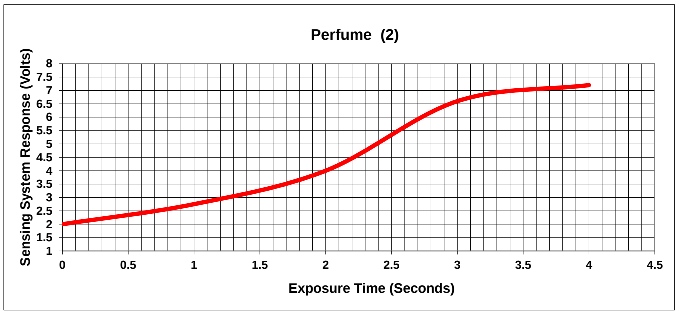

Figure 7. Sensing Systems Response to Perfumes.

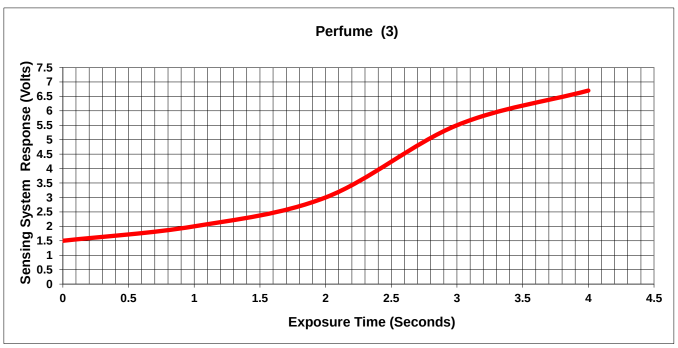

Figure 8. Sensing Systems Response to Perfumes.

Figures 3 to 5 can be represented by equations (1) to (3). Thus, the general used herb response in relation to time can be generalized as in equation (4).

$$SENSING\left(Herb(1)\right)_{(Volts)} = -0.022\,T^2 + 0.39\,T + 0.86 \tag{1}$$

$$SENSING\left(Herb(2)\right)_{(Volts)} = -0.029\,T^2 + 0.40\,T + 2.85 \tag{2}$$

$$SENSING\left(Herb(3)\right)_{(Volts)} = -0.037\,T^2 + 0.44\,T + 2.37 \tag{3}$$

$$SENSING\left(Herb(K)\right)_{(Volts)} = -\alpha\left(Herb(K)\right)T^2 + \beta\left(Herb(K)\right)T + \gamma\left(Herb(K)\right) \tag{4}$$

Where;
T: Response Time
K: Herb Sample Number

Figures 6 to 8 can be represented by equations (5) to (7) in the first part and equations (9) to (12) in the second part of the response curve.

$$SENSING\left(Perfume(1)_{Part1}\right)_{(Volts)} = 1.77\left(e^{(0.30T)}\right) \tag{5}$$

$$SENSING\left(Perfume(2)_{Part1}\right)_{(Volts)} = 1.98\left(e^{(0.35T)}\right) \tag{6}$$

$$SENSING\left(Perfume(3)_{Part1}\right)_{(Volts)} = 1.47\left(e^{(0.35T)}\right) \tag{7}$$

Thus, the general perfume response (Part1) in relation to time can be generalized as in equation (8).

$$SENSING\left(Perfume(j)_{Part1}\right)_{(Volts)} = \mu\left(Perfume(j)\right)\left(e^{\left(\lambda(Perfume(j))T\right)}\right) \tag{8}$$

Where;
T: Response Time
j: Perfume Sample Number

$$SENSING\left(Perfume(1)_{Part2}\right)_{(Volts)} = -0.65T^2 + 5.75\,T - 5.6 \tag{9}$$

$$SENSING\left(Perfume(2)_{Part2}\right)_{(Volts)} = -T^2 + 7.6\,T - 7.2 \tag{10}$$

$$SENSING\left(\left(Perfume(3)\right)_{part2}\right)_{(Volts)} = -0.65T^2 + 5.75\,T - 5.9 \tag{11}$$

Thus, the general perfume response (Part2) in relation to time can be generalized as in equation (12).

$$SENSING\left(Perfume(q)_{Part2}\right)_{(Volts)} = -\eta\left(Perfume(q)\right)T^2 + \rho\left(Perfume(q)\right)T - \sigma\left(Perfume(q)\right) \tag{12}$$

Where;
T: Response Time
q: Perfume Sample Number

From Equations (1) to (12), Figures (9) to (11)

1. Herbs curves follow a polynomial trend, whilst the perfumes curves have a hybrid or combined exponential (part1)-polynomial (part 2) trend.

2. Herb1 does not intersect with any of the perfumes present, which indicates that no common or shared features are between herb 1 and the three present perfumes in the spatial and temporal plane.

3. Herbs 2 and 3 intersects with the three present perfumes at the following points:

I. Herb 2:

$$Inter\,section_{Odor2}\left(Perfumes(1,2,3)\right) = \begin{bmatrix} Perfume & Time & Voltage \\ 1 & 2.2 & 3.70 \\ 2 & 1.8 & 3.60 \\ 3 & 2.3 & 3.73 \end{bmatrix} \tag{13}$$

II. Herb 3

$$Inter\,section_{Odor3}\left(Perfumes(1,2,3)\right) = \begin{bmatrix} Perfume & Time & Voltage \\ 1 & 1.9 & 3.18 \\ 2 & 1.3 & 3.08 \\ 3 & 2.1 & 3.22 \end{bmatrix} \tag{14}$$

From equations (13) and (14), the earliest intersection between herbs 2 and 3 and the three perfumes present in the same spatial and temporal plane, occurs between Herb 2 and perfume 2.

4. Intersection between herbs 2 and 3 and the three perfumes occurs between the all polynomial curve of the Herbs and the exponential part of the perfumes (part1). Thus indicating common features between the Herbs and the perfumes, whereby features of the herbs are masked by the presence of perfumes and through intersection can be unmasked. Thus, at the intersection point we can equate equation (4) to equation (8).

5. There is a common shape function (polynomial) shifted in time between perfumes and herbs. When intersection occurs, it shows the effect of interaction between Herbs and perfumes as the exponential part of the perfumes intersects with the polynomial part of the herbs, rather than an expected change in the shape function and/ or further shift in the polynomial part of the Herbs to match the perfumes polynomial part.

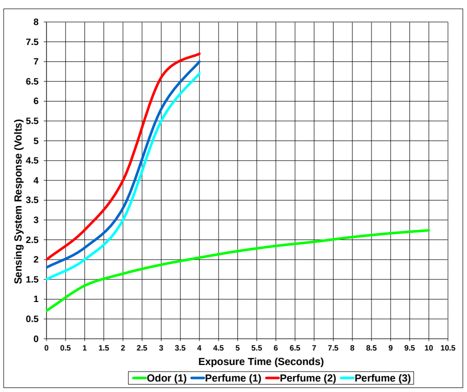

Figure 9. Correlative Sensing System Response to Odor 1 (Herb 1) and Perfumes.

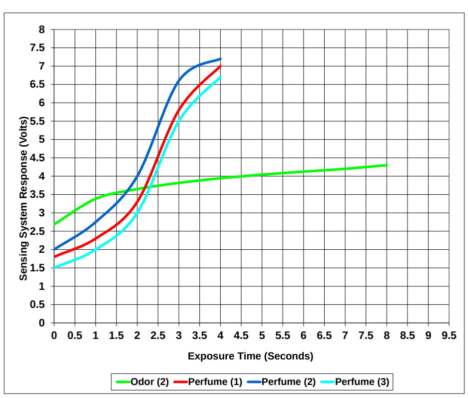

Figure 10. Correlative Sensing System Response to Odor 2 (Herb 2) and Perfumes.

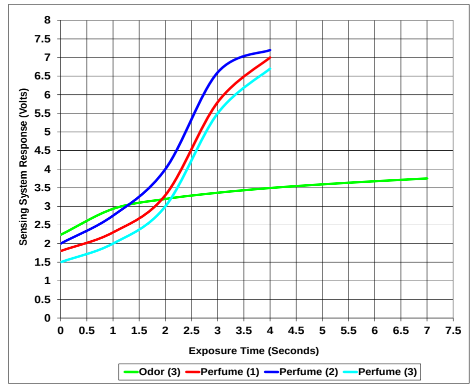

Figure 11. Correlative Sensing System Response to Odor 3 (Herb 3) and Perfumes.

Table III presents the intersection status between the unwanted herbs and sprayed perfumes, where the type of intersection between herbs and perfumes is identified either exponential or polynomial, depending on the status of the perfume curve as it possess both types of functions.

TABLE III
INTERSECTIONS BETWEEN HERBS AND PERFUMES

	Intersection Type					
Odor	Perfume 1		Perfume2		Perfume3	
	Exp.	Poly.	Exp.	Poly.	Exp.	Poly.
Herb 1	**No**	**No**	**No**	**No**	**No**	**No**
Herb 2	**No**	**Yes**	**Yes**	**No**	**No**	**Yes**
Herb 3	**Yes**	**No**	**Yes**	**No**	**No**	**Yes**

Table III presents two cases of perfumes that can mask herbs:

I. Spatial and Temporal Shifting of odor characterisitics, as the polynomial described herb response intersects with the perfume at the exponential part of the perfume response.

II. Functional Change in the in the herb response curve (deeper masking by perfume) leading to intersection only at the polynomial part of the perfumes response.

TABLE IV
INTERSECTIONS BETWEEN HERBS AND PERFUMES-LOGICAL REPRESENTATION

	Intersection Type					
Odor	Perfume 1		Perfume2		Perfume3	
	Exp.	Poly.	Exp.	Poly.	Exp.	Poly.
Herb 1	**0**	**0**	**0**	**0**	**0**	**0**
Herb 2	**0**	**1**	**1**	**0**	**0**	**1**
Herb 3	**1**	**0**	**1**	**0**	**0**	**1**

Based on Tables III, the following logical relationships can be established:

$$\left[Herb\,1:\left(Perfume\,1\right)\right]=\overline{Exponential}\quad AND\quad \overline{Polynomial} \tag{15}$$

$$\left[Herb\,1:\left(Perfume\,2\right)\right]=\overline{Exponential}\quad AND\quad \overline{Polynomial} \tag{16}$$

$$\left[Herb\,1:\left(Perfume\,3\right)\right]=\overline{Exponential}\quad AND\quad \overline{Polynomial} \tag{17}$$

$$\left[Herb\,2:\left(Perfume\,1\right)\right]=\overline{Exponential}\quad AND\quad Polynomial \tag{18}$$

$$\left[Herb\,2:\left(Perfume\,2\right)\right]=Exponential\quad AND\quad \overline{Polynomial} \tag{19}$$

$$\left[Herb\,2:\left(Perfume\,3\right)\right]=\overline{Exponential}\quad AND\quad Polynomial \tag{20}$$

$$\left[Herb\,3:\left(Perfume\,1\right)\right]=Exponential\quad AND\quad \overline{Polynomial} \tag{21}$$

$$\left[Herb\,3:\left(Perfume\,2\right)\right]=Exponential\quad AND\quad \overline{Polynomial} \tag{22}$$

$$\left[Herb\,3:\left(Perfume\,3\right)\right]=\overline{Exponential}\quad AND\quad Polynomial \tag{23}$$

Expressions (15) to (23) uncover the functional (logical) relationship between Herbs and Perfumes with all possible permutations. Based on the expressions (15) to (23), Table IV is obtained, which provides the decision making base for the presence and influence of perfumes over detected odors. From Table IV, the following is deduced:

1. Herb1 is not masked by any of the perfumes used, and of different composition than herb and herb 3.
2. Herb 2 is masked much deeper by perfumes 1 and 3 than perfume 2 and can be detected through intersection.
3. Herb 3 is masked much deeper by perfume 3 than perfumes 1 and 2 and can be detected through intersection.
4. Herb 2 and Herb 3 have similar patterns as the functions of perfumes 1, 2, and 3, as shown by expressions (18) to (20), and (23) and (19), (21), and (22).

IV. Conclusions

This work presented a different approach to determine if a perfume is suitable to mask unwanted odors Such as herbs in smart homes and vehicular environments, whereby the detection of odors and spraying of the right perfumes with deep masking is carried out automatically through sensor detection and spraying systems. The presented approach also allows to detect and unmask harmful odors that could risk human health but can go unnoticed due to the presence of perfumes and other odors. The work also highlights the fact that there is a difference in the shape and time response between manufactured perfumes and odors. This difference in the response characterisitics enables categorization of certain odors and what type of perfumes that can mask them in terms of ability of the perfume curve to encompass the odor curve and hide its presence, with the ability to carry out the reverse process. Thus, certain chemical properties and sensor properties can be utilized for optimum uncovering of presence of certain odors. With future applications in the vehicles and smart homes, which allow monitoring and detection of unwanted odors, harmful odors.

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