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ASYMMETRICAL FACTORIAL EXPERIMENT APPROACH FOR IMPROVED GAS/ODOR DISCRIMINATION USING THICK FILM GAS SENSOR DATA

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Abstract: An asymmetrical factorial experiment approach was used for improved gas/odor discrimination using thick film gas sensor data. The results revealed that the gases/odors(G), sensors(S), concentrations of gases(C), and interactions between GXS were found to be significant at 1% level of significance while the interaction between GXC was significant at 5% level. It indicated that the gas/odor, Methanol (CH3OH) and Acetone (CH3COCH3) were at par while Propanol (C3H7OH) was different at 1% level of significance. Among the sensors S_2 and S_4 were at par while S_1 and S_3 differed significantly at 1% level. The initial concentrations differed significantly while they did not differ at the later stages. Among the interaction of GXS, the sensor S_1 and S_4 were at par under Methanol, S_2 and S_3 were at par under Propanol and S_2 and S_4 were at par under Acetone respectively.

Keywords: Asymmetrical factorial experiment, gas/odor, sensors, interaction, analysis of variance.

1. INTRODUCTION

The growth of human progress has been a result of incessant endeavour towards technological development. This development provoked human beings to have the dream of building a highly intelligent machine that can do things like themselves. The motivation for this effort comes from the practical need to find more efficient ways to accomplish intellectual tasks in many areas such as manufacturing, biology, clinics, mining, communication and military applications. Intellectual tasks include realization, evaluation and interpretation of information that comes from sensors and other sources. Thus, scientists and engineers tried to develop artificial human sensory system so that it can be useful in the service of the mankind. For example, a gas sensor capable of detecting volatile gases can prevent hazards of fire and explosion.

A sensory system is a part of the nervous system responsible for processing sensory information. The sensory system of living organisms is categorized into five types as

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vision (sight), auditory (hearing), somatosensory (touch), gustatory (taste) and olfactory (smell) (Ketron, 1989). An organism uses this sensory system to react to the stimuli present in its environment for survival.

A lot of research has been made to develop gas selective sensors using different principles, materials etc., but sensors are not completely selective and there is some cross sensing effect. Also, a single sensor gives unitary response to a particular gas present in the ambient. Therefore to alleviate this problem, an array of sensors composed of different sensitive materials was taken by Nayak, Dwivedi and Srivastava(1994). Arrays were introduced as a method to counteract the cross selectivity of gas sensors by providing more than one response of a gas/ odor thereby generating a unique pattern for that particular gas/odor. A gas sensor array can be thought of as a mere mathematical construction where the sensor outputs are arranged as components of a vector. Doping of tin oxide (SnO_2) sensors with different materials such as lead oxide(PbO) platinum(Pt) or palladium(Pd) exhibits better responses to different gas concentrations. It is a known fact that doping of lead oxide to SnO_2 dramatically influences the defect chemistry and the sintering behavior of tin oxide. Also, the appearance of lead oxides on the surface of SnO_2 improves the sensitivity of sensors (Senguttuvan, Rai and Lakshmikumar, 2007).

For classification of gases based on information provided by sensors, earlier methods were based on distance, for example, Euclidean or Mahalanobis, likelihood and Bayesian probability. These measures lead to linear classification methods i.e. the decision boundary they generate are linear. Normally, a classifier can be designed in two ways, parametric and non-parametric. Parametric classifiers assume that the patterns in the training set fit a known statistical distribution .These classifiers are parametric in the sense that they are specified in terms of parameters such as mean or variance of the class distributions. Non-parametric classifiers are useful in cases where the underlying distribution cannot be easily known (Gardner, Hines and Tang, 1992). In such cases, we can either estimate the density function or create the decision boundary from the training data set itself (for example, the k-nearest neighbour). In our case of sensor data, the decision boundaries are intrinsically linear and therefore some parametric classifier such as asymmetrical factorial design is used.

The responses that are obtained from the sensors need to be processed through discrimination techniques so as to detect the gases/odors. The discrimination techniques are mathematical or statistical tools used to analyze the array of sensor responses to identify gases/odors present in the given ambient. These techniques may broadly be classified into three types such as projection method, pattern recognition method and modeling method (Kowalski, 1984).

In the past decade there has been a growing interest for the development of olfactory machines and electronic nose system that posses a human like discrimination property (Shurmer and Gardner, 1992). This surge has been mainly driven by a variety of real life applications but due to lack of specificity (partially overlapping sensitivity) and poor selectivity of multisensory arrays, pattern recognition techniques are widely employed to stimulate the mammalian olfactory system. Earlier several pattern recognition techniques were proposed and used such as partial model building (Horner and Hierold, 1990), Fourier Transform Techniques, Cluster Methods, Transformed Cluster Analysis (Nayak, 1992), Multiple Regression Methods and Discriminant Function Analysis (Gardner, Shurmer and Tan, 1992).

In the earlier methods of discrimination, affinity measure, modeling, probabilistic classification, correlation and cluster methods (Shurmer, Gardner and Chan, 1989) were widely used. These methods, however, suffer from many disadvantages such as large computational time, less reliability and had unsatisfactory approach of clustering.

2. MATERIAL AND METHODS

A sensor is any device that detects or measures physical quantity and converts it into a signal which can be read or interpreted by an observer. The data from the sensor represents the measurements of some physical process or phenomena. In our case, an array of gas sensors doped with varying concentrations of lead oxide (PbO) is taken to observe the presence of the following three gases/odors, namely Methanol (CH_3OH), Propanol (C_3H_7OH) and Acetone (CH_3COCH_3) in the ambient. Methanol and Propanol are important class of alcohols, while acetone is used as an industrial solvent. These compounds are highly inflammable because they form explosive mixtures with air and can be easily ignited by heat, sparks or flames. They can cause damage to both life and property if its presence is neglected. Hence, there has been a considerable need to detect these gases/odors to prevent any catastrophic event.

A solid state sensor consists of one or more metal oxides from the transition metals, such as tin oxide, tungsten oxide etc. The tin dioxide (SnO_2) has proved itself to be one of the most attractive materials for gas sensor applications from a viewpoint of gas sensitivity as well as chemical stability. These sensors are made when the metal oxides are vacuum deposited on a silica chip. A heating element is used to regulate the sensor temperature since the finished sensors exhibit different gas response characteristics at different temperature ranges.

The PbO based sensor data for analysis of improved gas/odor discrimination using thick film gas sensor data have been taken from Centre for Research in Microelectronics Engineering (CRME) laboratory of the department. We have taken an array of four thick film tin oxide sensors with different dopings of lead oxide (PbO) i.e.1%, 2%, 3% and 4% by weight. For simplicity, let us call these sensors as S_1,S_2,S_3 and S_4 i.e. S_1 is 1%PbO doped sensor,S_2 is 2%PbO doped, S_3 is 3% PbO doped and S_4 is 4% PbO doped sensor.

The doping of PbO oxides to SnO_2 dramatically influences the behavior of tin dioxide. The surface modification of tin oxide (SnO_2) films by lead oxide (PbO) is an effective method for influencing the response of both the oxidising as well as that of the reducing gases (Senguttuvan, Rai and Lakshmikumar (2007). Therefore, we have taken a sensor array characteristic having four integrated sensors with different doping concentrations of lead oxide (PbO). The sensor heater temperature reached about 350^0C. The sensor array was allowed to stabilize in the above ambient condition with heater power on for more than thirty minutes.

The sensor responses, as a function of concentration for three gases/odors namely, Methanol, Propanol and Acetone are assumed to follow intrinsically linear pattern and it can be analyzed using ANOVA technique of factorial.

The model for the asymmetrical factorial experiment for improved gas/odor discrimination using thick film gas sensor data is given below:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\beta\gamma)_{jk} + (\alpha\beta\gamma)_{ijk} + \varepsilon_{ijk}$$

where,

Y_{ijk} is the effect due to k^{th} concentration in the j^{th} sensor of the i^{th} gas/odor,

μ is the general mean,

α_i is the effect due to i^{th} gas/odor,

β_j is the effect due to j^{th} sensor,

γ_k is the effect due to k^{th} concentration,

$(\alpha\beta)_{ij}$ is the effect due to interaction of the j^{th} sensor of the i^{th} gas,

$(\alpha\gamma)_{ik}$ is the effect due to interaction of the k^{th} concentration of the i^{th} gas,

$(\beta\gamma)_{jk}$ is the effect due to interaction of the k^{th} concentration of the j^{th} sensor,

$(\alpha\beta\gamma)_{ijk}$ is the effect due to interaction of the k^{th} concentration of the j^{th} sensor of the i^{th} gas/odor, and

ε_{ijk} is the random errors which are supposed to be identically, independently and normally distributed with mean zero and a constant variance σ^2.

The data on the above aspects have been gathered merely on one replicate, hence the interaction $(\alpha\beta\gamma)_{ijk}$ is supposed to be considered the mean square error for testing the hypotheses in the asymmetrical factorial experiment.

3. RESULTS AND DISCUSSIONS

The data of improved gas/odor discrimination using thick film gas sensor have been analyzed through an approach of asymmetrical factorial experiment. The ANOVA table is given in Table 1.1.

Table 1.1. Analysis of variance table for gases/odors,sensors and concentrations

Source of Variation	d.f.	Sum of Square	Mean Square	F-calculated	$F_{5\%}$ and $F_{1\%}$	
Gases/Odors(G)	2	1445.62	722.81	10.44**	3.17	5.04
Sensors(S)	3	8243.86	2747.95	39.70**	2.77	4.17
Concentrations(C)	9	21513.36	2390.37	34.54**	2.06	2.75
GXS	6	30864.25	5144.04	74.33**	2.27	3.17
SXC	27	1213.87	44.96	0.65^{NS}	1.67	2.07
GXC	18	2686.81	149.27	2.16*	1.77	2.25
GXSXC(Error)	54	3737.24	69.21			
Total	119	69705.05				

* Significant at 0.05 level of probability
** Significant at 0.01 level of probability
NS: Non –significant.

Table 1.1 reveals about ANOVA table for gases/odors, sensors and concentrations. It is to be noted that the gases/odors (G), sensors(S), concentrations of gases (C), and interactions between GXS was found to be significant at 1% level of significance while the interaction between GXC was significant at 5% level. In indicates that the gas/odor, Methanol(CH_3OH) and Acetone(CH_3COCH_3) was at par while Propanol(C_3H_7OH) was different at 1% level of significance. Among the sensors S_2 and S_4 were at par while S_1 and S_3 differed significantly at 1% level. The initial concentrations differed significantly while they did not differ at the later stages. Among the interaction of GXS, the sensor S_1 and S_4 are at par under Methanol, S_2 and S_3 are at par under Propanol and S_2 and S_4 are at par under Acetone respectively.

Table 1.2. Mean table of the interaction between gases/odors and sensors:

Gases/ Sensors	Methanol	Propanol	Acetone	Average
Sensor 1%	53.89	23.15	73.49	50.18
Sensor 2%	18.78	70.74	28.99	39.50
Sensor 3%	62.19	67.74	51.11	60.35
Sensor 4%	46.93	49.27	27.55	41.14
Average	45.45	52.73	45.28	

Table 1.2 describes the mean table of the interaction between gases/odors and sensors. It indicates that the gas(Propanol) and Sensor(S_3) have the highest average. The gas/odor Methanol(CH_3OH) and Acetone(CH_3COCH_3) was at par while Propanol(C_3H_7OH) was different at 1% level of significance. Among the sensors S_2 and S_4 were at par while S_1 and S_3 differed significantly at 1% level.

Table 1.3. Mean table of the interaction between gases/odors and concentrations

Gases/ Concentrations	Methanol	Propanol	Acetone	Average
C_1	23.25	22.71	11.91	19.29
C_2	37.95	37.98	20.75	32.23
C_3	42.54	46.09	27.89	38.84
C_4	45.62	50.59	37.64	44.61
C_5	47.45	54.55	45.60	49.20
C_6	49.63	58.85	53.42	53.96
C_7	50.80	62.46	59.39	57.55
C_8	52.05	63.56	63.75	59.79
C_9	52.32	64.56	65.49	60.79
C_{10}	52.87	65.93	66.99	61.93
Average	45.45	52.73	45.28	

Among the concentrations of gases/odors, the highest average was found to be for the highest concentrations but they did not differ significantly. The initials concentrations of gases/odors differed significantly.

4. CONCLUSIONS

Earlier many methods have been used for discrimination of gases/odors. However, there has been no literature to somehow assess the quality of a particular sensor. This paper addresses the above issue and the results showed that among the sensors S_2 and S_4 were at par while S_1 and S_3 differed significantly at 1% level. The initial concentrations differed significantly while they did not differ at the later stages. Among the interaction of GXS, the sensor S_1 and S_4 were at par under Methanol, S_2 and S_3 were at par under Propanol and S_2 and S_4 were at par under Acetone respectively. Thus, this paper yielded that the sensor S_3 might be recommended, having the highest mean, for the discrimination of the gases/odors either belonged to Methanol(CH_3OH), Propanol(C_3H_7OH) and Acetone(CH_3COCH_3) or mixture of these combinations at the lower level of concentrations. This finding was consistent with the findings of Sharma (2010).

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APPENDIX

The sampled raw data for three gases/odors are as follows:

1. Methanol

Conc.(in ppm)	Sensor(1%PbO)	Sensor(2%PbO)	Sensor(3%PbO)	Sensor(4% PbO)
500	39.56	2.87	32.16	18.42
1000	54.2	4.71	58.48	34.42
1500	54.83	8.89	61.11	45.33
2000	54.83	12.82	61.98	52.84
2500	55.14	17.79	64.03	52.84
3000	55.45	23.54	66.67	52.84
3500	56.07	26.16	68.12	52.84
4000	56.07	27.99	71.05	53.09
4500	56.07	30.87	69.00	53.33
5000	56.69	32.18	69.29	53.33

2. Propanol

Conc.(in ppm)	Sensor(1% PbO)	Sensor(2%PbO)	Sensor(3%PbO)	Sensor(4%PbO)
500	20.56	38.72	17.25	14.3
1000	21.18	67.5	42.39	20.84
1500	22.11	71.94	57.31	32.97
2000	22.74	72.73	70.47	36.36
2500	23.05	73.77	73.39	48.00
3000	23.05	74.82	81.28	56.24
3500	23.36	76.13	82.45	67.87
4000	24.29	76.65	82.74	70.54
4500	24.92	77.44	83.62	72.24
5000	26.26	77.7	86.54	73.21

3. Acetone

Conc.(in ppm)	Sensor(1%PbO)	Sensor(2%PbO)	Sensor(3%PbO)	Sensor(4%PbO)
500	24.92	3.4	15.20	4.12
1000	45.17	7.84	20.76	9.21
1500	51.4	14.91	30.70	14.54
2000	70.71	19.36	38.88	21.57
2500	79.43	27.2	47.36	28.36
3000	85.98	36.1	57.89	33.69
3500	91.9	41.07	65.78	38.78
4000	94.7	45.52	74.26	40.48
4500	95.01	46.31	78.94	41.69
5000	95.63	48.14	81.28	42.91