

THE TEST OF ORGANIC SOLVENTS VAPOURS BASED ON COMMERCIAL TIN DIOXIDE GAS SENSORS

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Abstract. *This article describes the experiments carried out with the system of three tin dioxide gas sensors MQR 1003, TGS 822 and TGS 813, as well as the achieved results. Vapours of five industrial organic solvents were tested. The measurement values were processed by a cluster analysis. The programmes STATGRAPHIC 5.0 Plus and MATLAB 7.11 were used for data processing. The achieved results show, that the used commercial sensors are able to successfully distinguish chosen industrial solvents and the results can be used for discrimination of organic solvents vapours in air.*

processing, e.g. the principal component analysis [13], [14], the cluster analysis [15], [16], pattern recognition by using an artificial neural network [17], [18], [19].

The research was motivated by the following questions. Is it possible to construct a simple electronic nose based on the commercial gas sensors? What is the sensitivity and discrimination ability of the used sensors to the chosen substances? The set of the substances was chosen purposely because of their easy availability and a wide range of application as paint thinners or stain cleaners.

Keywords

Cluster analysis, electronic nose, gas sensor, tin dioxide.

1. Introduction

Metal oxide gas sensors have been produced for many years. Tin dioxide gas sensors are the most popular. These devices are small, high sensitive and relatively cheap, which enables their usage in portable equipment. Their practical applications are either leakage detectors, combustion gases alarms or electronic noises.

The metal oxide gas sensors have relative wide selectivity. Their detection properties depend on the operating conditions and there also exists the possibility of poisoning the sensor. Long term stability of the detection properties is also important. The research efforts are focused on the improvement of the imperfections. One direction leads to the researching new materials [1], [2], [3], [4], the second direction is focused on proper operating regime [5], [6], [7], [8] and proper methods of data processing [9], [10], [11], [12]. The system of several sensors based on various principles is used in electronic noses, as well as statistical methods for data

2. Experiments

The measuring apparatus, the block diagram of which is in Fig. 1, was used. The apparatus is composed of a testing glass chamber of a known volume, and the sensors are placed in it. Dry laboratory air, dried in the unit 7 (20 % RH), is led into the chamber. The sensors are heated by the heating voltage from 0 to 5 V. For the response measurement (electrical conductance of the detection layer) an 8 bit A/D converter is used. The principle of the response measurement is shown in Fig. 2. The heating system of the sensor is galvanically insulated from the detection system of the sensor. The response is measured as the direct voltage U_m across the resistor R . The detection system of the sensor and resistor R act as a voltage divider and the changes of electrical conductance of the sensor are converted to the changes of U_m . Unit 5 liquid manometer keeps the atmospheric pressure in the gas chamber.

Sensors TGS813 and MQR 1003 are meant for the methane detection, sensor TGS 822 is meant for the ethanol detection. The testing was carried out with each of the 5 organic solvents separately: C 6000, S 6006, S 6300, P 6413, CIKULI. These are the commercial marks of the used industrial solvents. Each of these solvents is a mixture of several organic substances.

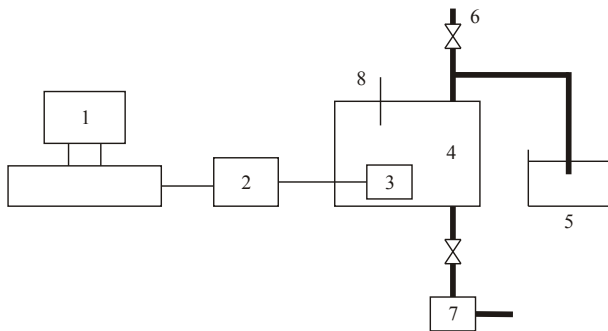


Fig. 1: The apparatus arrangement: 1 - personal computer, 2 - conductance meter and heating voltage source, 3 - the sensors, 4 - tested chamber, 5 - liquid manometer, 6 - gas output, 7 - the dry air pump unit, 8 - syringe needle.

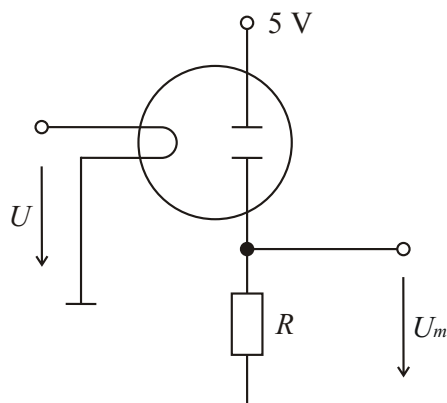


Fig. 2: The principle of the response measurement of the sensor. U - heating voltage, U_m - measured voltage, R - resistor 2 k. Positive voltages are indicated by arrows

The saturated vapours of the solvents were obtained by the solvents evaporating above their liquid phase in a closed bottle at the constant ambient temperature 22 °C. A proper volume (20 ml) of the saturated vapour was injected into the testing chamber (2700 ml) filled with dry clean air. The temperature of the apparatus and the closed bottle was kept at the ambient temperature.

The heating voltage was first increased to 5 V before each measurement of the given solvent to prepare the sensor for measurement [4]. The electrical conductance of the detection layer was tracked until it had reached the value in dry clean air. After that the heating voltage was decreased by step to 2 V and the saturated vapours were injected into the testing chamber. The temperature of the sensor is proper for chemisorption of the substance at this heating voltage [4], [10], [20]. Afterwards, the heating voltage was increased by step to 3 V. The range of 3 V up to 3,5 V was chosen purposely because it was experimentally discovered, that the response of the mentioned solvents is of the maximum value. Starting with the value of 3 V the heating voltage was increased every 10 seconds by 14 equal steps up to the value 3,5 V. The electrical value of the

detected layer was sensed every 10 seconds after the change of the heating voltage, because of thermal inertia of the sensor described in [20]. At the end of the measurement the testing chamber was purged by dry clean air and the heating voltage was increased by step to 5 V to prepare the sensor for the following measurement. The measurement with each solvent, including its new preparation of the concentration, was repeated 10 times. The response of sensors for solvent S 6006 is shown in Fig. 3.

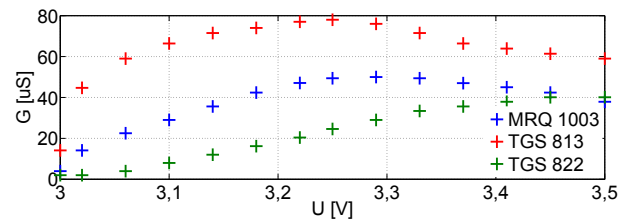


Fig. 3: Example of the response of sensors for solvent S 6006. U - heating voltage, G - conductance of the sensor.

3. Methods

Cluster analysis separates data into groups (clusters). This method is suitable for the data the natural property of which is forming of clusters. Generally, the goal of the cluster analysis is to separate the measured data into several fairly homogeneous clusters. There are two types of tasks. The goal of the first type is to split the data into the prescribed number of clusters, the goal of the second type of the task is to find out the optimal number of clusters for given data. The tasks with the prescribed number of clusters are solved by agglomerative or divisive methods [21].

Agglomerative clustering starts by considering each data point to be an independent cluster. Two clusters are merged at each step and the process is repeated until the desired number of clusters is obtained. The agglomerative methods, called the nearest neighbour, the furthest neighbour, centroid, median, group average and Ward's method are used here.

Divisive clustering starts by putting all data in a single cluster. A single cluster is split into two clusters and the centroid of each one is calculated. New clusters are created by the division of the existing ones and the process is repeated until the desired number of clusters is obtained. Divisive method called k-means was used here.

For clustering either the data measured in their natural units or the normalized data can be used. In our case it is more convenient to use the normalized data, since the obtained results are independent on the used units. The normalized data are calculated by the fol-

lowing formulas:

$$x_{ij} = \frac{z_{ij} - \bar{z}_{ij}}{S(z_j)} \text{ for } i = 1, 2, \dots, n \quad j = 1, 2, \dots, p, \quad (1)$$

$$\bar{z}_j = \frac{1}{n} \sum_{i=1}^n z_{ij},$$

$$S^2(z_j) = \frac{1}{n-1} \sum_{i=1}^n (z_{ij} - \bar{z}_j)^2. \quad (2)$$

where x_{ij} is the normalized value, z_{ij} is the original value, \bar{z}_j is the mean value, $S(z_j)$ is the standard deviation, n is the total number of input data of all solvents, p is the number of used sensors.

Clustering is also influenced by the type of distance calculation used between two clusters. Squared Euclidean distance was chosen as a proper distance measure since it puts greater weight on the objects that are farther apart and also it is also recommended for some methods of clustering described in this article. Squared Euclidean distance is calculated by formula:

$$D(x_i, x_m) = \sum_{j=1}^p (x_{ij} - x_{mj})^2, \quad (3)$$

where distance $D(x_i, x_m)$ is calculated between i -th object and m -th object.

The original clusters are merged into a new cluster by a linkage method. For the nearest neighbour linkage method this formula was used:

$$D_{gm} = \min(D_{rm}, D_{sm}), \quad (4)$$

where D_{gm} is the distance between new cluster g and others clusters m , D_{rm} is the distance between original cluster r and other clusters m , D_{sm} is the distance between original cluster s and other clusters m . Two minimally distant clusters are merged. The disadvantage of this method is its sensitivity to outliers, as well as the tendency to merge small clusters lying close to each other into one elongated cluster.

The following formula was used for the furthest neighbour linkage method:

$$D_{gm} = \max(D_{rm}, D_{sm}). \quad (5)$$

Two maximally distant clusters are merged. This method eliminates the disadvantage of the nearest neighbour method. The furthest neighbour method tends to form smaller more balanced clusters. The disadvantage is that this method tends to break the large clusters and the small clusters are merged into the larger ones.

This formula was used for the centroid linkage method:

$$D_{gm} = \frac{n_r D_{rm} + n_s D_{sm} - \frac{n_r n_s}{n_r + n_s} D_{rs}}{n_r + n_s}, \quad (6)$$

where n_r is the number of the objects in cluster r , and n_s is the number of the objects in cluster s . The other symbols have the same meaning as in the previous paragraph. The distance between two clusters is defined as squared Euclidean distance between their centroids. One disadvantage of this method is that the distance at which clusters are combined can decrease from one step to the next one, thus the farther clusters can be merged. The centroid method is more robust to outliers than most of the other methods.

For the median method this formula was used:

$$D_{gm} = \frac{D_{rm} + D_{sm}}{2} - \frac{D_{rs}}{4}. \quad (7)$$

In case of the median method the same importance is attached to two merged clusters regardless of how many objects there are in each cluster. This is an advantage compared to the centroid method. It is proper to use squared Euclidean measure.

For the group average method this formula was used:

$$D_{gm} = \frac{D_{rm} + D_{sm}}{n_r n_s}. \quad (8)$$

The distance between two clusters is the average distance between pairs of objects, one of which is placed in each cluster. This method is characterized by a compromise between the nearest and the farthest neighbours. The method is less susceptible to outliers. Its disadvantage is the tendency to form globular clusters. The group average tends to join clusters with small variances, and it is slightly biased toward producing clusters with the same variance.

For Ward's method this formula was used:

$$D_{gm} = \frac{[(n_r + n_m)D_{rm}] + (n_s + n_m)D_{sm} - n_m D_{rs}}{n_r + n_s + n_m}. \quad (9)$$

The distance is calculated as a total sum of the squared deviations from the mean of the cluster. Two clusters having the smallest possible increase in the error sum of squares are merged. Ward's method tends to form clusters of an equal number of objects and to reduce small clusters. The method is similar to the group average method and the centroid method. Therefore, it is proper to use squared Euclidean measure. The method is sensitive to outliers. This method is very

efficient and fits well if each cluster contains the equal number of objects.

K-means method does not require computation of all possible distances. The objects are assigned to the prescribed number of k clusters. Each object is assigned to the cluster with the shortest distance to the cluster mean. The distance between object x_i and cluster mean c_m is calculated by the squared Euclidean formula:

$$D(x_i, c_m) = \sum_{j=1}^p (x_{ij}, c_{mj})^2. \tag{10}$$

The cluster mean is calculated by the following formula:

$$c_j = \frac{1}{n} \sum_{i=1}^n x_{ij}, \tag{11}$$

where x_{ij} are the objects assigned to the cluster, n is the number of the objects in the cluster. The algorithm starts with the initial set of means and it classifies the objects based on their distances to the cluster means. Cluster means are computed again using the objects that are assigned to the cluster. Afterwards, all objects are reclassified on the basis of a new set of the means. These steps are repeated until the cluster means change. Finally, all cases are assigned to their permanent clusters. It follows from the algorithm that during the analysis the same object can move from one cluster to another one.

The cophenetic correlation coefficient is used for the measure of validity of a clustering structure. The coefficient is calculated by this formula For Ward's method this formula was used:

$$R = \frac{a \sum_{j=1}^{n-1} \sum_{i=j+1}^n D_{ij} C_{ij} - \mu_D \mu_C}{\sqrt{\left[a \sum_{j=1}^{n-1} \sum_{i=j+1}^n D_{ij}^2 - \mu_D^2 \right] \left[a \sum_{j=1}^{n-1} \sum_{i=j+1}^n C_{ij}^2 - \mu_C^2 \right]}} \tag{12}$$

$$a = \frac{2}{n(n-1)},$$

$$\mu_D = a \sum_{j=1}^{n-1} \sum_{i=j+1}^n D_{ij}, \tag{13}$$

$$\mu_C = a \sum_{j=1}^{n-1} \sum_{i=j+1}^n C_{ij}, \tag{14}$$

where D_{ij} and C_{ij} are the elements of the distance matrix \mathbf{D} and cophenetic matrix \mathbf{C} . Matrix \mathbf{D} contains the distances between i -th and j -th object, matrix \mathbf{C} contains the distances at which these two objects are first joined together. The μ_D and the μ_C are the mean values of the matrixes. For good validity R should be $R > 0,75$ and close to 1.

The correlation coefficient of the used sensors can be calculated by the formula:

$$r_{ik} = \frac{\sum_{j=1}^n (x_{ij} - \bar{x}_i)(x_{kj} - \bar{x}_k)}{\sqrt{\sum_{j=1}^n (x_{ij} - \bar{x}_i)^2 \sum_{j=1}^n (x_{kj} - \bar{x}_k)^2}}, \tag{15}$$

where x are the normalized values of the responses and i, k go from 1 up to p . It is obvious from the presented properties, that used linkage methods differ from each other. Therefore, a successive application of these methods on the same measured data generally leads to different assignment into the prescribed number of clusters. As the correct cluster assignments are given by the numbers and kinds of the tested solvents, it is easy to check if the used clustering method splits data into the clusters correctly or not. If a larger number of the used methods splits data into the clusters correctly, it means that such data are better distinguishable in comparison with the case in which only a smaller number of methods splits data correctly. It is possible to decide according to the value of R which linkage method fits better. The correlation coefficient r_{ik} is the measure of mutual similarity of the used sensors.

4. Result

Measured values of the responses were processed by a cluster analysis in programme STATGRAPHIC 5.0 Plus. Coefficient R was calculated by programme MATLAB 7.11 as the above-mentioned STATGRAPHIC is not able to calculate it. The measured values of the responses of three sensors for the tested substance at the given heating voltage present a cluster of 10 points in a three-dimensional area. Theoretically, there is a total of 5 clusters for 5 solvents if the sensors show mutual different sensitivity to the above-mentioned solvents. If the sensitivity to some solvents was the same for all sensors, the clusters of the solvents would fuse and could not be discriminated.

The ability of the sensor system to successfully discriminate the given number of the tested solvents under the given conditions was investigated by the cluster analysis. Successful discrimination means the faultless classification of the given number of substances into the same number of clusters.

In program STATGRAPHIC 5.0 Plus seven methods of clustering were used: the nearest neighbour method, the furthest neighbour method, centroid, median, group average, Ward's method and k-means. Squared Euclidean as a distance metric and standard-

ized data preprocessing were considered to be appropriate and that is why used here. When the number of successful discriminations in the given case increases, the clusters are better discriminable. The data taken at a certain level of the heating voltage represent one case of the analysis. Thus there is a total of 14 cases for each response. It follows from the obtained results that there is an optimal value of the heating voltage, at which the possibility of discriminating the tested solvents is the best one. In the heating voltage levels ranging between 3 V and to 3,5 V the responses of the sensors show the maximal values for the tested solvents. At this operating point the sensors show the maximal sensitivity according to the equation 15 in [22]. It means that this is the best operating point:

$$S = \frac{G - G_0}{G_0}, \tag{16}$$

where S is the sensor sensitivity, G_0 is the electrical conductance of the sensor in clean air, G is the electrical conductance of the sensor in tested gas. Thus, in the file of the measured data the maximum value of the reached electrical conductivity was searched out for each response and the reached value was used as the input data for processing.

At first, the data obtained from 5 solvents measured by 3 sensors were evaluated. All 7 methods were used simultaneously to faultlessly distinguish the 5 clusters. Six methods, except k-means, were successful in case of 5 solvents and 3 sensors. Coefficient R ranged between 0,8213 and 0,9914 for all successful methods. The correlation matrix was calculated by using STATGRAPHIC. The results are shown in Tab. 1.

Tab. 1: Correlation coefficient r of the used sensors. All 50 measured values were used.

	MQR 1003	TGS 813	TGS 822
MQR 1003	1	0,7552	0,9514
TGS 813	0,7552	1	0,8093
TGS 822	0,9514	0,8093	1

It is possible to imagine this result as 5 separated clusters in three-dimensional space, where each sensor represents one coordinate. A scatter plot in three-dimensional space can be drawn as a system of three two-dimensional graphs. It is shown in Fig. 4, 5 and 6.

In the next step the data of 5 solvents taken from each one pair of sensors were processed. For three pairs of used sensors we have three results. Overview of the number of successful methods for cluster separation is shown in Tab. 2.

It can be seen that pair 2 shows low discrimination ability, while pairs 1 or 3 show higher ability. Compared to the case where all three sensors were used

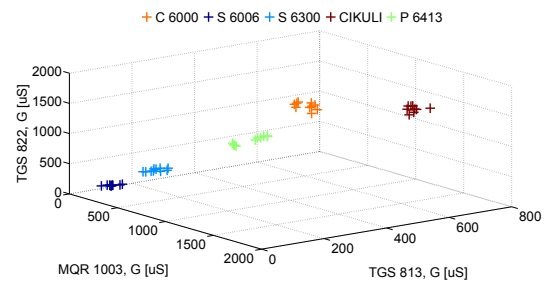


Fig. 4: The cluster scatter plot of 5 solvents in the system of 3 sensors. Each cluster contains 10 points. The dependency obtained from MQR 1003, TGS 813 and TGS 822.

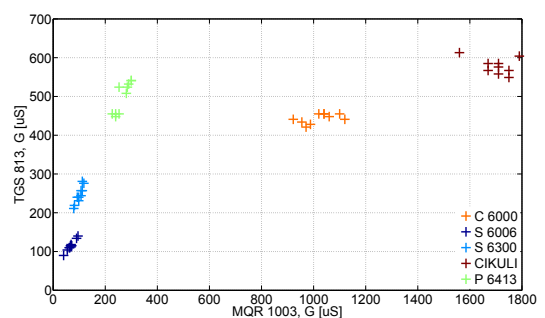


Fig. 5: The cluster scatter plot of 5 solvents in the system of 3 sensors. Each cluster contains 10 points. The dependency obtained from MQR 1003 and TGS 813.

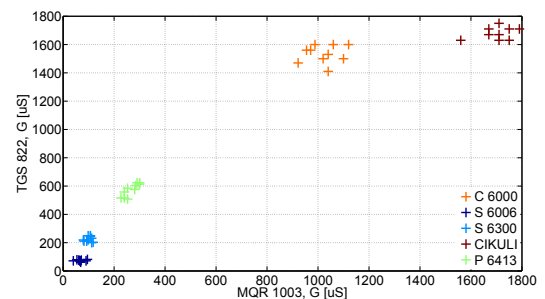


Fig. 6: The cluster scatter plot of 5 solvents in the system of 3 sensors. Each cluster contains 10 points. The dependency obtained from MQR 1003 and TGS 822.

it follows that the discrimination ability of the three sensors system is practically given by pair 1 or pair 3. This opinion is confirmed by the values of r_{ik} in Tab. 1, because pair 1 and pair 3 have lower values of r_{ik} .

It is possible to improve the number of the successful methods of each pair of the sensors if the number of the tested solvents is reduced. Thus, if the number of the tested solvents in the file of the measured data is reduced to 4, it is possible to constitute 5 combinations. Each combination contains 4 solvents. The combinations are itemized in Tab. 2. The described

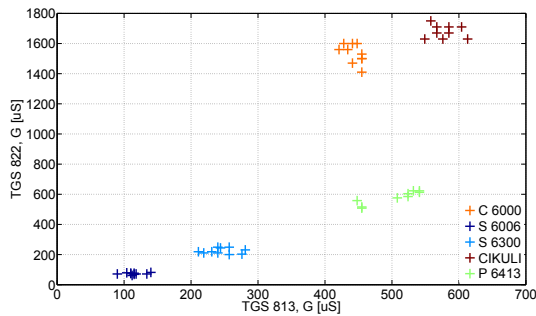


Fig. 7: The cluster scatter plot of 5 solvents in the system of 3 sensors. Each cluster contains 10 points. The dependency obtained from TGS 822 and TGS 813.

Tab. 2: Results of the discrimination of the normalized data of 5 solvents by a pair of sensors. Numbers of successful methods for separation into 5 clusters.

Pair 1	Pair 2	Pair 3
MQR 1003 TGS 813	MQR 1003 TGS 822	TGS 813 TGS 822
6	1	6
Except k-mean	Only Ward's	Except k-mean

methods of the cluster analysis were used for the data of each combination. A number of successful methods used for separation into 4 clusters was evaluated for each combination. The obtained results are in Tab. 3.

It follows from the Table 3, that the most successful pair are pairs 1 and 3, because of the maximum number of successful methods. Pair number 1 successfully detected the group of solvents in three cases (combinations 1, 2 and 5), as well as pair number 3 (combinations 1, 2, 4 and 5). The most proper group of the solvents are the combinations 2 and 5 because they are detectable by two pairs of sensors by 7 methods. The range of cophenetic coefficients R of the used linkage methods for combinations 2 and 5 and pair 1 and the pair 3 are shown in the Tab. 4.

The values in Tab. 4 are a bit lower, those obtained when using a full number of the above mentioned sensors ($R=0,8213$ and $0,9914$) for 5 solvents. It seems that the pair 2 also assists to the detection ability despite of its higher coefficient of correlation r_{ik} .

An example of the cluster scatter plot for successful case is shown in the Fig. 8.

The achieved results show, that system of two properly chosen commercial sensors is able to successfully distinguish 4 solvents if a proper choice of solvents is made.

The obtained results show that the detection system using commercial sensors has its value. It is possible to construct an electronic nose of two or three commercial

Tab. 3: Results of the discrimination of normalized data of 4 solvents by a pair of sensors. Numbers of successful methods for separation into 4 clusters.

Pair 1	Pair 2	Pair 3
MQR 1003 TGS 813	MQR 1003 TGS 822	TGS 813 TGS 822
Combination of solvents number 1 S 6006, S 6300, CIKULI, P 6413		
7	3	6
	Only Nearest, Ward's, k-mean	Except k-mean
Combination of solvents number 2 C 6000, S 6300, CIKULI, P 6413		
7	6	7
	Except k-mean	
Combination of solvents number 3 C 6000, S 6006, S 6300, P 6413		
6	2	6
	Only Nearest, Ward's	Except k-mean
Combination of solvents number 4 C 6000, S 6006, S 6300, CIKULI		
6	1	7
Except k-mean	Only Ward's	
Combination of solvents number 5 C 6000, S 6006, CIKULI, P 6413		
7	6	7
	Except k-mean	

Tab. 4: Range of values of cophenetic coefficient R for the combinations 2 and 5.

	Pair 1	Pair 3
Combination 2	0,8201 – 0,8773	0,8820 – 0,8942
Combination 5	0,8853 – 0,9591	0,9348 – 0,9516

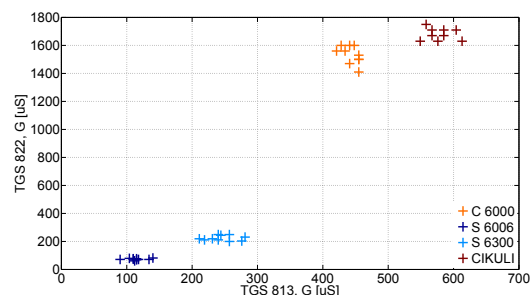


Fig. 8: The cluster scatter plot of 4 solvents in the system of 2 sensors. Each cluster consists of 10 points. The combination number 5 and the pair number 3 are used.

sensors of a described type to distinguish four or five mentioned solvents separately.

5. Conclusion

This article deals with the detection properties of commercial tin dioxide gas sensors. The properties were successfully tested on 5 chosen industrial solvents. It follows from this that it is possible to construct a relative simple discrimination system of industrial organic solvents with commercial tin dioxide gas sensors originally determined for methane or ethanol detection. The nose could use two or three commercial tin dioxide gas sensors and could discriminate four or five frequently used organic solvents. The methods described in this article can be used in practical applications.

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References

- [1] HUBNER, M., N. BARSAN and U. WEIMAR. Influences of Al, Pd and Pt additives on the conduction mechanism as well as the surface and bulk properties of SnO₂ based polycrystalline thick film gas sensors. *Sensors and Actuators B: Chemical*. 2012, vol. 171–172, iss. 1, pp. 172–180. ISSN 0925-4005. DOI: 10.1016/j.snb.2012.02.080.
- [2] YAMAZOE, N. Review toward innovations of gas sensor technology. *Sensors and Actuators B: Chemical*. 2005, vol. 108, iss. 1–2, pp. 2–14. ISSN 0925-4005. DOI: 10.1016/j.snb.2004.12.075.
- [3] MEIXNER, H. and U. LAMPE. Metal oxide sensors. *Sensors and Actuators B: Chemical*. 1996, vol. 33, iss. 1–3, pp. 198–202. ISSN 0925-4005. DOI: 10.1016/0925-4005(96)80098-0.
- [4] WATSON, J., K. IHOKURA and S. V. GOLES. The tin dioxide gas sensor. *Measurement Science and Technology*. 1993, vol. 4, iss. 7, pp. 711–719. ISSN 0957-0233. DOI: 10.1088/0957-0233/4/7/001.
- [5] BAIPAI, R., A. MOTAYED, A. V. DAVYDOV, V. P. OLESHKO, G. S. ALURI, K. A. BERTNESS, M.V. RAO and M. E. ZAGHLOUL. UV-assisted alcohol sensing using SnO₂ functionalized GaN nanowire devices. *Sensors and Actuators B: Chemical*. 2012, vol. 171–172, iss. 1, pp. 499–507. ISSN 0925-4005. DOI: 10.1016/j.snb.2012.05.018.
- [6] BABAEI, H. and M. ORVATINIA. Gas diagnosis based on selective diffusion retardation in an air filled capillary. *Sensors and Actuators B: Chemical*. 2003, vol. 96, iss. 1–2, pp. 298–303. ISSN 0925-4005. DOI: 10.1016/S0925-4005(03)00546-X.
- [7] CAVICCHI, R. E., J. S. SUEHLE, K. G. KREIDER, M. GAITAN and P. CHAPARALA. Optimized temperature-pulse sequences for the enhancement of chemically specific response patterns from micro-hotplate gas sensors. *Sensors and Actuators B: Chemical*. 1996, vol. 33, iss. 1–3, pp. 142–146. ISSN 0925-4005. DOI: 10.1016/0925-4005(96)01821-7.
- [8] NAKATA, S., H. NAKAMURA and J. YOSHIKAWA. New strategy for the development of a gas sensor based on the dynamic characteristics: principle and preliminary experiment. *Sensors and Actuators B: Chemical*. 1992, vol. 8, iss. 2, pp. 187–189. ISSN 0925-4005. DOI: 10.1016/0925-4005(92)80179-2.
- [9] GUNNEY, S. and A. ATASOY. Multiclass classification of n-butanol concentrations with k-nearest neighbor algorithm and support vector machine in an electronic nose. *Sensors and Actuators B: Chemical*. 2012, vol. 166–167, iss. 1, pp. 721–725. ISSN 0925-4005. DOI: 10.1016/j.snb.2012.03.047.
- [10] GAJDOSIK, L. The concentration measurement with SnO₂ gas sensor operated in the dynamic regime. *Sensors and Actuators B: chemical*. 2005, vol. 106, iss. 2, pp. 691–699. ISSN 0925-4005. DOI: 10.1016/j.snb.2004.09.017.
- [11] IONESCU, R. and E. LLOBET. Wavelet transform based fast feature extraction from temperature modulated semiconductor gas sensors. *Sensors and Actuators B: Chemical*. 2002, vol. 81, iss. 2–3, pp. 289–295. ISSN 0925-4005. DOI: 10.1016/S0925-4005(01)00968-6.
- [12] WILSON, D. M. and S. P. DE WEERTH. Odor discrimination using steady-state and transient characteristics of tin-oxide sensors. *Sensors and Actuators B: Chemical*. 1995, vol. 28, iss. 2, pp. 123–128. ISSN 0925-4005. DOI: 10.1016/0925-4005(95)80036-0.

- [13] YIN, Y. and X. TIAN. Classification of Chinese drinks by a gas sensors array and combination of the PCA with Wilks distribution. *Sensors and Actuators B: Chemical*. 2007, vol. 124, iss. 2, pp. 393–397. ISSN 0925-4005. DOI: 10.1016/j.snb.2007.01.008.
- [14] PENZA, M., G. CASSANO, F. TORTORELLA and G. ZACCARIA. Classification of food, beverages and perfumes by WO_3 thin-film sensors array and pattern recognition techniques. *Sensors and Actuators B: Chemical*. 2001, vol. 73, iss. 1, pp. 76–87. ISSN 0925-4005. DOI: 10.1016/S0925-4005(00)00687-0.
- [15] FALASCONI, M., M. PARDO, M. VEZZOLI and G. SBERVEGLIERI. Cluster validation for electronic nose data. *Sensors and Actuators B: Chemical*. 2007, vol. 125, iss. 2, pp. 596–606. ISSN 0925-4005. DOI: 10.1016/j.snb.2007.03.004.
- [16] ZHE, X., X. SHI and S. LU. Integrated sensor array optimization with statistical evaluation. *Sensors and Actuators B: Chemical*. 2010, vol. 149, iss. 1, pp. 239–244. ISSN 0925-4005. DOI: 10.1016/j.snb.2010.05.038.
- [17] ZHANG, L., F. TIAN, X. PENG, L. DANG, G. LI, S. LIU and Ch. KADRI. Standardization of metal oxide sensor array using artificial neural networks through experimental design. *Sensors and Actuators B: Chemical*. 2013, vol. 177, pp. 947–955. ISSN 0925-4005. DOI: 10.1016/j.snb.2012.11.113.
- [18] O FARRELLA, M., E. LEWIS, C. FLANAGAN, W. B. LYONS and N. JACKMAN. Combining principal component analysis with an artificial neural network to perform online quality assessment of food as it cooks in a large-scale industrial oven. *Sensors and Actuators B: Chemical*. 2005, vol. 107, iss. 1, pp. 104–112. ISSN 0925-4005. DOI: 10.1016/j.snb.2004.09.050.
- [19] NIEBLING, G. Identification of gases with classical pattern-recognition methods and artificial neural networks. *Sensors and Actuators B: Chemical*. 1994, vol. 18, iss. 1–3, pp. 259–263. ISSN 0925-4005. DOI: 10.1016/0925-4005(94)87091-8.
- [20] GAJDOSIK, L. and M. HUTYRA. Tin dioxide gas sensors operated at dynamic regime. In: *Conference PDS-98*. Gliwice: Universita Slaska, 1998, pp. 1–8. ISBN 83908409-5-2.
- [21] HEBAK, P. *Vicerozmerne statistické metody*. 1 ed. Praha: Informatorium, 2005. ISBN 80-7333-039-3.
- [22] BECKER, T., S. AHLERS, Chr. Bosch-v.BRAUNMUHL, G. MULLER and O. KIESEWETTER. Gas sensing properties of thin and thick-film tin-oxide materials. *Sensors and Actuators B: Chemical*. 2001, vol. 77, iss. 1–2, pp. 55–61. ISSN 0925-4005. DOI: 10.1016/S0925-4005(01)00672-4.

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