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REGULAR ARTICLE

Multisensor System Based on Porous Silicon with Multiagent Data Processing

S.E. Pritchin*, I.V. Shevchenko, A.P. Oksanich, M.G. Kogdas, Y.A. Rastoropov, O.S. Prytchyn, V.A. Palagin

Kremenchuk Mykhailo Ostrogradsky National University, 39600 Kremenchuk, Ukraine

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The article proposes a method for improving the selectivity of determining gas concentrations in gas mixtures using multisensor systems based on porous silicon with the application of a multiagent information processing system. A general formal description of the multi-agent system is provided, which is improved by the introduction of a set of fuzzy cognitive maps designed to recognize situations, forming a spectrum of representations, focusing attention, and evaluating the success of agents' actions, which allows for the construction of various multi-agent systems using a single methodology, in particular those used to improve the selectivity of sensors. The task description includes a set of classes to be recognized, a set of features, a measurement procedure, a set of associative models for transforming a set of features into a set of classes, which is a set of fuzzy cognitive maps, as well as procedures for automatic adjustment and correction of gas concentration measurement results. The proposed method is based on determining the composition of a gas mixture obtained by a matrix of gas sensor agents based on porous silicon with different porosity and at different temperatures. Using a multi-agent system, an extended feature space is formed, and the distances between measurement points in this space are calculated. The set of distances is converted into a distribution of gas concentrations, which simplifies the concentration measurement algorithm while maintaining the required measurement accuracy for determining the composition of the gas mixture and the concentration of its individual elements. The experiments performed and the analysis of the results show that the proposed system is capable of determining the composition of gas mixtures with sufficient accuracy.

Keywords: Porous silicon, Gas concentration sensors, Multisensor system, Multiagent system, Extended feature space.

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1. INTRODUCTION

Recently, much attention in gas sensor technology has been paid to the use of nanostructures, which are characterized by a large surface area, high porosity, and effective depletion [1]. However, despite progress in the development of such sensors, some issues remain insufficiently studied.

The general principles of interaction between gas molecules and solid surfaces are fairly well known, but the mechanisms of kinetics and thermodynamics of adsorption for different types of gases remain insufficiently studied. This is especially true for the influence of porous surface parameters, such as pore size and morphology, which affect the selectivity and sensitivity of gas sensors.

As is known, gas sensors on porous silicon have high sensitivity due to their large surface area and adjustable morphology [2,3]. However, their selectivity to gases, especially in gas mixtures, remains a significant limitation that hinders their wider practical application.

Increasing selectivity through surface functionalization methods or the use of modern information technologies such as multi-agent systems is a relevant area of scientific research.

The problems of gas sensor selectivity are caused by both a wide range of physical phenomena that occur in real sensor operating conditions and significant possible variations in operating conditions. In addition, experimental studies of sensors based on different materials and/or different architectures are not usually systematic, focusing on the analysis of results obtained for specific designs.

On the other hand, insufficient attention is paid to the opportunities offered by modern information technologies, in particular the paradigm of multi-agent systems, in which a multitude of individual agents perform either different tasks or solve the same task, giving their “own view” on the solution.

The issue of gas sensor selectivity is discussed in detail in [4]. The authors indicate that selectivity can be achieved by attaching functional organic groups to porous silicon. If the target molecules do not interact with the attached functional groups, the sensor response changes linearly in proportion to the concentration. However, in the case of strong hydrogen bonding, a much greater response is recorded at low concentrations than expected. The hydrogen bond either causes an increase in solvent penetration into the porous matrix or reduces the potential drop at the solvent/porous silicon interface, i.e., reduces the volume capacity in silicon nanorods.

* Correspondence e-mail: pritchinse@gmail.com

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The paper [5] analyzes progress in the development of resistive gas sensors. In particular, it describes new nanoarchitectures that significantly improve the performance of sensors. As shown, high sensitivity, fast response, short recovery time, a significant number of detectable gases, low detection limit, reliability, compactness, relative ease of manufacture, and low cost can be achieved through the use of nanostructured resistive gas sensors. The improvement in the characteristics of such sensors, in particular their sensitivity, is due to a significant reduction in interparticle barriers in nanopowders or other nanostructures.

In [6], approaches are developed for creating composite materials with a fractal-percolation structure based on intercalated porous matrices to increase the sensitivity of adsorption gas sensors. Porous silicon, nickel-containing porous silicon, and zinc oxide are synthesized as materials for such structures. Using impedance spectroscopy, it was shown that the obtained materials demonstrate high sensitivity to organic solvent vapors and can be used in gas sensors. A model has been proposed that explains the high sensitivity and inductive nature of impedance at low frequencies, taking into account the structural features and fractal-percolation properties of the obtained oxide materials.

Work [7] is devoted to the technology of improving the properties of silicon sensors by improving etching technologies. Coating with a thin layer of metal facilitates the etching of *p*-type silicon in an HF solution containing $KBrO_3$, KIO_3 or $K_2S_2O_8$ as an oxidizing agent. Chemical etching of *p*-Si with Ag enhancement in 22M HF containing 0, M $KBrO_3$ or KIO_3, resulted in the formation of micropores, while etching silicon in 22M HF/0.1M $K_2S_2O_8$ after Ag deposition resulted in a large area of silicon nanowires on the Si surface. The corresponding electrical equivalent circuit was used to reconcile the experimental impedance results of the metal-modified silicon surface in an HF/oxidant aqueous solution.

Researchers are paying a lot of attention to figuring out gas concentrations using spectral analysis, especially with porous silicon [8]. This method has a number of advantages, such as high sensitivity due to a large specific surface area and the ability to create photonic structures, optical flexibility, the possibility of multi-parameter analysis, and the ability to adjust selectivity to specific gases by modifying the surface structure. At the same time, the application of the method requires solving additional problems, one of which is multi-analytical selectivity, which involves the development of algorithms for separating overlapping components to recognize several gases simultaneously.

Such tasks can be solved by applying information technologies. For example, in [9], a neural network is used to process data from a multisensor system. To selectively determine the gas spectrum, the authors use a separate sensor for each gas, specially tuned to a specific gas. This is a very complex task from both a technological and technical point of view. There is also the problem of training a neural network created to solve the problem of multiple regression, which is precisely the task of determining the concentration spectrum. Quite a few layers and neurons are needed to successfully solve this problem.

The best results can be achieved by using agent technologies. These technologies now cover a very wide range of applications, including virtual sensor agents, software agents, intelligent agents, etc. [10].

The paper [11] explores the possibility of using multi-agent systems in distributed computing using the example of a universal multi-agent distributed computing system. The model was implemented in Fuzzy Cognitive Map (FCM). The proposed multi-agent system showed the expected characteristics. The conclusion is that the proposed universal model of a multi-agent system using FCM can be used as a basis for building multi-agent systems for various purposes.

In [12], a dynamic fuzzy cognitive map (DFCM) is proposed, which, according to the authors, is ideal for building control systems for multi-agent systems (MAS) to study and correct the behavior of a community of agents when they fail, use a lot of resources, etc. In this work, DFCM is used to build a control system for a fault management system based on multi-agent systems. Very good results were obtained, demonstrating that the use of these maps as a control tool for multi-agent systems is effective and reliable.

The combination of the concept of multi-agent systems and fuzzy cognitive maps is also described in [13, 14]. The goal of [13] was to create an online platform with a smart approach based on innovative technologies, such as multi-agent processing and fuzzy cognitive maps, which improves decision-making. In the approach proposed in [14], the result of using FCM is the basis for developing agent preferences and behavior rules in agent-oriented modeling.

The aim of the work is to improve the accuracy of determining the composition of gas mixtures and the concentration of individual gases by applying innovative approaches in both nanoelectronics, using a multisensor system on porous silicon, and information technology, using a multiagent system, by increasing the amount of data used to construct a vector response, increasing the size of the feature space, and applying a modified fuzzy cognitive map.

2. EXPERIMENTAL

To test the proposed system, we used a set of gas sensors based on porous silicon, which are combined into a matrix.

When manufacturing the matrix sensor, an Au/Ge-Ni-Au contact is applied to the back side of the semiconductor plate, and five layers of porous semiconductors with a diameter of 10 mm and different porosity are formed on the opposite side. A Pd contact with a diameter of 3 mm is deposited on each porous layer.

A stand was used for calibration and testing, which allows supplying both a single gas and a mixture of gases, controlling the gas concentration, and performing measurements [15]. A vacuum of up to 10^{-3} mmHg is created inside the flask. The gas flow rate was kept constant at 0.3 L/min. To study the effect of gas on the sensor, it was placed on a heater disc built into the flask, and its electrodes were connected to external contacts with platinum ties. After injecting gas into the flask through a flow meter, the resistance and response time of each sensor were measured at different temperatures (Fig. 1).

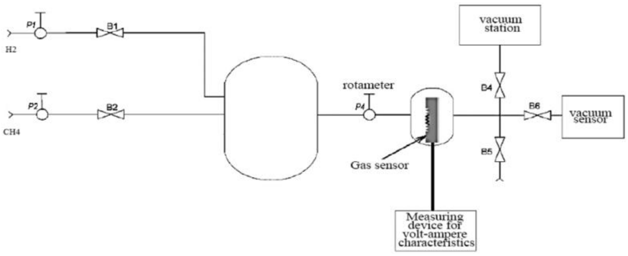

Fig. 2 – Diagram of a multisensor system on porous silicon [15]

3. RESULTS AND DISCUSSION

In general, agents that are part of a MAS are directly involved in processes that are specific to a particular subject area (SA). The ontology of the SA includes certain entities. There are certain relationships between entities that need to be reflected in the conceptual model. Therefore, we will present a conceptual model of a multi-agent system, taking into account the above, in the form of:

$$MAS = < PE(AP),\ AE(AA,\ RA,\ AS),\ SO,\ AR,\ R1,\ R2,\ AL,\ KB,\ IPS >, \quad (1)$$

where PE is the set of passive entities included in the ontology of the subject area; AP is the set of attributes of passive entities; AE is the set of agents that are active entities; AA is the set of agent parameters; RA is the functional roles of agents, each of which is expressed by the name of the agent; AS is the set of aspects of agent functioning within the defined roles; SO – set of classes of operations performed by agents; $R1 \subseteq SO \times AE \times AS$ – projection of the set of operations onto the set of agent roles and aspects of their functioning; $R2 \subseteq PE \times AE$ – relationship between passive and active entities; AL – library of data processing algorithms; KB – knowledge base for managing data processing processes in MaS; IPS – subsystem for processing and integrating information reported by agents. This subsystem is based on a set of fuzzy cognitive maps (FCM) that recognize situations, form a spectrum of ideas, focus attention, and evaluate the success of agents' actions. The latter is a new approach to building multi-agent systems.

Let us consider the task of processing data to determine the composition of gases and their concentrations by creating a multi-agent system.

Taking into account expression (1), the formal representation of the task is determined by the expression:

$$TR = < SC,\ SF,\ MP, AM,\ RCP >, \quad (2)$$

where SC is the set of classes; SF is the set of features; MF is the measurement procedure; CF is the set of associative models for transforming the set of features into the set of classes, which is a set of fuzzy cognitive maps; RCP is the procedure for automatic adjustment and correction of measurement results.

Typically, to solve this problem using methods based on semiconductor sensors, multisensor arrays containing a set of such sensors are used. Within our paradigm, each sensor is an agent that performs several measurements at different operating temperatures.

To store the reference and primary measurement results, it is necessary to create a set of matrices $M = \{M_0, M_1, M_2,\ldots M_i,\ldots, M_N\}$, containing the resistance values of the sensors, where each row corresponds to a specific k-th operating temperature of the sensor; each column corresponds to the j-th sensor with a specific permeability; i is the gas number, $i = 1\ldots N$. Each matrix from the set M must correspond to the average value from the known concentration range of each gas. Matrix M_0 is the "clean air" matrix, averaged over several experiments. This is a noise matrix. Sometimes noise must be included in the spectrum distribution.

The content of the matrices must be normalized by dividing the values of each matrix by its average value. After that, the average is equal to 1. Standardization of data by average allows you to compare samples with different average values, for example, to compare the spread of values relative to the average.

Let us also create a feature space with a dimension of $Q \times P$, where Q is the number of operating temperatures and P is the number of porosity gradations. In this space, we need to determine the points that correspond to the conditional average concentrations of each gas for the selected subject area. These will be the so-called resistance points.

Since in reality gases act simultaneously, in each cell of each matrix we see the result of the superposition of factors. Thus, each matrix point carries information about the entire composition of gases.

According to our hypothesis, the distances between points can be converted into gas composition. However, due to certain factors, the results of measurements and calculations will differ to some extent from the actual composition. Therefore, it is necessary to adjust the distances according to the actual concentrations, as there are errors. Among the factors that can affect the measurement results are individual sensor errors, which depend on deviations in operating temperature and other technical and technological factors.

To configure a multi-agent system for a specific gas mixture composition, it is necessary to have an FCM classifier that receives the current gas mixture composition from the researcher in the form of a binary code and accordingly configures the result correction subsystem by selecting the appropriate FCM association map.

Therefore, to correct the measurement results, we will use a type of fuzzy cognitive map (FCM), namely an association map (AM). Work [16] describes the AAM auto-association map, which is used to expand the feature space. AAM is a modification of FCM in which rows and columns correspond to the acting factors. The inputs and outputs of AAM are linked by an expression that we see in work [16].

$$s_i = F\left(\sum_{\substack{i=1 \\ i \neq j}}^{N+1} w_{ij} x_i\right), \quad (3)$$

where i is the AAM row number; F is the sigmoid function.

To solve our problem, we feed a set of values into the map

$$x_i = \frac{(d_i)^{-1}}{(\sum_i d_i)^{-1}} \quad i = \overline{1, N+1}, \tag{4}$$

where d_i is the distance between the working point of the feature space and the i-th reference point.

At the output of the map, we should obtain an integrated and corrected gas composition with the concentration of constituent elements. That is, it will be an association map (AM). We will convert the AM s_i outputs obtained using formula (3) into a distribution using the *softmax* function

$$y_i = \frac{e^{s_i}}{\sum_i e^{s_i}} \tag{5}$$

The values of the coefficients w_{ij} are calculated using the gradient method according to the recursive formula

$$w_{ij}^{t+1} = w_{ij}^{t} + \alpha x_i (y_j^* - y_j), \tag{6}$$

where y_i^* is the actual value of the gas composition in a specific training example; α is the learning rate coefficient, $0 < \alpha \le 1$. It is thanks to this training that the AAM matrix is able to subsequently correct the measurement results in the MaS.

Since the response of sensors to gas concentrations is nonlinear, it is advisable to have separately configured association maps for gas mixtures of different compositions. The selection of a specific AM is based on the decoder principle, namely $F_k = f(C_2(G_k))$, where F_k is the position code of a specific AM for the k-th mixture G_k; $C_2(G_k)$ is the binary code of the k-th mixture for which the composition needs to be determined.

If preliminary experiments with the sensor matrix have been conducted, the reference points obtained in the feature space and the AAM matrix are trained, the system's operating algorithm is as follows:

1. Technical preparation for sampling.
2. Setting the initial temperature of the sensor matrix.
3. Starting the cycle of taking measurements according to the meter, $k = 1$:

3.1. Fixing the k-th dimension in the corresponding local k-th matrix.

3.2. If $k = K$, proceed to step 4, otherwise set a new $(k + 1)$ operating temperature value and proceed to step 3.1.

4. Standardization of measurement results by dividing the measurement results for each matrix by the average value of that matrix.
5. Calculation of distances d_i between the working point of the current measurement g^o_{pq} and the i-th reference points using the square of the Euclidean metric

$$d_i = \sum_{p=1}^{P} \sum_{q=1}^{Q} (g^o_{pq} - g_{pqi})^2 , \tag{7}$$

6. We convert the array of distances d_i into an array $X = \{x_i\}$ using expression (4). We feed this array into the AM input.

6. Calculations on AM. As a result, we obtain a gas composition distribution that is close to the actual one, with an accuracy limited by instrumental error.

The experimental verification was performed on a multisensor system, the elements of which corresponded to the following grid of porosity and operating temperature values (Figures 2-4). Accordingly, Figures 3-5 show graphs of resistance changes.

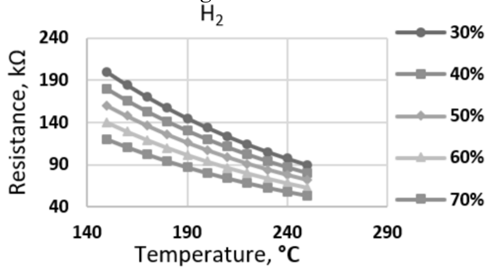

Fig. 2 – Temperature dependence of resistance for sensors with different porosity in H_2 environment

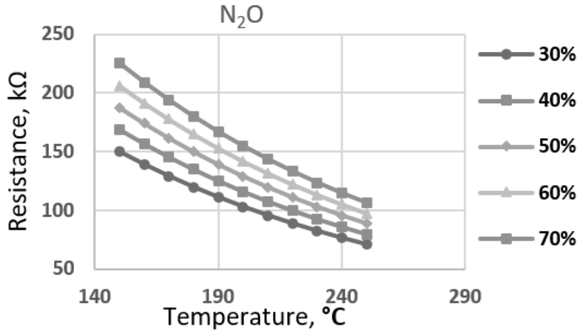

Fig. 3 – Temperature dependence of resistance for sensors with different porosity in N_2O environment

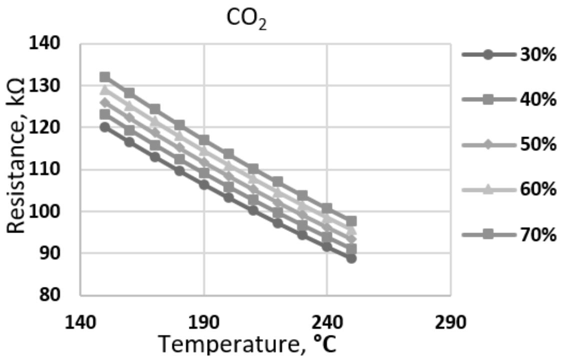

Fig. 4– Temperature dependence of resistance for sensors with different porosity in CO_2 environment

After processing the measurement data, which was collected and processed using the above method, the results shown in the following tables and diagrams were obtained. Tables 1 and 2 show the comparative results of measuring low (LC) and high concentrations (HC) in ppmV of three gases. Absolute and relative errors are provided.

Table 1 – Actual values and measurement errors at low gas concentrations

	H_2	N_2O	CO_2
Real	5.30	1.40	4.80
Measured	5.64	1.43	4.74
AbsErr	0.34	0.03	0.06
RelErr, %	6.42	2.14	1.25

Table 2 – Actual values and measurement errors at high gas concentrations

	H_2	N_2O	CO_2
Real	530.60	170.20	700.70
Measured	550.30	160.50	800.20
AbsErr	19.70	99.70	47.5
RelErr, %	3.7	5.7	6.78

It can be concluded that the error sizes for high and low gas concentrations are practically the same.

To verify the effectiveness of the proposed system, the gas composition was measured using a single sensor with 50 % porosity at the same operating temperature range. Table 3 shows the relative measurement errors using a single sensor and a multi-sensor system with the proposed data processing algorithm. Analysis of the obtained results allows us to conclude that the approach proposed in this work gives better results.

Table 3 – Relative errors in measuring gas concentrations in systems with different numbers of sensors.

Multisensor system			
	H_2	N_2O	CO_2
LC	6.42	2.14	1.25
HC	3.7	5.7	6.78
Single-sensor system			
	H_2	N_2O	CO_2
LC	11.75	15.87	13.12
HC	15.41	14.23	17.92

Separately, it is necessary to discuss and compare the proposed multi-agent data processing system and a multi-sensor system in which a neural network is used to process data and determine the composition of gases and their concentrations. When it comes to classification, i.e., determining the class of a particular object or symbol, the neurons of the output layer are trained on labeled examples in which the actual class of each object is clearly indicated. In their work, the authors applied a regression task, where the output of the model can be used to obtain an arbitrary value of the concentration of each gas in a certain range. Under such conditions, it is quite difficult to train a neural network with several hidden layers and several outputs. It is necessary to generate many examples and spend a lot of time on training.

In the proposed system, which uses the calculation of distances in a multidimensional feature space, the results are adjusted using a simple association map, which is a modified fuzzy cognitive map. Accordingly, the process of debugging such a system is relatively simple and fast. At the same time, despite the fact that several association maps have to be used to improve accuracy and flexibility, the time spent on debugging the system is significantly less than training a multilayer network on a multitude of different combinations in gas mixtures.

CONCLUSIONS

For the first time, a method for determining the composition of a gas mixture using a multi-agent system has been proposed, which is distinguished by the fact that it consists of a set of sensors on porous silicon, each of which performs the functions of a multi-mode agent and allows the formation of an extended feature space, calculate the distances between measurement points in this space, and convert the set of distances into a distribution of gas concentrations, which simplifies the algorithm for measuring the composition of the gas mixture and the concentration of gases while maintaining the required measurement accuracy.

The model of a multi-agent system has been improved by introducing a set of fuzzy cognitive maps designed to recognize situations, form a spectrum of ideas, focus attention, and evaluate the success of agents' actions, which allows various multi-agent systems to be constructed using a single methodology for application in different subject areas.

The experiments conducted and the analysis of the results show that the proposed multi-agent system is capable of successfully determining the composition of gas mixtures with the necessary accuracy. At the same time, in terms of complexity and time required for debugging, such a system surpasses known neural network systems of the "electronic nose" type. The development of the proposed approach will simplify the procedures for analyzing gas composition in applications such as the diagnosis of diseases accompanied by the release of specific gases, humanitarian demining by the "smell" of mines, etc.

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Мультисенсорна система на базі пористого кремнію з мультиагентною обробкою даних

С.Е. Притчин, І.В. Шевченко, А.П. Оксанич, М.Г. Когдась, Є.А. Расторопов,
О.С. Притчин, В. Палагін

Кременчуцький національний університету імені Михайла Остроградського, 39600 Кременчук, Україна

У статті запропоновано метод підвищення селективності визначення концентрації газів в газових сумішах використовуючи мультісенсорні системи на базі пористого кремнію з застосування мільтіагентної системи обробки інформації. Виконано загальний формальний опис мультиагентної системи, яка удосконалена за рахунок введення комплексу нечітких когнітивних карт, призначених для розпізнавання ситуацій, формування спектру уявлень, фокусування уваги та оцінки успішності дій агентів, що дозволяє за єдиною методологією конструювати різноманітні мультиагентні системи, зокрема таки, що застосовуються для підвищення селективності сенсорів. В опис задачі входять множина класів, що підлягають розпізнаванню, множина ознак, процедура вимірювання, набір асоціативних моделей перетворення множини ознак у множину класів, якій є набором нечітких когнітивних карт, а також процедури автоматичного налаштування та корекції результатів вимірювання концентрації газів. В основі запропонованого методу лежить визначення складу газової суміші який отримується матрицією газових сенсорів-агентів на основі пористого кремнію, з різною поруватістю та при різних температурах. За допомогою мультиагентної системи формується розширений простір ознак, обчислюються дистанції між точками вимірів у цьому просторі. Сукупність дистанцій перетворюється на розподіл концентрацій газів, що дозволяє спростити алгоритм виміру концентрацій при дотриманні необхідної точності вимірів і спростити процес налагодження системи визначення складу газової суміші та концентрації її окремих елементів. Виконані експерименти та аналіз результатів показують, що запропонована система здатна з достатньою точністю визначати склад газових сумішей.

Ключові слова: Пористий кремній, Сенсори концентрації газу, Мультисенсорна система, Мультиагентна система, Розширений простір ознак.