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Pattern recognition for sensor array signals using Fuzzy ARTMAP

Zhe Xu[a], Xiajing Shi[a], Lingyan Wang[b], Jin Luo[b], Chuan-Jian Zhong[b], Susan Lu[a,*]

[a] Systems Science and Industrial Engineering, State University of New York at Binghamton, Binghamton, NY 13902, United States
[b] Department of Chemistry, State University of New York at Binghamton, Binghamton, NY 13902, United States

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ABSTRACT

A Fuzzy ARTMAP classifier for pattern recognition in chemical sensor array was developed based on Fuzzy Set Theory and Adaptive Resonance Theory. In contrast to most current classifiers with difficulty in detecting new analytes, the Fuzzy ARTMAP system can identify untrained analytes with comparatively high probability. And to detect presence of new analyte, the Fuzzy ARTMAP classifier does not need retraining process that is necessary for most traditional neural network classifiers. In this study, principal component analysis (PCA) was first implemented for feature extraction purpose, followed by pattern recognition using Fuzzy ARTMAP classifiers. To construct the classifier with high recognition rate, parameter sensitive analysis was applied to find critical factors and Pareto optimization was used to locate the optimum parameter setting for the classifier. The test result shows that the proposed method can not only maintain satisfactory correct classification rate for trained analytes, but also be able to detect untrained analytes at a high recognition rate. Also the Pareto optimal values of the most important parameter have been identified, which could help constructing Fuzzy ARTMAP classifiers with good classification performance in future application.

1. Introduction

There are different types of poisonous gases or vapors in the environment, which have harmful effects on human health. One class of examples is volatile organic compounds (VOC). Their detection and identification are extremely important. Many types of chemical sensors have been reported for identification of VOCs. One example is chemiresistive sensor array, which is usually employed to acquire signals for different analytes such as VOCs and other toxic gases [1–5]. A sensor array has different response profiles or patterns to different VOCs. Its signals thus can be used to analyze and classify vapors with statistical or nonparametric intelligent methods.

To classify different VOCs, training for the classification model is usually necessary. For certain VOCs, all the relevant information, e.g., sensor signal, along with its corresponding class, is needed for obtaining classification models during the training stage. Especially when new VOCs are added, retraining for original and new VOCs is generally needed with current reported approaches. In addition, although various classification methods have been applied to classify VOCs, most of them only focus on identifying trained VOCs. There are few reports on the detection of untrained VOCs.

Fuzzy ARTMAP [6] is a constructive neural network model developed upon Adaptive Resonance Theory (ART) and Fuzzy set theory [6–10], which allows knowledge to be added during training if necessary. It avoids discarding the previous knowledge or model and spares repeating the whole training process. The Fuzzy ARTMAP classifier's continuous online learning capability greatly facilitates the dynamic changing of the classifier's knowledge base. The learning and forecasting mode of the Fuzzy ARTMAP system can function alternatively. Thus, the Fuzzy ARTMAP classifier is competent for working in a dynamic environment that is subjected to the presence of new vapor. For example, the Fuzzy ARTMAP classifier can always recognize new vapors, and learn to classify them by changing its structure and parameters without retraining for the original trained vapors. Because of Fuzzy ARTMAP system's self-organizing scheme, it does not need pre-determination of many parameters, e.g., some structure parameters; that is not the case for most traditional ANNs. For example, in multi-layer perceptrons (MLPs), the amount of its hidden layer(s), and the number of nodes in hidden layer(s) must be decided before training. Also, the training of the Fuzzy ARTMAP classifier is very fast compared with Back Propagation (BP) neural networks. In addition, a Fuzzy ARTMAP classification system based on the knowledge of several known or trained vapors can detect the presence of a new or untrained vapor. This function can alert to the presence of a potential threat from a new vapor in a dynamic environment.

To date, there are many studies and successful applications of Fuzzy ARTMAP in the pattern classification field [11–15]. However,

* Corresponding author.
E-mail address: slu@binghamton.edu (S. Lu).

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based on the authors' best knowledge, there are no reports using Fuzzy ARTMAP to identify the untrained analytes from sensor array responses. Instead, most current classifiers applied in this area have no capability to identify untrained new vapors. In addition, analysis of the effect of some important parameter toward the classification system was presented. Pareto optimization method was applied to analyze variation of classification performance corresponding to the change of vigilance parameter's value. The Pareto optimization analysis identified the general near optimal value of initial vigilance parameter. That provides some hint for constructing parameter set of Fuzzy ARTMAP classifier in similar application.

In this paper, the Fuzzy ARTMAP classifiers are applied to analysis of the responses of a chemiresistor sensor array with different nanostructured sensing materials [3–5] to a set of VOCs, namely vapors generated from organic solvents, benzene (Bz), hexane (Hx), p-xylene (Pxy), and toluene (Tl). The sensing array materials consist of (1) NDT-linked nanoparticles (NDT-$Au_{2\,nm}$), (2) PDT-linked nanoparticles (PDT-$Au_{2\,nm}$), (3) MUA-linked nanoparticles (MUA-$Au_{2\,nm}$), (4) MHA-linked nanoparticles (MHA-$Au_{2\,nm}$), (5) MPA-linked nanoparticles (MPA-$Au_{2\,nm}$) [1–4]. NDT: 1,9-nonanedithiol (HS–$(CH_2)_9$–SH), PDT: 1,5-pentadithiol (HS–$(CH_2)_5$–SH), MUA: 11-mercaptoundecanoic acid (HS–$(CH_2)_{10}$–CO_2H), MHA: 16-Mercaptohexadecanoic acid (HS–$(CH_2)_{15}$–CO_2H), and MPA: 3-mercaptopropanoic acid (HS–$(CH_2)_2$–CO_2H), were used as received (Aldrich). From the four vapors, three are alternatively selected as known vapors to the classifier viz. the Fuzzy ARTMAP. This classifier will then be trained to learn the above three selected vapors. The fourth vapor is considered a new vapor to the classification model. Partial data for the chosen known vapors are employed to build a PCA model, and the main PC variables are then served as input to train the Fuzzy ARTMAP classifier. The remaining data for the trained vapors and complete set of data for untrained vapor together constitute the testing data set. The new PC scores from testing data are then calculated from the previously built PCA model. After transformation, the adjusted PCs are fed to Fuzzy ARTMAP classifier to test the classification performance. Finally, the Pareto optimization method is applied to analyze the relationship between parameter setting and performance of Fuzzy ARTMAP system.

2. Experiment

Sensor-response measurements were performed using a customized interdigitated microelectrode (IME) device, which has 300 pairs of platinum electrodes of 5 μm width and 5 μm spacing on glass substrate (100-nm thick). The thickness of the coating of molecularly linked nanoparticle thin film was below or close to the finger thickness. Details about the preparation of molecularly linked nanoparticle thin film assembly were described previously [2,4]. Briefly, the thin films were prepared via "exchanging–crosslinking–precipitation" route. The reaction involved an exchange of linker molecule (NDT, PDT, MUA, MHA, MPA) with the gold-alkanethiolates, followed by crosslinking and precipitation via either Au S bonding at both ends of NDT or PDT, or hydrogen bonding at the carboxylic acid terminals of MUA, MHA or MPA. The platinum-coated IME devices were immersed into the solution of the mixed nanoparticles and thiols at room temperature, and solvent evaporation was prevented during the film formation. The thickness of the thin films grown on the surface of the substrates was controlled by immersion time [2,4].

A computer-interfaced multi-channel multimeter (Keithley, Model 2700) was used to measure the lateral resistance of the nanostructured coating on IME. The resistance and frequency measurements were performed simultaneously with computer control. All experiments were performed at room temperature, $22 \pm 1\,^{\circ}C$. N_2 gas (99.99%, Progas) was used as reference gas and as diluent to change vapor concentration by controlling mixing ratio. The gas flow was controlled by a calibrated Aalborg mass-flow controller (AFC-2600). The flow rates of the vapor stream were varied between 5 and 50 mL/min, with N_2 added to a total of 100 mL/min. The vapor generating system followed the standard protocol [6b]. The vapor stream was produced by bubbling dry N_2 gas through a bubbler of the vapor solvent using the controller to manipulate vapor concentration [2,4].

The measured resistance (R) values were expressed as relative differential resistance change $\Delta R/R_i$ for the evaluation of the vapor sorption responses. ΔR is the difference between the maximum and minimum values in the resistance response and R_i is the initial resistance of the film [2,4].

3. Classification methodology

The following schematic diagram (Fig. 1) depicts the general classification procedure in this study. The original responses from sensor arrays are preprocessed and the principal component analysis method is applied to extract feature vectors. Through PCA, the dimension of signal is reduced, and the noise in original signals could be eliminated to some extent. The feature vectors are then projected into range [0,1] and serve as the input to Fuzzy ARTMAP classifier, which can identify the both trained and untrained vapors. Normalization and complimentary coding are important steps to get appropriate input for Fuzzy ARTMAP system. The performance of classifier is tested by classifying the new data from both trained and untrained vapors.

The classification results are also been analyzed by multiple objective optimization method. In this study, Pareto optimization is implemented to identify optimal parameter set for Fuzzy ARTMAP classifiers. For different parameter settings of Fuzzy ARTMAP classifiers, there is a trade-off between successful classification rate for trained and untrained vapors. When there is a change in the value of a decision variable or parameter in certain direction, one objective, e.g., one correct classification rate, will increase, while the other objective will show some deterioration. Since the two objectives could not reach their global optima simultaneously, a multi-objective optimization technique is employed to identify a Pareto optimal set.

3.1. Principal component analysis

Principal component analysis is a multivariate analysis method which transforms a set of correlated variables into a set of uncorrelated variables. Assuming there are p variables in original data X, i.e. $X = (x_1, \ldots, x_p)$, PCA forms p linear combinations [16]:

$$\begin{aligned}
PC_1 &= w_{11}x_1 + w_{12}x_2 + \cdots + w_{1p}x_p \\
PC_2 &= w_{21}x_1 + w_{22}x_2 + \cdots + w_{2p}x_p \\
&\vdots \\
PC_p &= w_{p1}x_1 + w_{p2}x_2 + \cdots + w_{pp}x_p
\end{aligned}$$

$$w_{i1}^2 + w_{i2}^2 + \cdots + w_{ip}^2 = 1 \quad i = 1, \ldots, p$$

$$w_{i1}w_{j1} + w_{i2}w_{j2} + \cdots + w_{ip}w_{jp} = 0 \quad \text{for all } i \neq j \tag{1}$$

where new variables $PC_1, PC_2, \ldots, PC_p$ are p principal components (PCs). The first principal component, PC_1, accounts for the maximum variance in the original data; and PC_2, the second principal component, accounts for maximum variance that has not been accounted for, by the first PC, etc. [16]. The weight of the jth original variable for the ith PC is w_{ij}.

The PCA method can reserve most information in the original data while at the same time eliminate a certain amount of

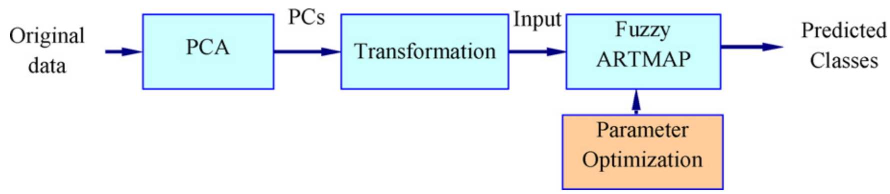

Fig. 1. Schematic diagram of classification procedure.

noise. It is a widely used tool for data reduction purpose, in which, depending on the amount of variance accounted by the new variables, less than P impendent new variables can be selected to represent the original p-dimensional original variables. In this study, PCA is employed as a data dimension reduction and feature extraction technique to generate input vector to Fuzzy ARTMAP classifier.

3.2. Fuzzy ARTMAP

3.2.1. Fuzzy ARTMAP structure

The general Fuzzy ARTMAP has two main components: Fuzzy ART module and map field. For most problems in which the desired classes are directly provided to the classifier, a simplified Fuzzy ARTMAP with only one Fuzzy ART module can fulfill the classification task. Further simple Fuzzy ARTMAP is more computationally efficient than the full version without undermining classification performance in many cases. The structure of simple Fuzzy ARTMAP is shown in Fig. 2.

An input layer consists of some neurons that each can accept continuous value within the range of [0,1]. The category layer directly connected with the input layer includes some cells that each represents a possible category. Those two layers that belong to a Fuzzy ART A module are connected by a weight matrix noted as Z. For example, input neuron i and category neuron j are connected by weight z_{ij}. The other category layer can accept target in training stage, and yield estimated class as output in prediction mode, and the map field includes same amount of neurons as that in the category layer taking class vectors, i.e., targets. The nodes in category layer of Fuzzy ART A module and those in map field are connected by a weigh matrix labeled as W. A match tracking system controls the vigilance parameter ρ_A, where $\rho_A \in [0,1]$. That parameter determines the final amount of categories in the category layer of Fuzzy ART A module, and significantly affects classification performance of Fuzzy ARTMAP system.

3.2.2. Normalization of input

An input vector can be normalized through simply dividing its components by the norm, i.e., the sum of absolute values of all components of that input vector. That normalizing method requires less system resources. But complement coding is preferred and applied frequently, for it could avoid category proliferation problem [9].

Complement coding doubles the amount of components in original input vector. For an input with N elements, $X=(x_1,x_2,\ldots,x_N)$, the coded input to a Fuzzy ARTMAP system will be a $2N$-dimensional vector [9,17]

$$(X, X^c) \equiv (x_1, x_2, \ldots, x_N, x_1^c, x_2^c \ldots, x_N^c) \tag{2}$$

where, for $i=1,2,\ldots,N$,

$$x_i^c = 1 - x_i \tag{3}$$

3.2.3. Working theory

Fuzzy ARTMAP system can work in either learning or recall operation mode [18]. In learning mode, the system is trained by data composed of input-target pairs, while in recall mode it produces estimated class for corresponding input. The schematic flow diagram for learning operation mode is depicted in Fig. 3.

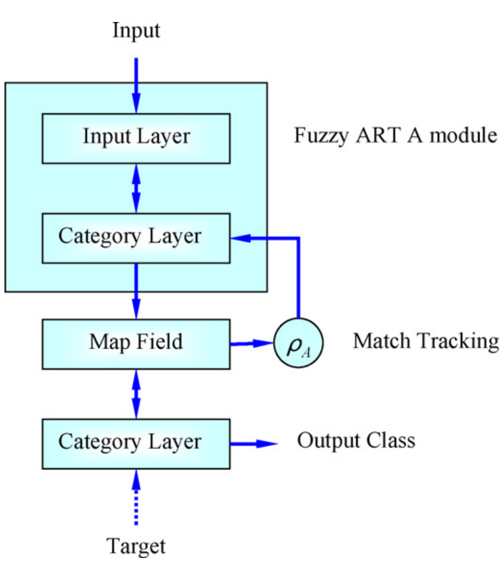

Fig. 2. Structure of simple Fuzzy ARTMAP classifier.

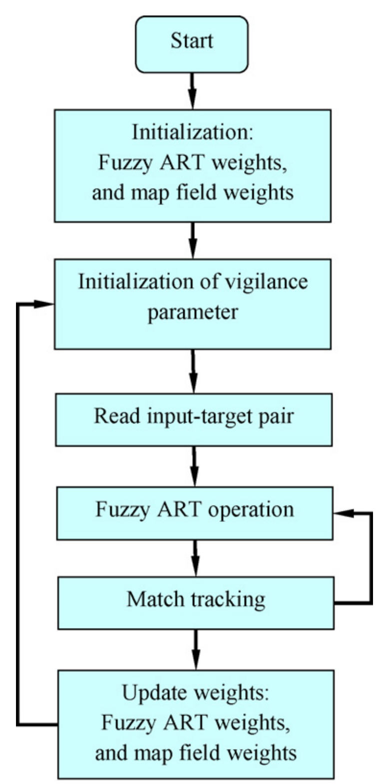

Fig. 3. Flow diagram for learning operation mode of Fuzzy ARTMAP.

In training stage, first the weights of Fuzzy ART A, z_{ij} and map field, w_{jk} are initialized, i.e., let $z_{ij}=1$, and $w_{jk}=1$. Vigilance parameter ρ_A is set to an initial value $\overline{\rho_A} \in [0,1]$. Later, ρ_A can only increase from $\overline{\rho_A}$. Every time an input-target pair is fed into Fuzzy ARTMAP. Then, Fuzzy ART operation is conducted to determine a category J satisfying the current ρ_A criterion. Each neuron of category layer will receive an input T_j to measure the similarity between the input pattern X and the weight template of category j, i.e. $Z_j = (z_{1j}, z_{2j}, \ldots, z_{N_A j})$ where N_A is the amount of nodes in input layer [18]. For category layer, the category J with template Z_j which is most similar to input, is selected, following the winner-take-all rule. The winning category J must satisfy the vigilance criterion [9], i.e.

$$\frac{|X \wedge Z_J|}{|X|} \geq \rho_A \tag{4}$$

Otherwise, T_J is set to 0, and current category J is abandoned, another category J with largest T_J will be selected. This process will repeat till a winning category that satisfies the vigilance criterion is found.

Then the match tracking system works. For the identified category J and corresponding target class K, if $w_{JK}=0$, then match tracking systems will increase vigilance parameter by

$$\rho_A = \frac{|X \wedge Z_J|}{|X|} + \varepsilon \tag{5}$$

where ε is a small positive value close to 0 [18]. With the increased ρ_A, the Fuzzy ART operation and match tracking operation will be repeated, till a $w_{JK}=1$ is found. Then the weights of Fuzzy ART module and map field will be updated accordingly. (The detailed algorithm can be seen in Ref. [18].).

After training, Fuzzy ARTMAP can estimate class for a new input vector without corresponding target by recall operation. There is no match tracking, weight initialization or weight updating operation in recall mode. The vigilance parameter will be equal to its initial value $\overline{\rho_A}$. The output class vector will take the value of identified w_J. If there is only one element in output equal to '1', the input pattern is estimated as belonging to class K. Otherwise, it is considered as belonging to a new class, because this unknown class' pattern is too different from the stored knowledge.

3.3. Pareto optimization

The decision of initial vigilance parameter will depend on the comparative importance of correct classification rate for trained and untrained vapors. The Pareto optimization method is widely used for multiple objective optimization problems. For a minimization problem, if Z is defined as feasible objective region, an objective (function) vector z^* is Pareto optimal if there is no other objective vector $z \in Z$ such that at least one component $z_i < z_i^*$, and $z_j \leq z_j^*$ for all the other components $j \neq i$ [19]. In this study, Pareto optimization analysis is conducted to reveal the association between initial vigilance parameter, and the corresponding classification performance of Fuzzy ARTMAP system.

4. Results and discussion

The data set is composed of 120 measurements for four test vapors (Hx, Bz, Tl, Pxy) in which the test vapor concentrations range from 3% to 30%. One of the four vapors is considered as "unknown" vapor in every classification test. Each classifier training data set is composed of data belonging to only selected "known" vapors. For the 'known' vapors' data (total 90 samples), two thirds of them (60 samples), are selected as training data. The testing data set consists of the rest of the data (60 samples) for both trained and untrained vapors.

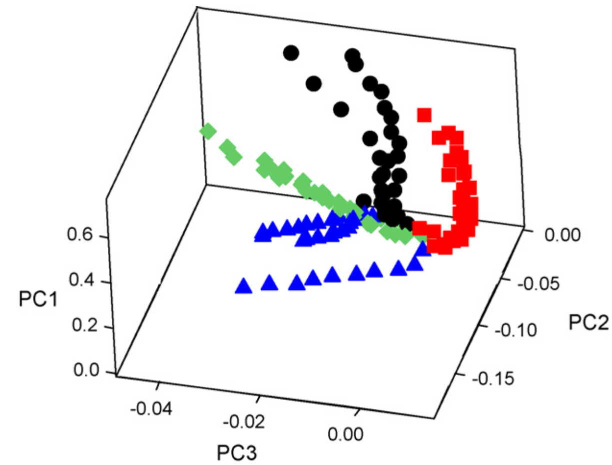

Fig. 4. PCA score plot of the first principal component (PC_1), the second (PC_2), and the third (PC_3) for responses of Bz (black), Hx (red), Pxy (green), and Tl (blue). For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.

4.1. PCA result

PCA is employed to extract features from the original response for a Fuzzy ARTMAP classifier. The first three PCs are selected for the analysis of the data since they account for nearly 100% of variation. The three-dimensional PCA score plot is shown in Fig. 4.

The four classes, or vapors, could be observed from the three-dimensional PC plot. However, some data points belonging to different classes immingle with each other, especially those responses having smaller absolute values in PC score for all the three PCs. In view of those PCA scatter plots between two PCs, the trend of PC scores presents nonlinear curve within a vapor class, for almost all four vapors, and there are some overlapping among classes; thus they are hard to distinguish by any two PCs.

4.2. Fuzzy ARTMAP

To served as the input of Fuzzy ARTMAP classifier, the first three PC scores are projected into range [0,1], with equation

$$x' = \frac{(x-a)}{(b-a)} \times (b'-a') + a' \tag{6}$$

Here, x is the original PC score value; while a and b are lower and upper limit of x. To guarantee that the new data's PCs will always be within the range, in transformation, a is set to the value that is smaller than real upper limit of x; and b is set to a value that is larger than upper limit of x. x' is the projected value within appropriate range, a' and b' are lower and upper limit of new value x'. Thus, in this study $a'=0$, $b'=1$; $a=-0.3$, and $b=0.8$.

The most important parameter for simplified Fuzzy ARTMAP is the initial value of vigilance parameter. Due to the working theory of Fuzzy ARTMAP, that value will directly affect the performance and final result of the classifier. Fuzzy ARTMAP with smaller initial vigilance parameter will produce fewer categories to summarize the input, while the precision of classification will decrease accordingly. In other words, with a loose criterion of similarity, an input will be easier to be attributed to an existing class according to the stored knowledge. If the initial value of vigilance parameter for a Fuzzy ARTMAP classifier is set high, i.e., near 1, there will be more categories inside the model. And, the correct classification rate will improve consequently. To test the relation between initial vigilance parameter and classification performance, for each classifier, different values of initial vigilance parameter are chosen. In the experiment, the classification results for test-

Table 1
Fuzzy ARTMAP classifiers and corresponding vapors: benzene (Bz), hexane (Hx), p-xylene (Pxy), and toluene (Tl).

Classifier	Combination	
	Known vapors	Unknown vapor
A	Bz, Hx, Pxy	Tl
B	Bz, Hx, Tl	Pxy
C	Bz, Pxy, Tl	Hx
D	Hx, Pxy, Tl	Bz

Table 2
Classification rate (%) of four Fuzzy ARTMAP classifiers with different initial vigilance parameter (IVP).

Classifier	IVP	Trained				Untrained
A	0.994	Bz: 80	Hx: 100	Pxy: 100	Average: 93.3	Tl: 86.7
B	0.9955	Bz: 60	Hx: 100	Tl: 70	Average: 76.7	Pxy: 93.3
C	0.9952	Bz: 80	Pxy: 90	Tl: 70	Average: 80.0	Hx: 100
D	0.9955	Hx: 100	Pxy: 90	Tl: 70	Average: 86.7	Bz: 86.7

ing data sets are mainly represented by the successful classification rate.

In experiments, for each combination of trained and untrained vapor, different values of initial vigilance parameter are tested. Partial experimental results are shown in Table 1, using the value of the choice parameter α as 0.000001.

In all, 105 experiments with different initial vigilance parameter values were conducted. Here the classifiers A, B, C, and D are built according to Table 1. For example, Fuzzy ARTMAP classifier A is built on data from vapor: Bz, Hx, and Pxy. Its classification performance was evaluated according to the successful classification rate on new data from both those three trained vapors and untrained vapor Tl. In experiment, all the simulations ended within one second, or even in much shorter time when implemented in a common personal computer. That is quick enough for most industrial applications.

The experimental results are shown in Fig. 5 and Table 2 in detail. The classification performance is evaluated mainly by successful classification rate. For all the classifiers, the value of initial vigilance parameter has effect on the successful classification rate. Generally, when initial vigilance parameter is small (smaller than 0.8), there is no obvious change in successful classification rate for trained and untrained vapors. And successful classification rate for trained vapors is much higher than that for untrained. It can be seen that for all classifiers, when initial value of vigilance parameter is set to a high value (greater than 0.99 in this study), a high successful classification rate for untrained vapor can be acquired. Generally, when the initial vigilance parameter value is greater than a high value, e.g., 0.995, the higher the value of $\overline{\rho_A}$ is, the larger will be the chance of getting a high correct classification rate for untrained vapor. Thus, in this study, if initial vigilance parameter is set to a large value, e.g., $\overline{\rho_A} = 0.997$, those Fuzzy ARTMAP classifiers can identify untrained vapor with a high success rate, even 100%. However, the generalization performance for classification of trained vapor deteriorates, after the initial vigilance parameter exceeds certain value. If $\overline{\rho_A}$ is larger than 0.996, the successful classification rate for trained vapor will decrease. Generally, Hx has better classification results when it is chosen as trained vapor, which conforms to the previous PCA analysis. The fact that classification rate for some vapor cannot reach 100% is probably due to the input data. There

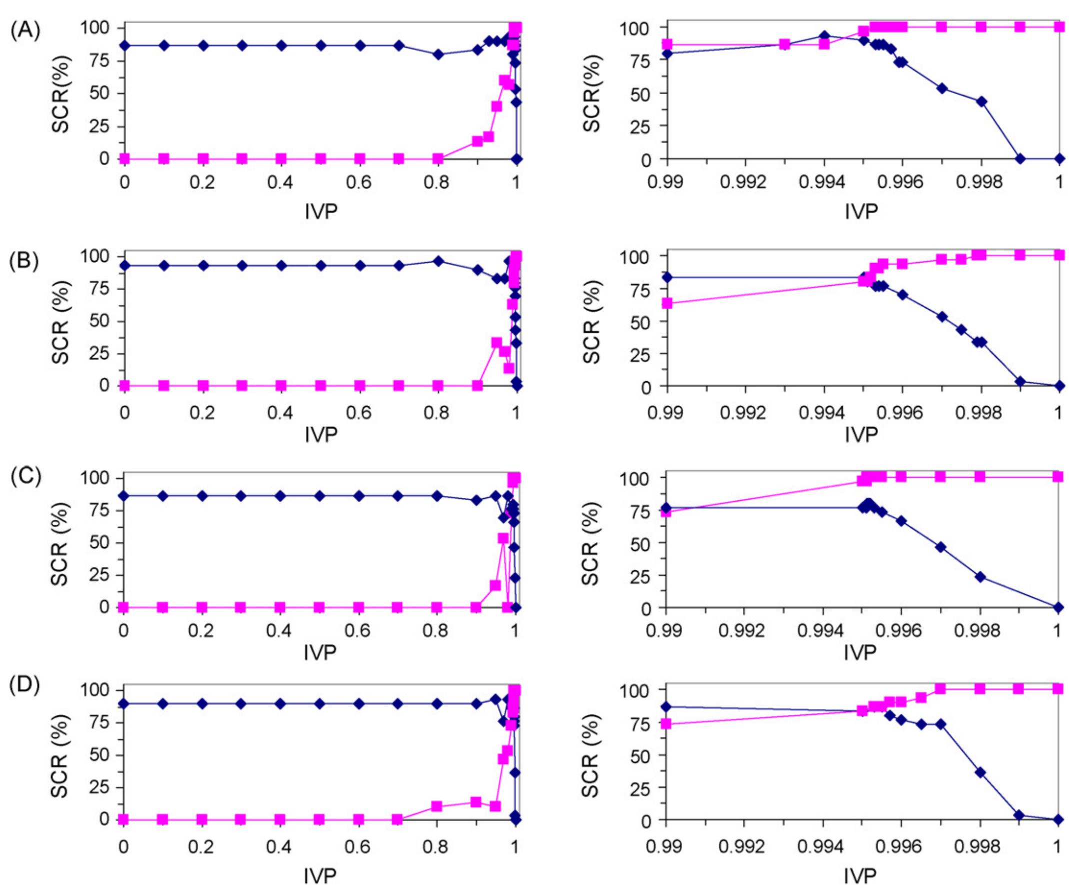

Fig. 5. Successful classification rate (SCR) of Fuzzy ARTMAP classifiers: A, B, C, and D with different initial vigilance parameter (IVP). The right graph is a magnified view of its left graph, showing the SCR corresponding to IVP value between 0.99 and 1. (untrained vapor, pink; trained vapors, blue). For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.

is overlapping between different classes, which is obvious in the previous PCA score plot figures. For a specific classifier, there may exist some optimal values of $\overline{\rho_A}$, when successful classification rate for both trained and untrained vapor are taken into consideration.

The decision of initial vigilance parameter will depend on the comparative importance of correct classification rate for trained and untrained vapors. For further analysis of the relationship between initial vigilance parameter and performance of Fuzzy ARTMAP system, multiple objective optimization analysis is conducted.

4.3. Results for multiple objective optimization

For further analysis of the relationship between initial vigilance parameter and performance of Fuzzy ARTMAP system, multiple objective optimization analysis is conducted. As shown by the experimental results, initial vigilance parameter has obvious effect on the performance of Fuzzy ARTMAP system, which is weighted mainly by the successful classification rate (SCR) of both untrained and trained vapors. Those two are considered as two objectives to maximize. The problem can be defined as a multiple objective optimization. The decision vector is composed of only one component, the initial vigilance parameter. The linear 2D (L2D) algorithm [20] is employed to construct Pareto optimal Set. To identify some general good value of initial vigilance parameter, the search operation is implemented on all the classification results acquired from the experiment. The Pareto Set produced is shown in Fig. 6. The Pareto optimal points lie in the upper right corner of the figure. Those points denote solutions with high successful classification rates for both trained and untrained vapors. Some Pareto optimal solutions lie much closely, or even overlap with one another. When initial vigilance parameter takes a value about 0.995, usually the solution is Pareto optimal in this study, and the corresponding classification performance of Fuzzy ARTMAP classifier seems good in view of SCR of both trained and untrained vapors.

The sensitivity analysis of choice parameter α is also conducted by varying its value during the experiment keeping the initial vigilance parameter same. In the experiment, α has been set to large values which are near to 1. However, there is no change in classification performance corresponding to variation of choice parameter in this study.

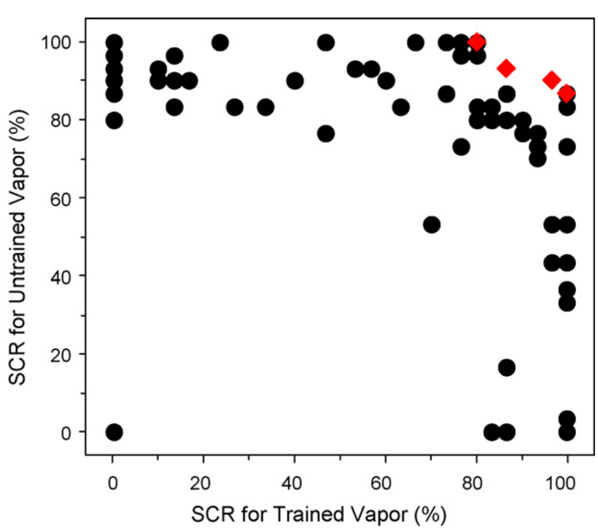

Fig. 6. Pareto optimal solutions in plane of successful classification rate (SCR) of trained vapor vs. that of untrained vapor. (Pareto optimal, red diamond; otherwise, black round). For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.

5. Conclusion

In this study PCA and Fuzzy ARTMAP are jointly applied to the classification of sensor array responses to four volatile organic vapors: Bz, Hx, Pxy, and Tl; emphasizing detecting untrained vapors. Unlike most current classifiers, e.g., multi-layer perceptron, and support vector machine (SVM) classifiers, etc., which have difficulty in identifying new analytes, the Fuzzy ARTMAP system can successfully recognize untrained VOCs based on their sensor-response profiles. Further, the built Fuzzy ARTMAP classifiers could recognize new analytes without retraining process, which is required by most traditional neural network classifiers, e.g., radial-basis function (RBF) network, and multi-layer perceptron classifiers, etc. By carefully selecting the value of the most important parameter, i.e., initial vigilance parameter, the experiment results show that Fuzzy ARTMAP classifiers can identify untrained vapors with a quite high correct recognition rate (up to 100%), while maintaining a decent classification performance on recognizing trained vapors. Taking the input processed by PCA, Fuzzy ARTMAP classifiers can generally recognize certain vapor without being trained by data containing information about that vapor. Experiments show that the initial vigilance parameter is critical for the performance of Fuzzy ARTMAP classifier. Trading-off both successful classification rates for trained and untrained vapors, there are some near optimal values of initial vigilance parameter. Pareto optimization method was applied to analyze variation of classification performance corresponding to the change of vigilance parameter's value. Through analysis, the Pareto optimal values of initial vigilance parameter were identified. Generally, when that parameter is set to a high value, the performance of Fuzzy ARTMAP classifier will be good for identifying untrained vapor. That observation generally conforms to the Fuzzy ARTMAP theory, and could provide some hint for constructing good parameter set of Fuzzy ARTMAP classifier in similar application. Thus, a Fuzzy ARTMAP classifier combined with PCA seems to be promising in identifying untrained vapors.

To test the general performance of both trained and untrained vapor classification by Fuzzy ARTMAP classifier, more experiments involving more vapors are needed in the future. By selecting different combinations of sensors, the successful classification rate could be improved further. Optimization of sensor array combination beforehand might decrease the effects on classification results, which is due to input signals acquired from specific combined sensors. To improve the generalization performance of classification, some strategy, e.g., voting strategy [10], or some improved algorithm based on Fuzzy ARTMAP might be employed in further study to improve the generalization performance of classification.

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Biographies

Zhe Xu is a Ph.D. candidate at the Department of Systems Science and Industrial Engineering, SUNY-Binghamton. He received his M.S. and B.S. from the Department of Automation at North China Electric Power University in 2002 and Northeast China Institute of Electric Power Engineering in 1998, respectively. His current research interests include pattern classification, applied statistics, and optimization.

Xiajing Shi is a postdoctoral researcher at the Department of Chemistry, SUNY-Binghamton. She received her Ph.D. in systems science from the Department of Systems Science and Industrial Engineering, SUNY-Binghamton in 2007, M.S. and B.E. from the Department of System Engineering at Xiamen University in 1999 and 1994, respectively. Her current research interests include information technology, pattern recognition, and optimization.

Lingyan Wang is a postdoctoral researcher in the Department of Chemistry, SUNY-Binghamton. She received her Ph.D. in chemistry from the Department of Chemistry at SUNY Binghamton in 2007 and B.S. degree in chemistry from Nanjing University in 1994. Her current research interests include nanostructured materials, catalysts, sensors, and biosensors.

Dr. Jin Luo is a senior associate scientist working in the Department of Chemistry, SUNY-Binghamton. He received his Ph.D. in Physical Chemistry at Xiamen University and the University of Tokyo. His research interests include interfacial electrochemistry, catalysis, sensors, and scanning probe microscopic techniques.

Dr. Chuan-Jian Zhong is a professor in the Department of Chemistry, SUNY-Binghamton. His research interests are in the interdisciplinary areas of analytical and materials chemistry, and currently focus on developing advanced materials and devices for chemical/bio sensors, fuel cells, and other advanced technologies.

Dr. Susan Lu is an associate professor at the Department of Systems Science and Industrial Engineering, SUNY-Binghamton. She received her Ph.D. from the Department of Industrial Engineering at Texas Tech University in 1999. Her current research interests include pattern recognition, reliability, and process optimization.