

Paper:

# Space Invariant Independent Component Analysis and ENose for Detection of Selective Chemicals in an Unknown Environment

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In this paper, we present a space invariant architecture to enable the Independent Component Analysis (ICA) to solve chemical detection from two unknown mixing chemical sources. The two sets of unknown paired mixture sources are collected via JPL 16-ENose sensor array in the unknown environment with, at most, 12 samples data collected.

Our space invariant architecture along with the maximum entropy information technique by Bell and Sejnowski and natural gradient descent by Amari has demonstrated that it is effective to separate the two mixing unknown chemical sources with unknown mixing levels to the array of two original sources under insufficient sampled data. From separated sources, they can be identified by projecting them on the 11 known chemical sources to find the best match for detection. We also present the results of our simulations. These simulations have shown that 100% correct detection could be achieved under the two cases: a) under-completed case where the number of input (mixtures) is larger than number of original chemical sources; and b) regular case where the number of input is as the same as the number of sources while the time invariant architecture approach may face the obstacles: overcomplete case, insufficient data and cumbersome architecture.

**Keywords:** space invariant independent component analysis, ENose, chemical detection

## 1. Introduction

The need for low-power, miniature sensor devices that can monitor air quality in an enclosed space with multi-compound capability and minimum human operation has led to the development of polymer-carbon composite based electronic nose (ENose) at NASA's Jet Propulsion Laboratory (JPL) [1–3]. The sensor array in the JPL ENose consists of 32 conductometric sensors made from insulating polymer films loaded with carbon. In its current design, it has the capability to detect 10 common contaminants which may be released into the recirculated breathing air of the space shuttle or space station from a spill or a leak; target concentrations are based on the 1-hour Space-

**Table 1.** Target gases and concentrations.

Target Compound	Conctr Rang Tested (ppm)	1 hr. SMAC (ppm)	Ref Num
Benzene	10-50	30	1
Ethanol	10-130	2000	2
Freon	50-525	50	3
Indole	0.006-0.06	1	4
Methane	3000-7000	5300	5
Methanol	10-300	30	6
Propanol	75-180	400	7
Toluene	30-60	16	8
Ammonia	10-50	30	9
Formaldehyde	50-510	0.4	10
Medical Wipe	500-4000	–	13

craft Maximum Allowable Concentrations (SMAC) set by NASA (see **Table 1**) [4], and are in the parts-per-million (ppm) range. The ENose was intended to fill the gap between an alarm which has little or no ability to distinguish among chemical compounds causing a response and an analytical instrument which can distinguish all compounds present but with no real-time or continuous event monitoring ability.

As in other array-based sensor devices, the individual sensor films of the ENose are not specific to any one analyte; it is in the use of an array of different sensor films that gases or gas mixtures can be uniquely identified by the pattern of measured response. The response pattern requires software analysis to deconvolute gas compounds and their concentrations.

An example of a sensor set is shown in **Fig. 1**, and the complete device on which the data was used in this study is shown in **Fig. 2**.

The specific analysis scenario considered for this development effort was one of leaks or spills of specific compounds. It has been shown in analysis of samples taken from space shuttle flights that, in general, air is kept clean by the air revitalization system and contaminants are present at levels significantly lower than the SMACs [5]; the JPL ENose has been developed to detect target compounds released suddenly into the breathing environment. A leak or a spill of a solvent or other compound would be

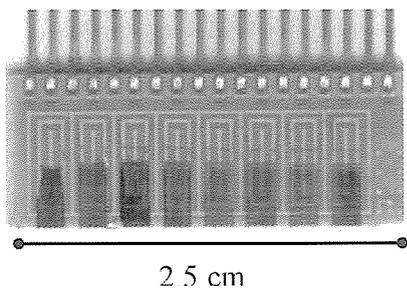


Fig. 1. JPL ENose sensor substrate on the left with eight polymer-carbon composite sensors.

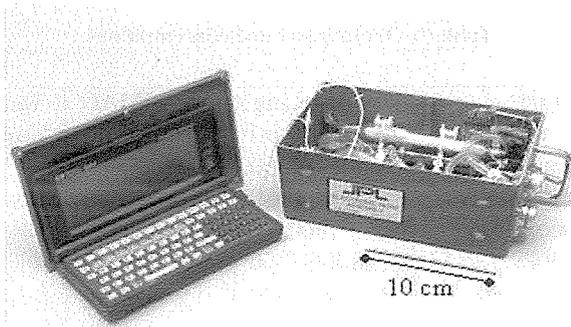


Fig. 2. The complete JPL ENose on the right.

an unusual event. Release of mixtures of more than two or three compounds would be still more unusual; such an event would require simultaneous leaks or spills to occur from separate sources. Thus, for this phase of development, mixtures of more than two target compounds were not considered.

In this paper, we consider an approach to analysis of sensor responses to mixture so that use of the JPL ENose may be extended to detection of chemical compounds in an open and changing environment, such as a building or a geographical area where air exchange is not controlled and limited.

As such operation in the open environment, the collected sensory data will be a mixing between the unknown chemicals with the unknown mixing levels (coefficient) between them. The identification of the chemical compounds among these mixing chemicals is a real challenge for real world applications.

To search for a chemical compound whether it exists in the operating environment, one of the most robust techniques is to recover the original chemicals. When done, the detection can be an easy step by finding the maximum correlation between the predicted original chemicals and the target chemicals. More sophisticated way, the neural network approach [6–10] can be employed to capture the target chemicals in various conditions through learning e.g., concentration levels through the parameterized weight set, then the strongest correlation between parameterized weight and the predicted original can be used to identify the intended chemical.

Recently, Independent Component Analysis (ICA)

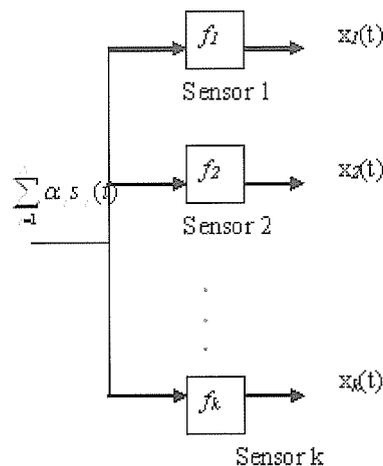


Fig. 3. The system model and set up of the ENose array.

[11–19] has proven that it not only de-correlates the second order statistics of the signals but also reduces the higher order statistical dependencies. ICA transforms an observed signal vector into a set of signals that are as statistically independent as possible. Theoretically, ICA is an information-theoretic approach, which exploits concepts from information theory such as entropy and mutual information.

The ICA roots in the early work of Herault and Jutten [11] who first introduced an adaptive algorithm in a simple feedback architecture that was able to separate several unknown independent sources. ICA was further developed by [12–17]. Amari et al. [18] have used natural gradient descent based on the Riemannian metric tensor to optimize the curvature of a particular manifold in n dimensional space. This technique is employed to apply to the Infomax [16] to simplify the learning rule that is used in this paper. ICA has applications for feature extraction in speech recognition systems, in communication systems, in medical signal processing, and in image processing.

## 2. Technical Approach

In this study, we based on the approximation of the set up architecture shown in Fig. 3.

In Fig. 3, the collected sensing data  $x_i(t)$  consists of changes in electrical resistance corresponding to sensor response to the unknown mixture  $\sum_{j=1}^N \alpha_j s_j$  of chemical sources  $s_j(t)$  and their densities (or concentrations)  $\alpha_j$  at the time  $t$ .

Due to the small spatial separation between the sensors themselves, the input of chemical exposure on each sensor is assumed to be uniquely distributed. The sensory data can be modeled as follows:

$$x_i(t) = f_i(\alpha_1 s_1(t), \dots, \alpha_N s_N(t)) \dots \dots \dots (1)$$

where  $f_i$  is the unknown non linear activation function,  $\alpha_j$

is the unknown mixing coefficient of chemical source  $j$ , and  $i$  is the index of sensor number and  $N$  as number of chemical source.

Assume that there exists an operating point  $V^o = \{v_1^o, \dots, v_N^o\}$  and  $v_i^o = \sum_{j=1}^N \alpha_j s_j^o(t)$  so that the Eq. (1) can be approximated by the first order of a Taylor expansion and it is written:

$$x_i = a_i + \sum_{j=1}^N \gamma_{ij} s_j \dots \dots \dots (2)$$

where

$$a_i = f_i(\alpha_1 s_1^o(t), \dots, \alpha_N s_N^o(t)) - \frac{\partial f_i}{\partial v_i} \Big|_{v_i^o} \sum_{j=1}^N \alpha_j s_j^o (3)$$

and

$$\gamma_{ij} = \frac{\partial f_i}{\partial v_i} \Big|_{v_i^o} \alpha_j \dots \dots \dots (4)$$

and  $s_j^o$  is an operating point of the source  $s_j$ .

For each sampling data point in time for the same sensor  $i$ ,  $x_i$  fluctuates around its bias point  $a_i$  and it can be considered as a common bias for  $x_i(t)$  with  $t \in [t, t + k\Delta t]$ . From this argument, Eq. (2) can be simplified to:

$$Y = \begin{bmatrix} x_1 - a_1 \\ x_2 - a_2 \\ \dots \\ x_k - a_k \end{bmatrix} \dots \dots \dots (5)$$

$$Y = \Gamma S \dots \dots \dots (6)$$

where  $Y$  is unbiased mixture data,  $\Gamma$  is the unknown mixing matrix and  $S$  is the chemical source signal.

The learning rule based on the maximum entropy algorithm [16] is given by:

$$y = g(u) = g(Wx) \dots \dots \dots (7)$$

where  $g$  is a non linear function e.g. the logistic function or hyperbolic tangent function. The update weight can be calculated as:

$$\Delta W = W^{-T} + \Phi(u)x^T \dots \dots \dots (8)$$

where  $W^{-T}$  as an inverse transport of the  $N \times N$  weight matrix  $W$ ,  $x^T$  as a mixing input vector (observed vector), and

$$\Phi(u) = [\phi_i(u_i)] = \frac{\partial y_i'}{\partial y_i} \dots \dots \dots (9)$$

To simplify Eq. (7) using a natural gradient descent by Amari [18], the learning rule can be:

$$\Delta W = (I + \Phi(u)u^T)W \dots \dots \dots (10)$$

with  $u = Wx$ . The details can be found in [19].

### 3. Space Invariant Architecture

The most common ICA approach is that the number of variables and the number of sources are the same. How-

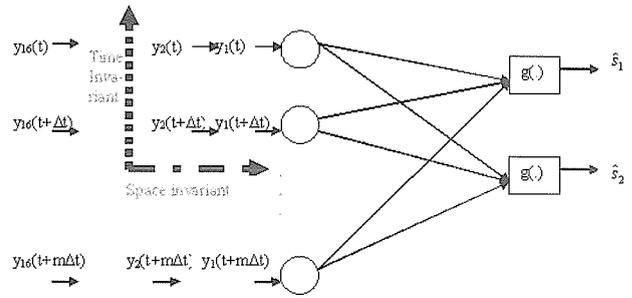


Fig. 4. The space invariant ICA architecture ( $m = 2, \dots, 12$ ).

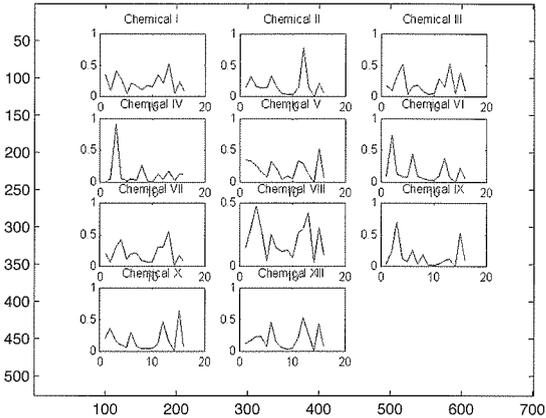


Fig. 5. Classes of 11 chemical sources.

ever, in this study we faced two obstacles: 1) there are 12 or less samples (mixing chemical compounds) from each sensor and the total number of sensor is 16 which it does not have sufficient data set (at least 16 data samples required); and 2) the number of variables is 16 as number of sensors while the number of compounds in a mixture is 2 and it is considered over complete case.

For the time invariant approach, the data that will flow perpendicularly (dotted arrow) to the time invariant direction as shown in Fig. 4 will require 32 outputs (16 channels for each chemical compound). The architecture is 16 inputs, 32 outputs and 12 or less sample data which may not be a solvable approach. Instead of using a time invariant approach, we use the space invariant approach (Fig. 4 with dashed and dotted arrow) which allows us to have more data points and enable the square mapping matrix (the dimension of mixing sources and sensors are the same). This approach is feasible due to the mathematical model based on Eqs. (2) and (6). The architectures are shown in Fig. 4.

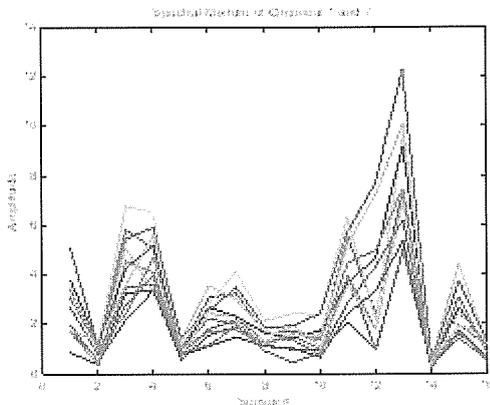
In Fig. 4, the unbiased input  $Y_i(t)$  ( $i = 1, \dots, k$ ) is based on temporal mixture data and the sensory data are spatially invariant.

From laboratory set up, we have collected a set of single of spectra of 11 chemicals using 16 elements in the ENose sensor array; it is averaged and shown in Fig. 5.

In this study, the number of sensors used is 16 and mixing chemical sources is 2; we will examine two sets of data, as shown in Table 2.

**Table 2.** Parameters of chemical mixture.

Data set	Num. of Variables	Mixture	Num. Samples Available
1	16	1 and 7	12
2	16	3 and 10	9



**Fig. 6.** The mixture data of chemical 1 and 7.

### 4. Simulation Results

Based on the data available provided in **Table 2**, we divided this study into two experiments: 1) Under complete case: in this case we used complete sample data (see column 4 in **Table 2**) as input to the network and the output size is 2 as two original sources recovered. 2) Squared case: this is a straight forward with 2 inputs and 2 outputs case when the data was rearranged so that each input is from the same sensor with non-overlapped consecutive sampling times:  $t + i\Delta t$  and  $t + (i + 1)\Delta t$ .

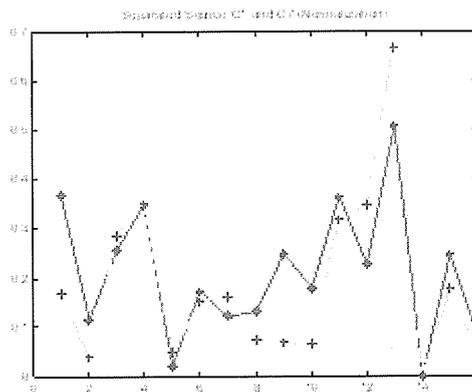
#### 4.1. Experiment 1

In this case, we have studied the two data sets in **Table 2** and we used all data vectors available (The maximum number of data vectors is 12), which is less than the number of sensors (16). For data set 1, there are 12 mixtures of chemical 1 and 7 and the data are shown in **Fig. 6**.

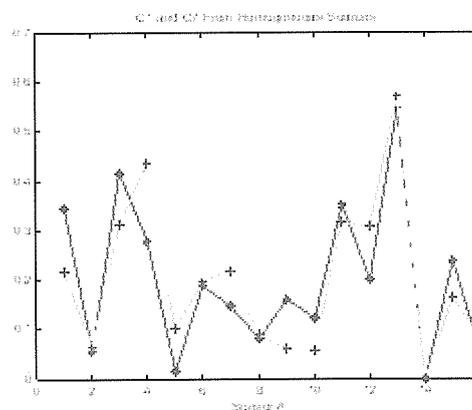
##### 4.1.1. Data Set 1

Using the space invariant ICA approach, the recovered signal sources (chemical 1 and 7 sources) are shown in **Fig. 7** and the average of the single chemical source 1 and 7 are shown in **Fig. 8**. **Figs. 7** and **8**, show a strong correlation between the chemical 1 and separated chemical 1 (\* traces) and chemical 7 and separated signal named 7 (+). To confirm its performance, we projected the separated sources 1 and 7 by ICA technique on the known 11 chemical sources shown in **Fig. 3**, the results are provided in **Table 3**.

From **Table 3**, it has demonstrated that the single source of chemical 1 has the greatest overlap (bold face



**Fig. 7.** Separated signal sources 1 and 7 via space invariant ICA of 12 inputs.



**Fig. 8.** Original chemical sources 1 and 7 by averaging technique.

**Table 3.** The Projection of the separated chemical sources 1 and 7 on the original chemical.

Sing. chem. source	Separated chemical 1	Separated chemical 7
1	<b>0.8457</b>	0.9601
2	0.4772	0.6291
3	0.7325	0.9369
4	0.6286	0.5258
5	0.7433	0.6996
6	0.4872	0.4304
7	0.7944	<b>0.9876</b>
8	0.7938	0.9014
9	0.6679	0.5737
10	0.5271	0.6051
13	0.6223	0.7896

value) with the separated source, labeled separated chemical 1. Similarly, single source chemical 7 has the greatest overlap (bold face value) with separated chemical 7 from the mixture shown in **Fig. 6**.

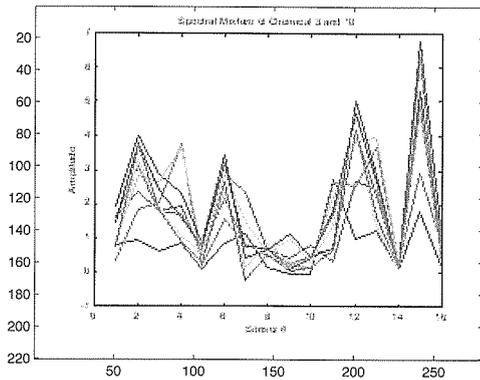


Fig. 9. The mixture data of chemical 3 and 10.

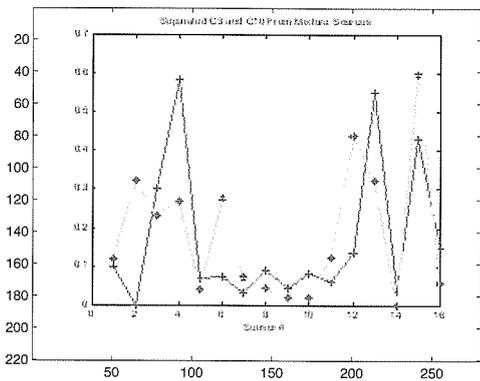


Fig. 10. Separated signal sources 3 and 10 via space invariant ICA with 9 inputs and 2 outputs.

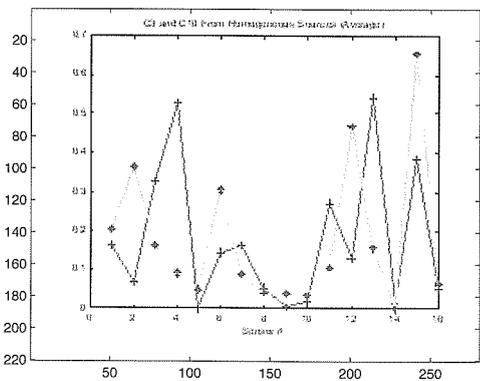


Fig. 11. Original chemical sources 3 and 10 by averaging technique.

4.1.2. Data Set 2

Data set 2, a mixture of chemicals 3 and 10, is shown in Fig. 9. For the mixture from data set 2, the performance of space invariant ICA has demonstrated its effective capability to separate the mixture of chemical 3 and 10 as shown in Figs. 10 and 11.

In Table 4 it shows the maximum correlation (bold face values) between the original and separated source of chemical 3 and 10.

Table 4. The Projection of the separated chemical sources 3 and 10 on the original chemical.

Sing. chem source	Sep. chem. 3	Sep. chem. 10
1	0.8250	0.7723
2	0.4760	0.8282
3	<b>0.9464</b>	0.8254
4	0.5235	0.4420
5	0.6134	0.8935
6	0.3414	0.7670
7	0.8681	0.7829
8	0.8165	0.8887
9	0.6561	0.7803
10	0.6125	<b>0.9619</b>
13	0.7200	0.9444

Table 5. The mean and standard deviation of its projection of separated sources C1 and C7 on each single chemical source.

Sing. chem. source	Mean Sep. chem. 7	Stand. dev.	Mean Sep. chem. 1	Stand. dev.
1	0.8851	0.0830	<b>0.8959</b>	<b>0.0890</b>
2	0.5893	0.1405	0.5551	0.0792
3	0.8728	0.0784	0.8046	0.0397
4	0.4973	0.0723	0.5057	0.1541
5	0.6611	0.0599	0.7285	0.0742
6	0.4161	0.0970	0.4465	0.0903
7	<b>0.9222</b>	<b>0.0765</b>	0.8664	0.1104
8	0.8398	0.0604	0.8141	0.1099
9	0.5539	0.0460	0.5601	0.1031
10	0.5671	0.1103	0.5702	0.1141
13	0.7342	0.1096	0.6902	0.1101

4.2. Experiment 2

In this experiment, we paired data set 1 (16 × 12) in columns to obtain the data set 96 × 2. From this conversion, data values in a single row are the data from the same sensor with consecutive sampling times  $t + i\Delta t$  and  $t + (i + 1)\Delta t$ ; this new data set allows the same number of mixing sources and of original sources. Using this new data set, space invariant ICA has produced the results that were validated with the 11 known chemicals. Classification was 100% correct, based on the projection on 11 classes shown in Fig. 5. To simplify the results, we tabulated the mean and standard deviation of its projection (separated sources C1 and C7) on each single chemical source and the results are summarized Table 5.

Table 5 is compact information to show that the separation sources from the mixture have successfully identified the original chemical sources.

Due to limited data set, the distributions based on the mean and standard deviation in Table 5 are not Gaussian distributions, according to the Central Limit Theorem.

## 5. Discussions

To separate two (2) mixing sources from a sixteen (16) element sensory data array, known as the over complete case, poses a challenges for mathematical model and network architecture. The non overlapped pair-wise (i.e. sensor  $i$  and sensor  $i + 1$ ) or overlapped pair-wise (i.e. (sensor  $i$  and sensor  $i + 1$ ) and (sensor  $i + 1$  and sensor  $i + 2$ ) so on) may face cumbersome and ineffective techniques.

As shown above, the mathematical model has demonstrated space invariant ICA to be an effective architecture to overcome insufficient data samples and the over complete case. Moreover, the chemical data itself is fuzzy and inconsistent, and the optimal architecture is not answered in this study. By simulation we have shown that chemical source separation problem can be solved effectively with complete time sampling data ( $k = 12$ ) (under complete case) and two consecutive sampling data ( $k = 2$ ). Optimal architecture may require a model of noise in order to determine the size of the sampling input. Moreover, space invariant ICA governed by Eq. (6) is only valid when the sampling time is sufficiently small. Hence, the sampling time also plays an important role to ensure that the model approach holds.

## 6. Conclusions

We have provided a mathematical model to enable the space invariant ICA architecture from which Informax and natural gradient descent technique can be applied and simulation has confirmed that our modeling is effective and sufficient to perform chemical source separation to enable the smart ENose.

Further study will be conducted to validate its usefulness for the real world and open environment for chemical detection. In addition, the miniaturized, compact, light weight and low power hardware approach is also a driven force for NASA mission from which System-On-a-Chip approach will be our next focus based on this modeling approach.

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### References:

- [1] M. A. Ryan, M. L. Homer, M. G. Buehler, K. S. Manatt, F. Zee, and J. Graf, "Monitoring the Air Quality in a Closed Chamber Using an Electronic Nose," Proc. of the 27th Int. Conf. on Environmental Systems, Society of Automotive Engineers 1997, 97-ES84.
- [2] M. A. Ryan, M. L. Homer, M. G. Buehler, K. S. Manatt, B. Lau, D. Karmon, and S. Jackson, "Monitoring Space Shuttle Air for Selected Contaminants Using an Electronic Nose," Proc. of the 28th

- Int. Conf. on Environmental Systems, Society of Automotive Engineers 1998, 98156.
- [3] M. A. Ryan, M. L. Homer, H. Zhou, K. S. Manatt, V. S. Ryan, and S. P. Jackson, "Operation of an Electronic Nose Aboard the Space Shuttle and Directions for Research for a Second Generation Device," Proc. of the 30th Int. Conf. on Environmental Systems, Society of Automotive Engineers 2000, 00ICES-259.
- [4] "Spacecraft Maximum Allowable Concentrations for Selected Airborne Contaminants," National Academy Press: Washington, DC, Vols.1 and 2, 1994.
- [5] J. T. James, T. F. Limero, H. J. Leano, J. F. Boyd, and P. A. Covington, "Volatile Organic Contaminants Found in the Habitable Environment of the Space Shuttle: STS-26 to STS-55.," Aviation Space Environmental Medicine, Vol.65, No.9, pp. 851-857, 1994.
- [6] D. E. Rumelhart and J. L. McClelland, "Parallel Distributed Processing: Explorations in the Microstructure of Cognition," Vol.1: Foundation, MIT Press, Cambridge, MA, 1986.
- [7] S. E. Fahlman and C. Lebiere, "The Cascade Correlation learning architecture, Advances in Neural Information Processing Systems II," D. Touretzky, M. Kaufmann, and S. Mateo (Eds.), CA, pp. 524-532, 1990.
- [8] M. Cohen and S. Grossberg, "Absolute stability of global pattern formation and parallel memory stage by competitive neural networks," IEEE Trans. Systems, Man, Cybernetics, Vol.SMC-13, pp. 815-826, 1983.
- [9] B. Widrow, "Generalization and information storage in networks of ADALINE neurons," G. T. Yovitt (Ed.), Self-Organizing Systems, Spartan Books, Washington DC, 1962.
- [10] T. A. Duong and A. R. Stubberud, "Convergence Analysis Of Cascade Error Projection: An Efficient hardware learning algorithm," International Journal of Neural System, Vol.10, No.3, pp. 199-210, June, 2000.
- [11] J. Herault and C. Jutten, "Space or time adaptive signal processing by neural network models," J. S. Denker (Ed.), Neural network for computing: AIP Conference proceedings 151, New York, American Institute for Physics, 1986.
- [12] C. Jutten and J. Herault, "Blind separation of the sources, part I: an adaptive algorithm based on neuromimetic architecture," Signal Processing, Vol.24, pp. 1-10, 1991.
- [13] P. Common, "Independent component Analysis a new concepts?" Signal Processing, Vol.36, Issue 3, pp. 287-314, 1994.
- [14] D.-T. Pham, P. Garrat, and C. Jutten, "Separation of a mixtures of independent sources through a maximum likelihood approach," EU-SIPCO, pp. 771-774, 1992.
- [15] J. Cardoso, "High-order contrast for independent component analysis," Neural Computation, 1998.
- [16] A. J. Bell and T. J. Sejnowski, "An Information-Maximization Approach to Blind Separation and Blind Deconvolution," Neural Computation, Vol.7, pp. 1129-1159, 1995.
- [17] V. A. Duong, "Independent Component Analysis for Space-Time and Nonlinear Mixtures," Ph.D. Thesis UCI, 2004.
- [18] S. I. Amari, "Natural gradient works efficiently in learning," Neural Computation, 1998.
- [19] A. Bell, "Information Theory, Independent-Component Analysis and Applications, Unsupervised Adaptive Filtering," S. Haykin (Ed.), Vol.1: Blind Source Separation, Chapter 6, John Wiley and Son Inc., 2000.



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- A. V. Shevade, M. L. Homer, C. J. Taylor, H. Zhou, A. D. Jewell, K. S. Manatt, A. K. Kisor, S. P. S. Yen, and M. A. Ryan, "Correlating Polymer-Carbon Composite Sensor Response with Molecular Descriptors," *Journal of The Electrochemical Society*, Vol.153, pp. H209-H216, 2006.
- M. A. Ryan, A. V. Shevade, H. Zhou, and M. L. Homer, "Polymer-Carbon-Composite Sensors for an Electronic Nose Air Quality Monitor," *MRS Bulletin*, Vol.29(10), p. 714, 2004.
- M. A. Ryan, M. L. Homer, H. Zhou, K. Manatt, A. Manfreda, A. Kisor, A. Shevade, and S. P. S. Yen, "Expanding the Analyte Set of the JPL Electronic Nose to Include Inorganic Species," *Journal of Aerospace, SAE Transactions*, 2005-01-2880, 2005.