Fuzzy Learning Vector Quantization Based on Particle Swarm Optimization For Artificial Odor Dicrimination System

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Abstract:- An electronic nose system had been developed by using 16 quartz resonator sensitive membranes-basic resonance frequencies 20 MHz as a sensor, and analyzed the measurement data through various neural network as a pattern recognition system. The developed system showed high recognition probability to discriminate various single odors even mixture odor to its high generality properties; however the system still need improvement. In order to improve the performance of the proposed system, development of the sensor and other neural network are being sought. This paper explains the improvement of the capability of that system from the point of neural network system. It has been proved from our previos work that FLVQ (Fuzzy Learning Vectoq Quantization) which is LVQ (Learning Vector Quantization) together with fuzzy theory shows high recognition capability compared with other neural networks, however FLVQ have a weakness for selecting the best codebook vector that will influence the result of recognition. This problem will be anticipated by adding the PSO (Particle Swarm Optimization) method to select the best codebook vector. Then experiment showt that the new recognition system (FLVQ-PSO) has produced higher capability compared to the earlier mentioned system.

Keywords: Fuzzy Learning Vector Quantization, Matrix Similarity Analysis, Particle Swarm Optimization, Codebook, Electronic Nose, Odor

1 Introduction

There are several reports on the use of neural network in gas/odor identification. Many reports are available in the literature on the application of different neural network architectures in processing sensor array data, i.e. back propagation trained neural network and its variance [1]-[4], radial basis function neural network [5], probabilistic neural network [6], genetically trained ANN [7], adaptive resonance theory [6], self-organizing network [6] and learning vector quantization [8],[9].

From the best of our knowledge, to classify the problem with very similarity data, like discrimination odor mixture, learning vector quantization (LVQ) proposed by Kohonen is a powerful method for realizing an alternative neural network, since the neuron in LVQ learning is non-linear, localized updated and the network does not take much time to converge [8],[9]. It has been proved from our previous work, an electronic nose system had been developed by using 16 quartz resonator sensitive membranes-basic resonance frequencies 20 MHz as a sensor, and analyzed the measurement data through various neural network as a pattern recognition system, that FLVQ (Fuzzy Learning Vectoq Quantization) which is LVQ (Learning Vector Quantization) together with fuzzy theory shows high recognition capability compared with other neural networks [10],[11]. However FLVQ still have a weakness for selecting the best codebook vector that will influence the result of recognition. This problem will be anticipated by adding the PSO (Particle Swarm Optimization) method to select the best codebook vector.

One popular swarm inspired methods in computational intelligence areas; particle swarm optimization (PSO) which related with optimization in engineering aplication has been introduced. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography a flock of birds or a school of fish. However, it was found that particle swarm model can be used as an optimizer [12]-[16]. Applying PSO model to solve optimization code book at FLVQ problem, we must do some reformulate approach in theoretical frame work to implement PSO approach. Two steps of the implementation will be conducted including ; (1) representation the solution, (2) fitness function to verify the best solution.

This paper is organized as follows. Section II explains the neural network with fuzzy theory as classifier and section III presents the fuzzy learning vector quantization and particle swarm optimization. Section IV present the electronic nose discrimination system while section V discusses the experimental design and the results of the proposed algorithm; the automated pattern discrimination system and finally, section VI presents the concluding remarks.

2 Neural Networks With Fuzzy Theory As Classifier

The output pattern recognition methods applied in the electronic nose are cluster analysis, discrimination of functions analysis and neural network [7],[17]. The neural network method is generally used because it has an easier recognizing process algorithm and better odor recognizing result than any other methods [7],[17] as being reported in some literatures on ANN application.

Fuzzy learning vector quantization (FLVQ) is developed based on learning vector quantization and extended by using fuzzy theory. In this FLVQ, neuron activation is expressed in terms of fuzzy number for dealing with the fuzziness caused by statistical measurement error. Fuzzification of all components of the reference and the input vectors is done through a normalized triangular fuzzy numbers process; with the maximum membership value is equal to *1*. A normalized triangular fuzzy number *F* s designated as [8],[9]:

$$F = (f , f_l , f_r) \tag{1}$$

Where f the center-peak position of F, f_l left part fuzziness and f_r right part one. Fuzziness is expressed by the skirt width of the membership function. Figure 1 shows the normalized triangular fuzzy number of the normalized output frequency from *sensor1* for a citrus with alcohol 0% fragrance; with its center of position f *(0.674)* is the mean of the normalized frequency-data. The membership function of this center position is one. The left and right part fuzziness, f_l (0.670) and f_r (0.678 Hz), respectively, are the minimum and maximum value of the normalized frequency-data, with membership function of zero [8],[9].

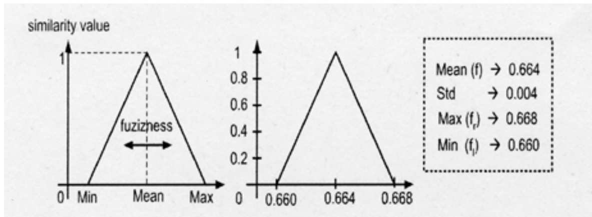

Fig. 1 Fuzziness of CiA0% fragrance taken from sensor 1 of the recognition system.

As the neuron of FLVQ deals directly with a fuzzy quantity, the concept of Euclidean distance in the conventional LVQ is modified by a fuzzy similarity that is calculated by using max-min operation over its input and the reference vectors. As a consequence, the network architecture should also be modified to accommodate the max-min operation of the two vectors [9]

The architectural network of FLVQ is depicted in figure 2, which consists of one input layer, one cluster layer as a hidden layer and one output layer. Neurons in the input layer are connected to a cluster-of-neurons in the hidden layer, which is grouped according to the odor-category of the input data. Thus, the number of cluster-of-neurons in the hidden layer is as many as the odor categories, while each cluster composes of neurons, which corresponds to each of the used sensors. Each cluster has a fuzzy codebook vector as a reference vector for its known-category that should be represented.

When an input vector is fetched to the neural system, each cluster performs the similarity calculation of fuzziness between input vector and the reference vector through max operation. Output of each cluster is then propagated to output neuron that performs the minimum operation. Output neuron that has the maximum similarity value is then determined as the winning-reference vector. It is easy to notice that fuzziness of the input vector depend on the statistical distribution of the input data, while fuzziness of the reference

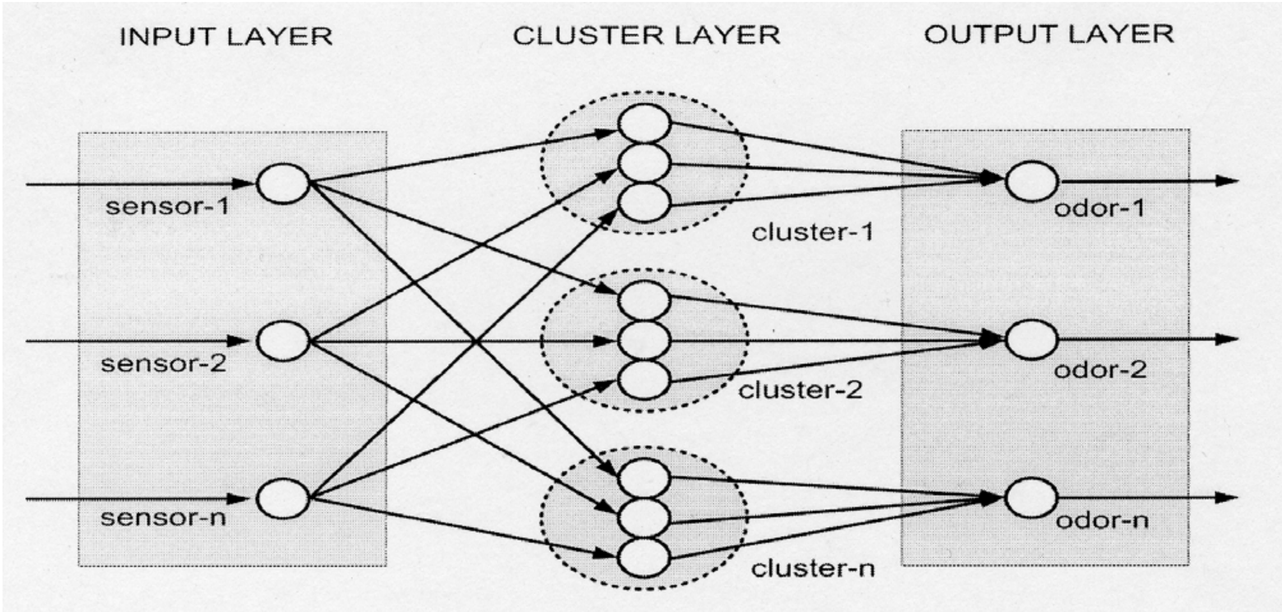

Figure 2. Architecture of the FNLVQ that is used as the discrimination system in the artificial nose system.

vector is adaptively determined during learning process.

Let vector $x(t)$ denote an input vector in an n-dimensional sample space with T as the known-target category, that can be expressed by:

$$x(t) = (x_1(t), x_2(t), \ldots\ldots, x_n(t)) \quad (2)$$

Where n number of sensors, t denotes the time instance, and x_1 is a normalized triangular fuzzy number of the sensor 1 (see Fig.1). The membership function of $x(t)$ can be expressed by:

$$hx(t) = (hx_1(t), hx_2(t), \ldots\ldots, hx_n(t)) \quad (3)$$

Suppose the fuzzy reference vector for category i is w_i that can be expressed by:

$$w_i(t) = (w_{i1}(t), w_{i2}(t), \ldots\ldots, w_{in}(t)) \quad (4)$$

And the membership functions of w_i can be expressed by:

$$hw_i(t) = (hw_{i1}(t), hw_{i2}(t), \ldots\ldots, hw_{in}(t)) \quad (5)$$

Each cluster in the hidden layer then determines the similarity between the two vectors by calculating the fuzzy similarity $\mu_i(t)$ between fuzzy number of $x(t)$ and $w_i(t)$ for all of the axial components through a max operation, defined by

$$\mu_i(t) = max(h_x(t), h_{wi}(t)) \quad (6)$$

Where $i = 1,2, \ldots, m$ number of the category of the odors.

Schematic diagram of fuzzy similarity calculation

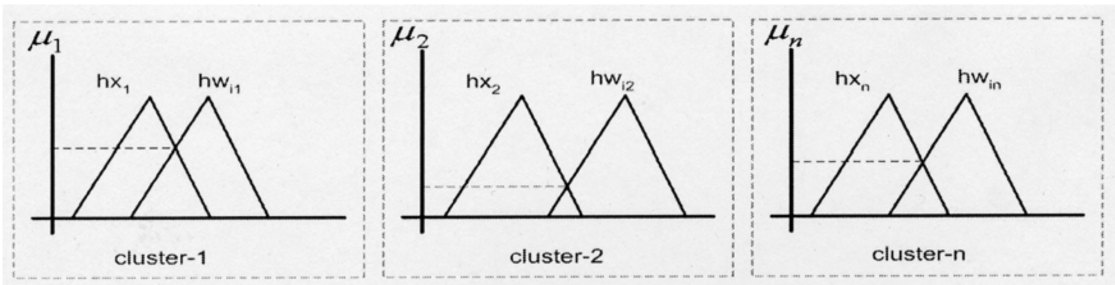

Fig. 3 Fuzzy similarity calculation in the cluster neuron between the input vector and the reference vector in respect to its sensor number.

between inputs vectors with a reference vector in each cluster is depicted in figure 3. Neuron in the output layer received the fuzzy similarity μ_i from hidden layer, and, as in LVQ, determines the minimum one among all the axial similarity components by,

$$\mu(t) = min(\mu_i(t)) \quad (7)$$

Which is the output from the i^{th} output neuron. The winning-neuron of the output layer is determined by which its $\mu(t)$ is maximum, and the reference vector of the cluster of neurons in the hidden layer which corresponds to that winning-neurons could also be determined. When the winning-neuron has a similarity value of $\mu(t)$ is one, the reference vector and the input vector exactly resemble; while if the $\mu(t)$ is zero, the reference vector and the input vector do not resemble at all.

Learning in FLVQ is accomplished by presenting a sequence of learning vector with its known category, and the similarity value between the learning vector and the reference vectors for all categories are calculated. After the winning-neuron and its cluster of neurons in the hidden layer could be determined, both the winning and the non-winning reference vectors are updated repeatedly for reducing the difference between the output and the target. During learning, two steps of updating procedure are done. The first step is done, by shifting the central position of the fuzzy reference vector toward, or moving away from, the input vector. The second step is called fuzziness modification, which is done by increasing or decreasing the fuzziness of the reference vector. The purpose of this fuzzy modification is to increase the possibility of making intersect between an input vector and the winning-reference vector, which in turn will increase the similarity value between those vectors. We developed two types of this fuzziness modification; the first is by multiplying the fuzziness with a constant factor [8], while the second is by multiplying it with a variable factor [8],[9].

By using these procedures, FLVQ has three cases that are possibly occurred; the first is when the network outputs the right answer, and the second is when the network outputs the wrong answer, while the third is when the reference and the output vector has no intersection of their fuzziness.

For the first case, when the network outputs the category of the learning vector *Cx* is the same as the target category *T*, the reference vector of the winning cluster is updated according to [8]:

Step 1. The central position of the reference vector is shifted toward the input vector

$$w_i(t+1)= w_i(t) + \alpha(t)\{(1- \mu_i(t))*(x(t)-w_i(t))\} \quad (8)$$

Step 2. Increase the fuzziness of the reference vector for the next learning steps:

a. Modific ation by constant factor

$$\begin{aligned} f_l(t+1) &= f_l(t) - (1+\beta)*\{f(t) - f_l(t)\} \\ f_r(t+1) &= f_r(t) + (1+\beta)*\{f_r - f(t)\} \quad (9) \\ f(t+1) &= w_i(t+1) \end{aligned}$$

b. Modification by a variable factor

$$\begin{aligned} f_l(t+1) &= f_l(t) - (1-\mu)*\{(1+\eta)*\{f(t)- f_l(t)\} \\ f_r(t+1) &= f_l(t) + (1+\mu)*\{(1+\eta)*\{f_r(t)- f(t)\} \quad (10) \\ f(t+1) &= w_i(t+1) \end{aligned}$$

For the second case, when the network outputs the category of the learning vector *Cx* that is not the same as the target-category *T*, the reference vector of the winning cluster should be moved away, and is updated according to:

Step 1. The reference vector is shifted away from the input vector

$$w_i(t+1)= w_i(t) - \alpha(t)\{(1- \mu_i(t))*(x(t)-w_i(t))\} \quad (11)$$

Step 2. Decrease the fuzziness of the reference vector for the next learning step:

a. Modification by constant factor

$$\begin{aligned} f_l(t+1) &= f_l(t) + (1+\gamma)*\{f(t)- f_l(t)\} \\ f_r(t+1) &= f_r(t) - (1+\gamma)*\{f_r(t)- f(t)\} \quad (12) \\ f(t+1) &= w_i(t+1) \end{aligned}$$

b. Modification by a variable factor

$$\begin{aligned} f_l(t+1) &= f_l(t) + (1-\mu)*\{(1-\kappa)*\{f(t)- f_l(t)\} \\ f_r(t+1) &= f_r(t) - (1-\mu)*\{(1-\kappa)*\{f_r(t)- f(t)\} \quad (13) \\ f(t+1) &= w_i(t+1) \end{aligned}$$

For the third case, when the reference vector and the input vector has no intersection of their fuzziness, the fuzziness of the reference vector is updated in order to have the possibility of being crossed the input vector, according to:

$$w_i(t+1)= \xi(t) * w_i(t) \quad (14)$$

The nomenclature we use is as follows:

$w_i(t+1)$ = the winner reference vector after being shifted

$w_i(t)$ = the winner reference vector before being shifted

$\alpha(t)$ = learning rate, a monotonically decreasing scalar gain factor ($0<\alpha\leq 1$), that is defined as

$$\alpha(t+1) = 0.9999\ \alpha(t)$$

$$\alpha(0) = 0.05 \quad (15)$$

β,γ = constant value of increasing or decreasing the fuzziness within interval of [0,1]

η,κ = variable value of increasing or decreasing the fuzziness through

$$\eta(t+1) = 1/100\ \{1-\alpha(t+1)\}$$

$$\kappa(t+1) = 1-\alpha(t+1) \quad (16)$$

ξ = constant value of *1.1*

3 Fuzzy Learning Vector Quatization Based On Particle Swarm Optimization

The weakness of the conventional FLVQ algorithm is in selecting the best codebook vector will influence the result of recognition. In order to improve the performance FLVQ, the development of FLVQ-PSO method is being sought. This methodology is a combination of FLVQ, Matrix Similarity Analysis (MSA), and PSO methods in which the advantage derived from FLVQ is the speeding up of its convergence in the learning process. Meanwhile MSA is employed to determine its accuracy value/ fitness and PSO is to change fuzzy vektor position for optimum recognition.

The learning process of FLVQ-PSO is to find the best posisition of the particle. Before this process commences, it is essential to put in order all the input factors as a matrix, so that each step of all class iteration to the input factors is included in the learning process accordingly. During this mentioned process, this FLVQ-PSO algorithm will optimize each reference vector in the cluster layer by PSO algorithm, where these reference vectors are assigned randomly in accordance with the number of the particles. Then, those reference vectors are compared by MSA algorithm. The reference factors with the best MSA value should be the next codebook vector.

MSA is computed by the following algorithm :

$$m_{mj} = \frac{1}{N}\sum_{k=1}^{N} \max\min \mu_{ij}(k) \quad (17)$$

Where,
i = The sensor's number
j = The reference vektor of odor category
m = The learning vector of odor category
N = The number of learning vektor in each class
k = 1,2,3,...N

The next is an example of the matrix of similarity on FLVQ:

$$M = \begin{bmatrix} m_{11} & m_{21} & . & . & m_{m1} \\ m_{12} & m_{22} & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ m_{1j} & . & . & . & m_{nn} \end{bmatrix}$$

Fig. 4 Matrix Similarity

Where,
M= the matrix of similarity n x n matrix element
n = the number category of learning process

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Fig. 5 An ideal condition of MSA is written as a matrix

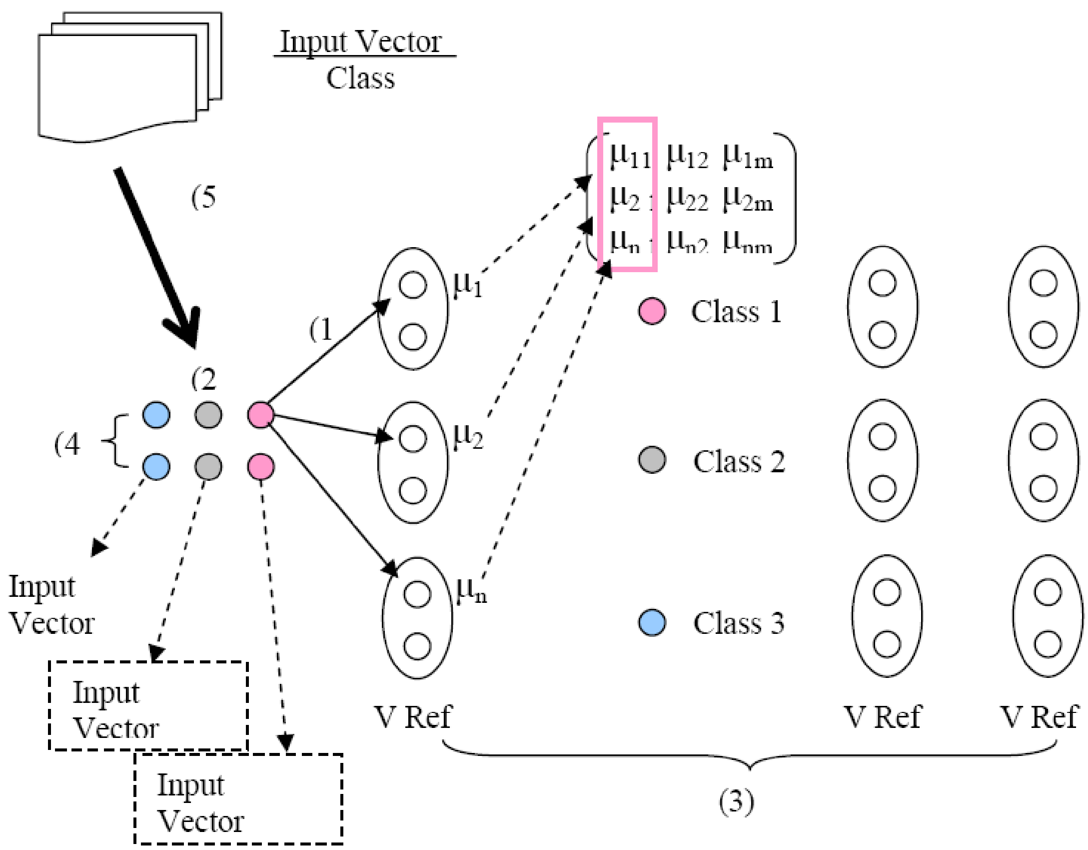

Fig. 6 Fuzzy similarity calculation in the cluster neuron between the input vector and the reference vector in respect to its sensor number.

The ideal type of the similarity matrix is similar to the identity matrix, which in turn will produce higher recognition rate. It means the recognition process can be conducted 100% and the classification processed by FLVQ in a class is not affected by other reference Vektors of other class.

The details of FNLVQ-PSO learning process is the following:

1. FNLVQ-PSO forms a number of the intended cluster layer. This formation can be done by putting the input data randomly.
2. Then, each particle will update the position of the fuzzy reference vektor shifting toward the input vektor as it mentioned in FLVQ theory , the fuzziness of the reference vector should be updated according to:

$$fl(t+1) = fl(t) - \{rand()*c*[f(t) - fl(t)]\} \quad (18)$$

$$fr(t+1) = fr(t) + \{rand()*c*[fr(t) - f(t)]\} \quad (19)$$

Where,

$fl(t+1)$ = the minimum value of the reference Vector after shifting.

$fl(t)$ = the minimum value of the reference Vector before shifting

$fr(t+1)$ = the maximum value of the reference Vector after shifting.

$fr(t)$ = the maximum value of the reference Vector before shifting.

$f(t)$ = the mean of the reference Vector

rand( )= the random value between $0 <$ *up to* $. \leq 1$.

c = the constant value

3. The particle will calculate the similarity value among the input vectors against the shifted reference vector. Then the similarity value of the MSA will be upgraded.
4. All the input data are then compared to all particles in which the particle with the highest *fitness* value is the winner.
5. The reference Vektor of this winning particle will be the reference vector for the next iteration.
6. Carry out 2 – 5 phases till all the input vector finish the learning process.

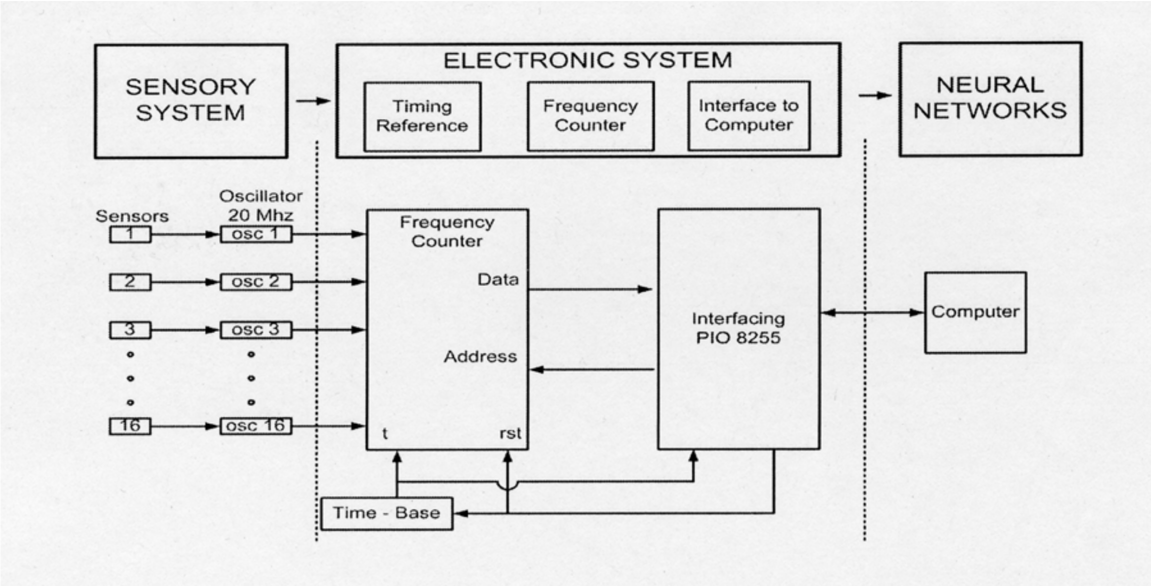

Fig. 7 The artificial nose system diagram.

7. At the end of the learning session, the most representative to the reference vector is found. Then, the learning process will end up if the process complies with the termination criterion

Then FLVQ-PSO some creteria termination algorithm during the learning process can be determined as the followings:

1. This Algorithm should end up if MSA *threshold* value crossess the intended value with the assumption the threshold value relatively is very high. Thus, there will be an expectation for highly recognition as well.
2. The last is when the epoh of the learning process has accomplished, the algorithm will end up automaically, even though the calculation has not found the optimal solution

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4 Electronic Nose Discrimination System

The electronic nose system then consists of three parts namely: a sensory system, an electronic system and a neural network system. Sensory

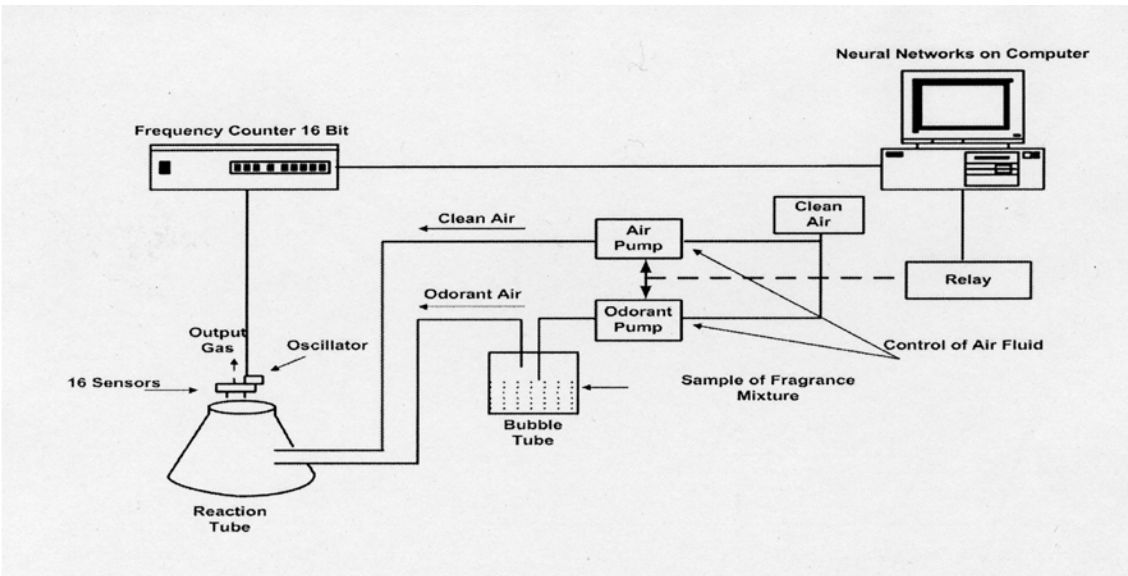


Fig. 8 Schematic diagram of the measurement system.

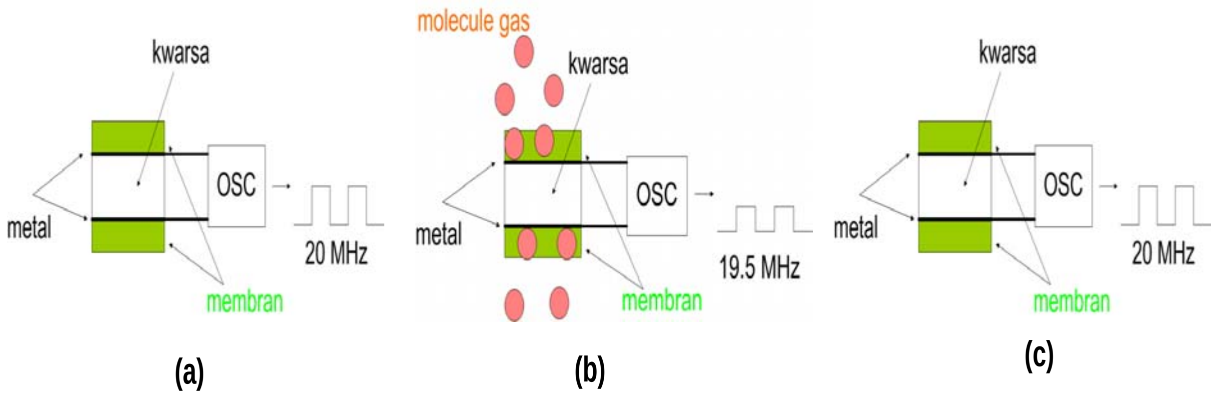


Fig. 9 The characteristic-frequency of the sensor; (a) Normal condition (b) Adsorption procedure (c) Recover to normal condition.

system and electronic system are used to measure the frequency declines of odor identification while neural network system is used to recognize and classify the odor that will be detected. Figure 7 shows the detail parts of artificial n system based on the function and the process. In this figure sensory sub-system and frequency counter sub-system components become the sensing system and neural network component becomes the automated pattern recognition system. This combination of broadly tuned sensors coupled with sophisticated information processing makes the artificial nose system powerful [18],[19].
The schematic diagram of the measurement system is depicted in figure 8. The electronic nose system consists of a quartz crystal microbalance as a sensor and a frequency counter, both combined for measuring the shifted frequency of the sensor as it adsorbed the odorant molecule and a computer to perform neural network analysis of the data and determined the odorant category.

A chamber made of Corning Glass that has a volume of 1300 ml is placed in a temperature-controlled bath. Sixteen AT cut quartz crystal microbalance sensors and its oscillation circuits are attached on the inner and outer sides of the chamber lid, respectively. The water bath with the chamber and its oscillation circuits is placed in a heat-insulated box to keep the temperature at 27^0C. Each sensor is constructed by applying a sensitive membrane on the two surfaces of 20 MHz quartz resonator crystals. After a sample is injected and evaporated in the chamber, the frequency shift is measured at the equilibrium point. Then the next sample is repeatedly injected in the same manner. When the odorant molecules are adsorbed onto the membrane, the characteristic-frequency of the sensor will reduce to a certain degree, and will recover to its characteristics-frequency after adsorption procedure. This phenomenon is called

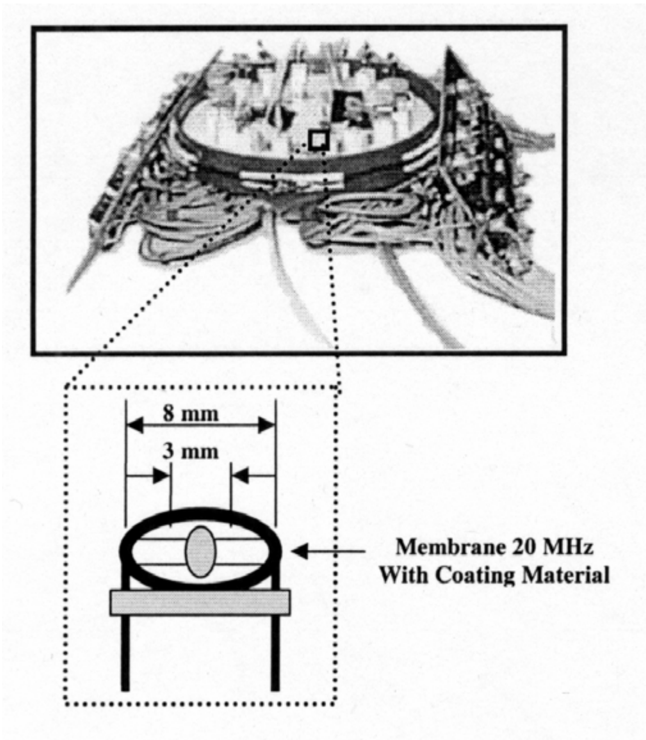
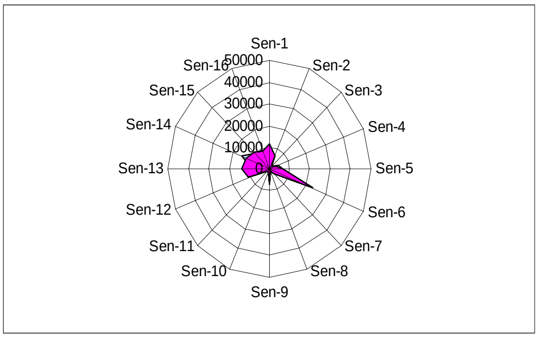
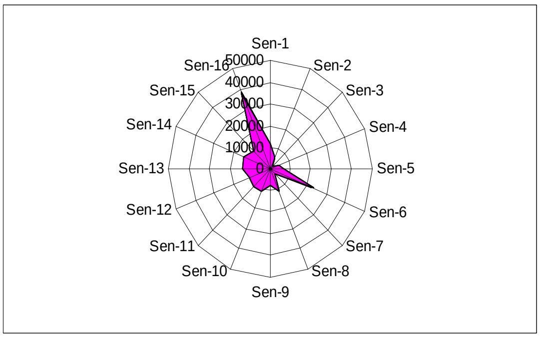


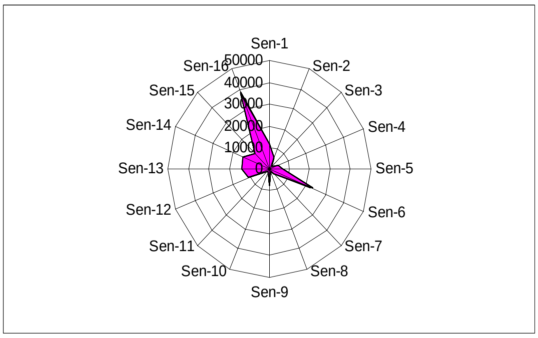
Fig. 10 QCM sensor array with 20 MHz base frequency



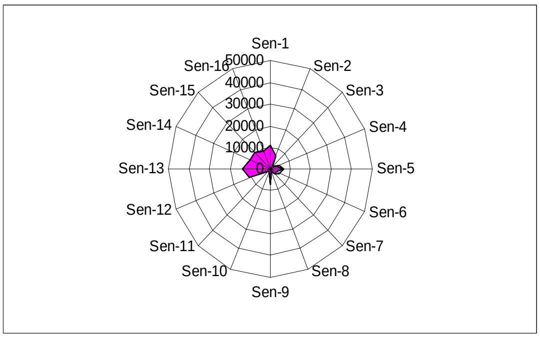
(i). Cananga-Alcohol 0 %



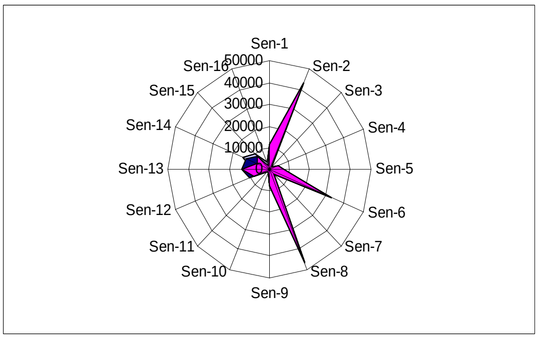
(iv).Citrus-Cananga-Alcohol 0%



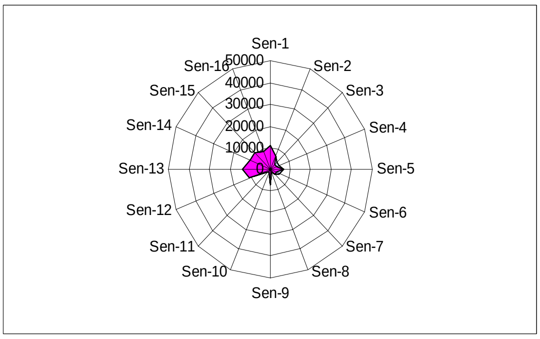
(ii). Citrus-Alcohol 0 %



(v). Cananga-Rose-Alcohol 0%



(iii). Rose-Alcohol 0 %



(vi). Rose-Citrus-Alcohol0%

(a). Two Mixture Odor (b). Odor Concentration

Fig. 11 Pattern Characteristic: (a) various pattern of two mixture odor and (b) various pattern of concentration odor

the mass-loading effect [20], as illustrated in figure 9. A 16-bit frequency counter system is used to get a higher data accuracy, and the data is transferred to the computer for further analysis.

Since the shifted frequency is proportional to the total mass of the adsorbed odorant molecules, it is possible to use this mechanism as the fingerprint of the odor concern. To increase the accuracy of the recognition system, various types of membrane-coated sensors are necessary, which is arranged as an arrayed sensor. The shift of the frequency is given by [20]:

$$\Delta F = -2.3 \times 10^6 F^2 \frac{\Delta M}{A} \qquad (20)$$

Where F denotes the characteristics frequency (MHz), ΔM the total mass of the adsorbed molecule (g) and A the electrode area (cm^2). The quartz sensor has higher sensitivity than other chemical sensors. But the quartz sensor will be effective only in low temperature condition ($<50^0$C).

. The experimental set-up for determining the category of odor uses two small pumps as can be seen in figure 8, for delivering the fresh air and the aroma-contained air. These pumps are controlled by microcomputer through magnetic relay. The process begins by flowing fresh air to the glass chamber and after the frequency shift is recovered to its standard values, the aroma-contained air is delivered to the glass chamber. The frequency shift by this aroma is then measured and transferred to the computer.

The QCM sensor array with 20 MHz base frequency is depicted in figure 10. Sixteen chemical vapors were being used as sensor in the experiment. The wide range of different coatings has proven to be useful [18],[19]. The following is a list of coating materials used by our experiment:

- Phosphaticid
- Lecithin
- Cholesterol
- Phospatidyl Inositol
- Phospatidyl Serine
- Phospatidyl Ethanol amine
- Phospatidy Chorine
- Phospatidy Choline 63% Sphingomyelin37%
- Sphingomyelin
- Lecithin 63% Cholesterol 37%
- Cardioliin
- Ethyl Cellulose
- Silicone OV101
- Silicone OV17
- Silicone 50MB/2.000
- Silicone 75MB/90.000

Sixteen chemical vapors are being used as sensor in the experiment. Each chemical vapor presented to the sensor array produces a signature or pattern characteristic of the vapor. By presenting many different chemicals to the sensor array, a database of signatures can be built up. This database of labeled signatures is used to train the pattern recognition system. The purpose of the learning process is to configure the recognition system in order to produce a unique classification of a chemical input, so that an automated identification can be implemented.

Figure 11 is the database of signature from two odor mixtures and concentration of fragrance. The patterns were shown overlapping one another for those odors, especially in odor concentration ,i.e CiRoAlch0% (Citrus-Rose with Alcohol 0%) and CnRoAlch0% (Cananga-Rose with Alcohol 0%); consequently, it was very difficult to discriminate between the odors in conventional way.

5 Experimental Example

The group of odor mixture is prepared such as depicted in Table 1, respectively. The complex odor mixture is combination from three-mixture of odors, each odor-mixture is prepared by mixing a 33.3%of odor#1, 33.3% of odor#2 and 33.3% of alcohol with various gradient concentrations ranging from 0% to 70%.

The number of each odor data (i.e. CiCnA0%) is 200. To perceive the distribution of that number in the training and testing process, *the cross-validation* should be carried out. That is the statistical terminology for grouping and separating data into several sub-groups for analysis. Then, the information from this technique is used to confirm the truth and validation of the initial data accordingly.

The cross-validation K-Fold is the data resulted from the observation of the mentioned sub-groups to be K which denotes the number of sub-groups. A sub-group of data is used for validation and testing and the rest sub-group K – 1 is for training process. The mentioned process is repeated for K times with each sub-group used

Table 1. Sample of complex odor mixture with various gradient alcohol concentrations

No	Type of Complex odor-mixture	Complex Odor-mixture with various gradient alcohol concentration
1	**CiCnAlch** Citrus-Cannagga based Alcohol	CiCnA0%, CiCnA15%, CiCnA25%, CiCnA35%, CiCnA45%, CiCnA70%,
2	**CiRoAlch** Citrus-Rose based Alcohol	CiRoA0%, CiRo15%, CiRoA25%, CiRoA35%, CiRoA45%, CiRoA70%
3	**CnRoAlch** Cannagga based Alcohol	CnRoA0%, CnRoA15%, CnRoA25%, CnRoA35%, CnRoA45%, CnRoA70%

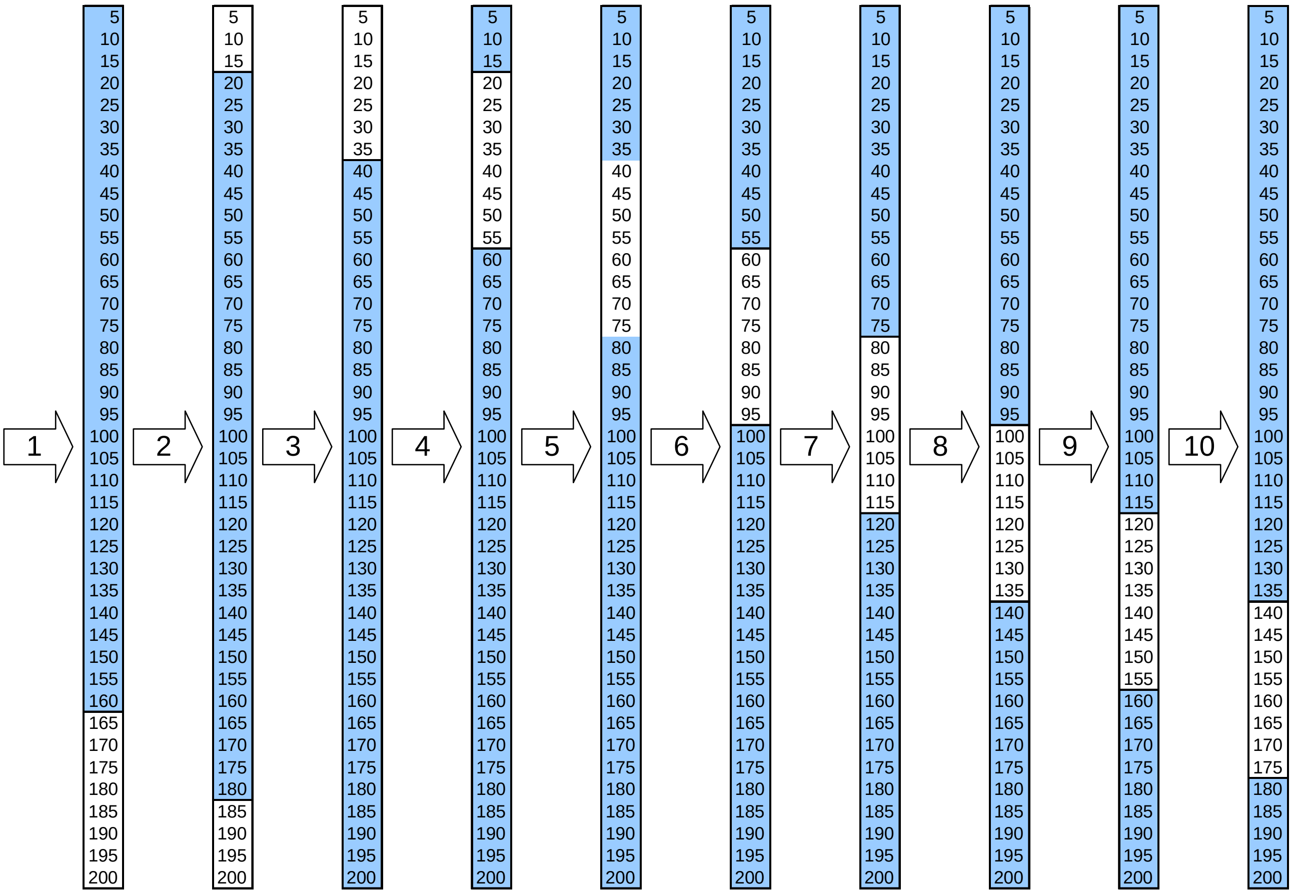


Fig. 12 Cross validation Illustration

one time only. The yield of such calculation is the mean value to get the final value. The advantage of this method is that all observed data is used either in training or testing process. This research the cross-validation 10-fold is being utilized.
The following illustration reveals the cross-validation for training process using 80% training data and 20% testing data:

For instance, there are 200 initial data. Then, using Cross-validation 10-Fold, we create 10 sub-groups of data for training and testing process. From each group the recognition rate is calculated and after all recognation rates are counted then the recognition rate of the cross-validation is derived from the mean value of all sub-group cross validation.

Table 2 The recognition rate of FLVQ using the cross-validation

	Number of Experiment										
Combination Output	1	2	3	4	5	6	7	8	9	10	Average
CiCnAlch	89	96	94	96	100	94	96	86	96	72	92
CiRoAlch	70	96	91	72	72	93	73	84	93	75	85
CnRoAlch	88	95	76	91	86	78	78	72	72	72	78
CiCnAlch-CiRoAlch	83	95	91	85	89	93	88	83	90	73	87
CiCnAlch-CnRoAlch	86	95	73	92	89	88	87	74	80	72	84
CiRoAlch-CnRoAlch	71	94	80	80	83	89	72	72	72	72	79
CiCnAlch-CiRoAlch-CnRoAlch	80	94	85	85	84	91	81	72	80	72	82
Average	81	95	84	86	86	89	82	76	83	73	84

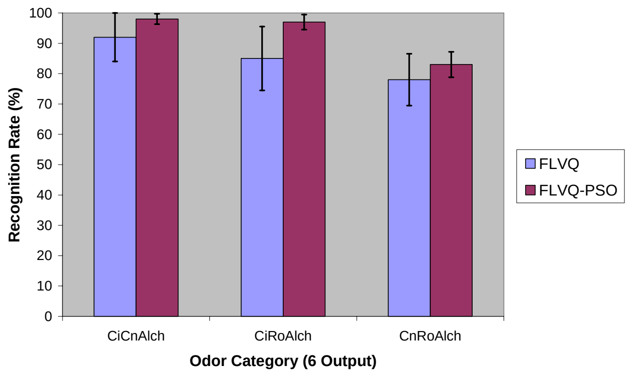
Table 3 the recognition rate of FLVQ-PSO by *the cross-validation*

	Number of Experiment										
Combination Output	1	2	3	4	5	6	7	8	9	10	Average
CiCnAlch	98	99	98	98	99	100	100	99	99	94	98
CiRoAlch	97	98	97	96	99	99	99	98	95	91	97
CnRoAlch	85	87	82	84	86	84	84	82	81	72	83
CiCnAlch-CiRoAlch	95	96	96	94	97	95	95	95	94	83	94
CiCnAlch-CnRoAlch	90	92	87	89	92	89	89	89	89	76	88
CiRoAlch-CnRoAlch	87	91	86	86	91	90	89	87	87	76	87
CiCnAlch-CiRoAlch-CnRoAlch	86	94	90	90	93	89	88	85	89	81	88
Average	91	94	91	91	94	92	92	91	91	82	91

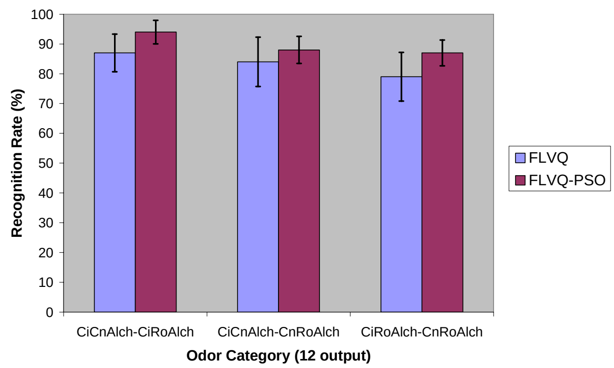
The result of the experiment using cross-validation produces the different recognition from each sub –group of data. Table 2 shows the recognition rate from the fragrance mixture data using FLVQ is different one and another with the highest average value 95% for sub-group 2nd and the least 73 % for sub-group 10th. Even all the recognition rate using FLVQ decreases for sub-group 10th . Due to this experiment using initial data, this indicates that the initial reference vector of the sub-group is not satisfactorily well

From the experiment using cross-validation, the conclusion shows that the different rate of recognition using FLVQ at least depends on 2 factors :

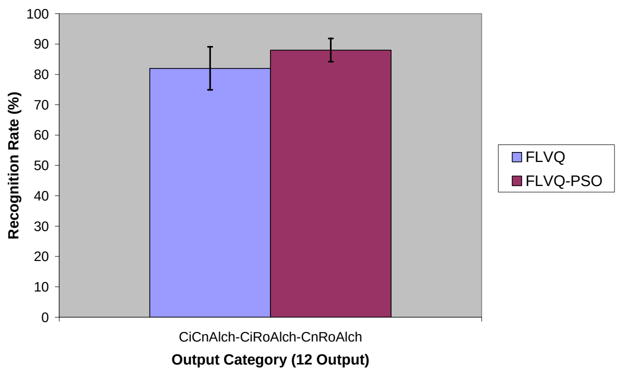
1. The 1st factor determining the different rate of recognition using FLVQ is the representative character of the initial reference vector. It means that at the end the training process, that vector enables to recognize the input



(a)



(b)



(c)

Fig. 13 The comparison between FLVQ and FLVQ-PSO by the *cross-validation*

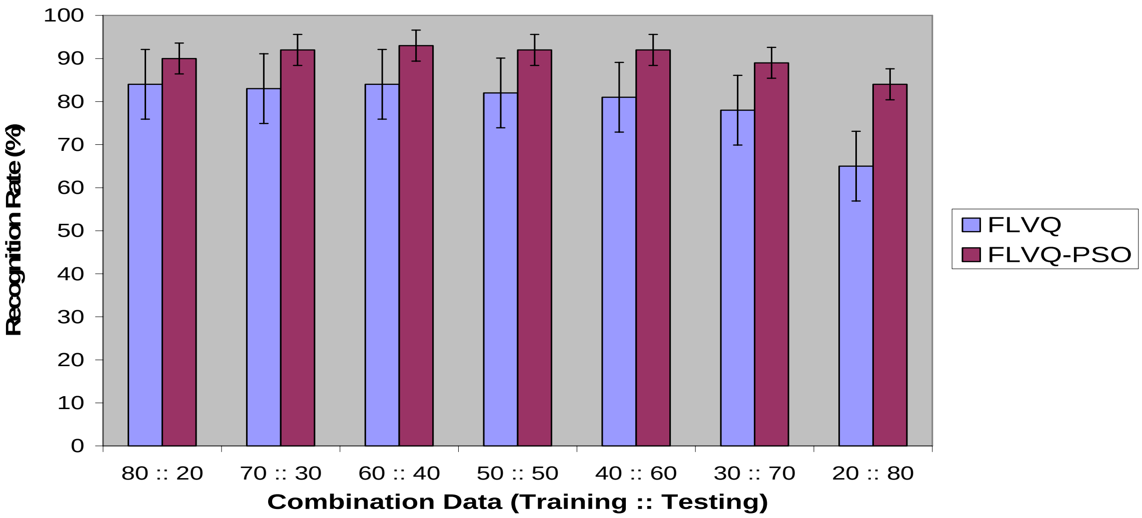


Fig. 14 The comparison between FLVQ and FLVQ-PSO Using Some Combination of Learning Data Configuration

vector well. If the initial reference vector is unknown, FLVQ learning process can not recognize the testing data at the end.

2. The 2nd factor is the organised pattern of data. It means that if the learning data is not well organized, it will be difficult to have a representative final reference vector. thus, that data recognition is good somehow.

Next, for the recognition rate of FLVQ-PSO by *the cross-validation* can be seen in table 3 below. It shows that the average recognition rate for the above three fragrance mixture has exceeded 80% .
In table 3 depicts FLVQ-PSO recognition rate by *cross-validation* for 10th sub-group data doesn't decrease significantly. It shows the FLVQ-PSO method has reduced the initial dependency FLVQ by looking for the finest reference vector of a swarm of the reference vector randomly.
The comparison between FLVQ and FLVQ-PSO is depicted comprehensively in figure 13.
Besides, the reseach also needs to perceive the recognition rate by comparing the learning data configuration and the testing data configuration. As an example, a sample which is comprises of seven combinations (80:20, 70:30, 60:40, 50:50, 40:60, 30:70 and 20:80) is taken. The result of this experiment can be seen in figure 14.
In figure 14 it shows that the recognition rate of FLVQ tends to decrease. However, FNLVQ-PSO method tends to be consistent. It proves that the less learning data used by metode FLVQ-PSO method is able to discriminate fragrance mixture better.

6 CONCLUSISON

This research has produced a new method of odor discriminating system by FLVQ-PSO which is a combination method between FLVQ and PSO where the process in determining the reference vector by PSO algorithm. The experiment shows the satisfactorily result thatFLVQ-PSO is better and more stable that conventional FLVQ.
Electronic nose technology is likely to make many advances in the near future, given the greatly increased numbers of researcher tuning their attention to this field and presence of commercial instruments stimulating interest in the applications technology. In the following section we consider some possible future applications area:

<u>*Applications Standard*</u>
There are many sizeable commercial manufactures, and it is likely that this number will be exponential in the next few years as some of the many prototype instruments currently under development in research institute and university department make their way to the marketplace. As choice in increase, there will be an increasing desire to have standard benchmark test to allow comparison of the performance of one instrument against another. This standard can achieve with some sharing information, for example developing data base repositories, which is similar to those

that have been promoted in machine learning (UC Irvine) and speech processing (TIMIT).

Environmental monitoring

One of the most demanding application areas for electronic nose is the monitoring of our environment. Electronic Noses ystem of gas distributions could be very useful for a number of industrial applications. However, while individual gas sensors can be relatively cheap, they can only cover a small area. To cover larger scale of environments such as warehouse and factories with a fixed installation of sensors, an arbitrarily large number of sensors would be required, resulting in very high set-up costs. As an alternative solution, we tried to use mobile robot become inspection robots.

But the integration of an electronic nose that can plan and act autonomously requires a forethought act at each level of the robotic architecture. More rigorous study related the Integration of electronic nose to become inspection robot is under consideration.

References

[1] Dae-Sik Lee, et. al,"SnO2 gas sensing array for combustible and explosive gas leakage recognition," IEEE Sensor Journal, Vol 2, No. 3, June 2002.

[2] Matteo Pardo and Giorgio Sberveqlieri,"Remarks on the use of multilayer perceptron for the analysis of chemical sensor array data", IEEE Sensor Journal, Vol 4, No. 3, June 2004.

[3] Haoxian Zhang, Murat O. Balaban and Jose C. Principe," Improving pattern recognition of electronic nose data with time-delay neural networks," Sensors and Actuators B 96, 2003.

[4] M. Penza and G. Cassano, "Application of principal component analysis and artificial neural networks to recognize the individual VOCs of methanol/2-ptopanaol in a binary mixture by SAW multi-sensor array ," Sensors and Actuators B 89, 2003.

[5] Gao Daqi, Wang Shuyan and Ji Yan," An electronic nose and modular radial basis function network classifer for recognition multiple fragrant materials," Sensors and Actuators B 97, 2004.

[6] T. Masters, "Advanced algorithms for neural network", New York:Wiley 1995.

[7] J. W. Gardner, P. Boilot and E. L. Hines ,"Enhancing electronic nose performance by sensor selection using a new integer-based genetic algorithm approach," Sensors and Actuators in press, 2004.

[8] Paul E. Keller, "Overview of electronic nose algorithms," IJCNN99, Washinton, DC, USA.

[9] Kohonen, T.,"Improved vesion of learning vector quantization ," Proc. of IEEE-IJCNN,1990,I,545-550.

[10] Wisnu Jatmiko, T. Fukuda, F. Arai, and B. Kusumoputro, "Artificial Odor Discrimination System Using Multiple Quartz Resonator Sensor and Various Neural Networks for Recognizing Fragrance Mixtures, IEEE Sensors Journal, vol. 6. no. 1, pp. 223–233, Feb. 2006.

[11] Wisnu Jatmiko, T. Fukuda, T. Matsuno, F. Arai and B. Kusumoputro," Robotic Applications for Odor-Sensing Technology: Progress and Challenge, " WSEAS Transaction on System, Issue 7, Volume 4, pp. 1134-1141, July 2005.

[12] R.C. Eberhart and J. Kennedy, Swarm Intelligence, The Morgan Kaufmann Series in Artificial Intelligence, 2001.

[13] A.P. Engelbrecht, Fundamentals of Computaional Swarm Intelligence, John Wiley & Sons, 2005.

[14] Wisnu Jatmiko, K. Sekiyama and T. Fukuda, "Modified Particle Swarm Robotic for Odor Source Localization in Dynamic Environment ", The International Journal of Intelligent Control and Systems: Special Issue on Swarm Robotic, Vol. 11, No 3, pp.176-184, September 2006.

[15] Wisnu Jatmiko, K. Sekiyama and T. Fukuda," A PSO-based Mobile Robot for Odor Source Localization in Extreme Dynamic Advection-Diffusion Environment with Obstacle: Theory, Simulation and Measurement ". IEEE Computational Intelligence Magazine: Special Issue on Biometric. Vol. 2, Issue 2, pp. 37-51, May 2007.

[16] Wisnu Jatmiko, Petrus Mursanto, Benyamin Kusumoputro, K. Sekiyama and T. Fukuda," Modified PSO Algorithm Based on Flow of Wind for Odor Source Localization Problems in Dynamic Environments ", WSEAS Transaction on System, Issue 3, Volume 7, pp. 106-113, March 2008.

[17] S. Haykin," Neural network, a comprehensive foundation, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 1999.

[18] T.C. Pearce, S. S. Schiffman, H. T. Nagle, and J. W. Gardner , "Handbook of machine olfaction : electronic nose technology ", Weinheim Germany : Wiley-VCH-2002.

[19] J. W. Gardner and P. N. Bartlett, "Electronic nose : principles and applications",New York : Oxford Univ. Press 1999.

[20] Sauerbrey, G., "Vermendung von schwingquaren zur wagung dunner schichten und zur wagung," Z.Phys., 1959,155, 206-209.