Artificial Odor Discrimination System Using Multiple Quartz Resonator Sensors and Various Neural Networks for Recognizing Fragrance Mixtures

Wisnu Jatmiko, *Student Member, IEEE*, Toshio Fukuda, *Fellow, IEEE*, Fumihito Arai, *Member, IEEE*, and Benyamin Kusumoputro

***Abstract*—An electronic odor discrimination system had been developed by using four quartz resonator-sensitive membranes basic-resonance frequencies at 10 MHz as a sensor and analyzed the measurement data through a back propagation (BP) as the pattern recognition system. The developed system showed high recognition probability to discriminate various single odors to its high generality properties; however, the system had a limitation in recognizing the fragrances mixture. This system also had other disadvantages, such as classifying the unknown category of odor as the known category of odor. In order to improve the performance of the proposed system, development of the sensor and other neural networks (NNs) are being sought. This paper explains the improvement of the capability of that system. In this experiment, the improvement is conducted not only by replacing the last hardware system from four quartz resonator-basic resonance frequencies at 10 MHz with new 16 quartz resonator-basic resonance frequencies at 20 MHz, but also by replacing the pattern classifier from BP NNs with the variance of BP, probabilistic NNs, and fuzzy-neuro learning vector quantization (FNLVQ). Matrix similarity analysis (MSA) is then proposed to increase the accuracy of the FNLVQ, to become FNLVQ-MSA neural systems in determining the best exemplar vector, for speeding up its convergence. The purpose of the recent study is to construct a new artificial odor discrimination system for recognizing the fragrance mixtures, in addition to recognizing the unknown fragrance mixtures. The use of new sensing systems and FNLVQ-MSA has produced higher capability, compared to the previously mentioned system.**

***Index Terms*—Fuzzy-neuro learning vector quantization (FNLVQ), matrix similarity analysis (MSA), multiple quartz-resonator sensors, neural networks (NNs), odor discrimination system.**

I. Introduction

THE amount of research in the field of robotics application for odor-sensing technology has grown substantially. This work can be broadly categorized into two groups namely odor source localization by autonomous mobile sensing system and artificial odor discrimination system [1]. The odor source localization can be used for various attractive applications, including the search for toxic gas leak, the fire origin at its initial stage, etc. The second prime area of robotics application for odor-sensing technology is artificial odor discrimination system. Artificial odor discrimination system is being developed for automated detection and classification of aromas, vapors and gases. This paper would address the second area of application

Conventionally, odors are discriminated by very trained persons based on their human sensory system. These human sensory tests have been used to evaluate odors in a variety of industrial fields, such as food and beverage industries, cosmetics industries and in the environment tests. However, the human sensory test is unavoidably affected by the state of the health and mood of the inspector, resulting in discrepancies among panelists. Another method that can be used is analytical techniques such as gas chromatography (GC) or liquid chromatography (LC). However, these analytical methods are expensive and time consuming, especially for aromatic and fragrance odors.

The artificial odor discrimination system is constructed to overcome the limitation of the existing sensory test systems. This system is composed of an arrayed chemical sensing system and a pattern recognition system [1]–[3]. Each chemical vapor being 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 training 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 [4]–[7].

The conventional electronic odor discrimination system had been developed by using four quartz resonator-sensitive membranes basic-resonance frequencies with a 10-MHz sensor, and analyzed the measurement data through a back propagation (BP) as the pattern recognition system [8]. Even though the system showed high recognition probability to discriminate various single odors to its high generality properties, however, it had a limitation in recognizing the fragrance mixture [9]. As a matter of fact, in recent years, many researchers in artificial discrimination system give more attention to solve the odor mixture problem [10]–[12]. This system also had disadvantages, such as the unknown category of odor would be classified as the known category of odor [8], [13], [14]. In order to improve the performance of the proposed system, development of the sensor and other neural networks (NNs) are being sought.

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W. Jatmiko, T. Fukuda, and F. Arai are with the Micro-Nano Systems Engineering, Nagoya University, Nagoya 464-8603, Japan (e-mail: wisnu@robo.mein.nagoya-u.ac.jp).

B. Kusumoputro is with the Computational Intelligence Research Laboratory, Faculty of Computer Science, University of Indonesia, Jakarta 10002, Indonesia.

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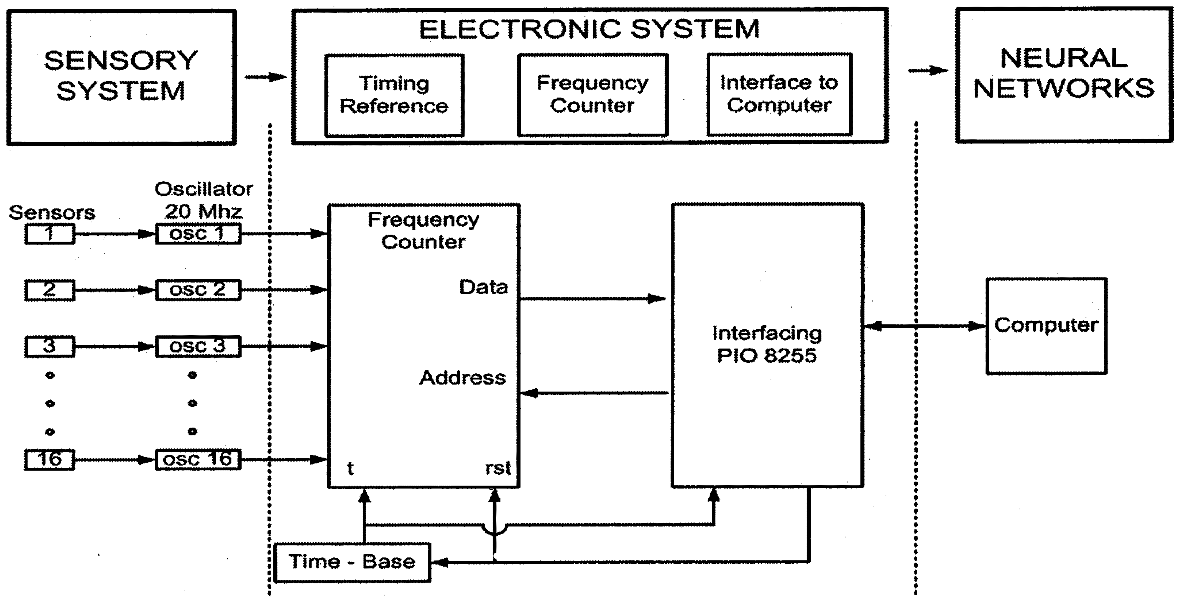

Fig. 1. Artificial odor discrimination system diagram.

This paper will explain the improvement of the capability of the system. The purpose of the recent study is to construct a new artificial odor discrimination system for recognizing the fragrance mixtures [9], [15], in addition to recognizing the unknown fragrance mixtures [14].

This paper is organized as follows. Section II explains the artificial odor discrimination system. Section III presents the fuzzy-neuro learning vector quantization and matrix similarity analysis (FNLVQ-MSA) algorithm. Section IV discusses the experimental design and the results of those algorithms as the automated pattern discrimination system, and, finally, Section V presents the concluding remarks.

II. Artificial Odor Disrimination System

A. System Design Diagram

From the theory, the condition of material can be smelled if they can vaporize. In biology, the mammalian uses a variety of chemical sensors, known as olfactory receptors, combined with an automated pattern recognition system incorporated in the olfactory bulb and higher portions of brain. It is the collective set of receptors combined with pattern recognition that identifies each odor. The olfaction process begins with sniffing. Sniffing brings odorant molecules from the outside world into the nose. With the aid of turbinate (bony structures in the nose which produce turbulence), sniffing also mixes the odorant molecules into uniform concentration and delivers these molecules to the mucus layer lining the olfactory epithelium in the upper portion of the nasal cavity. Next, the odorant molecules dissolve in this thin mucus layer which then transport them to the cilia (hair like fibers) of the olfactory receptor neuron [6]–[8]. Reception involves binding the odorant molecules to the olfactory receptors. These olfactory receptors respond chemically with the odorant molecules. From the olfactory bulb, the receptor response information is transmitted to the limbic system. The olfactory information is also transmitted to the cerebral cortex. It is the brain that associates the collection of olfactory signal with odor [8].

The artificial odor discrimination system then consists of three parts namely: a sensory system, an electronic system and a NN system. Sensory systems and electronic systems are used to measure the frequency declines of odor identification while NN system is used to recognize and classify the odor that will be detected. The NN system is similar with the human brain. It has neurons that connect each other to respond the effective recognition.

Fig. 1 shows the detail parts of artificial odor discrimination system based on the function and the process. In this figure sensory subsystem and frequency counter subsystem components become the sensing system and NN component becomes the automated pattern recognition system. This combination of broadly tuned sensors coupled with sophisticated information processing makes the artificial odor discrimination system powerful [1]–[3].

B. Sensory and Measurement System

The schematic diagram of the measurement system is depicted in Fig. 2. The odor discrimination 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 NN 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 °C. 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

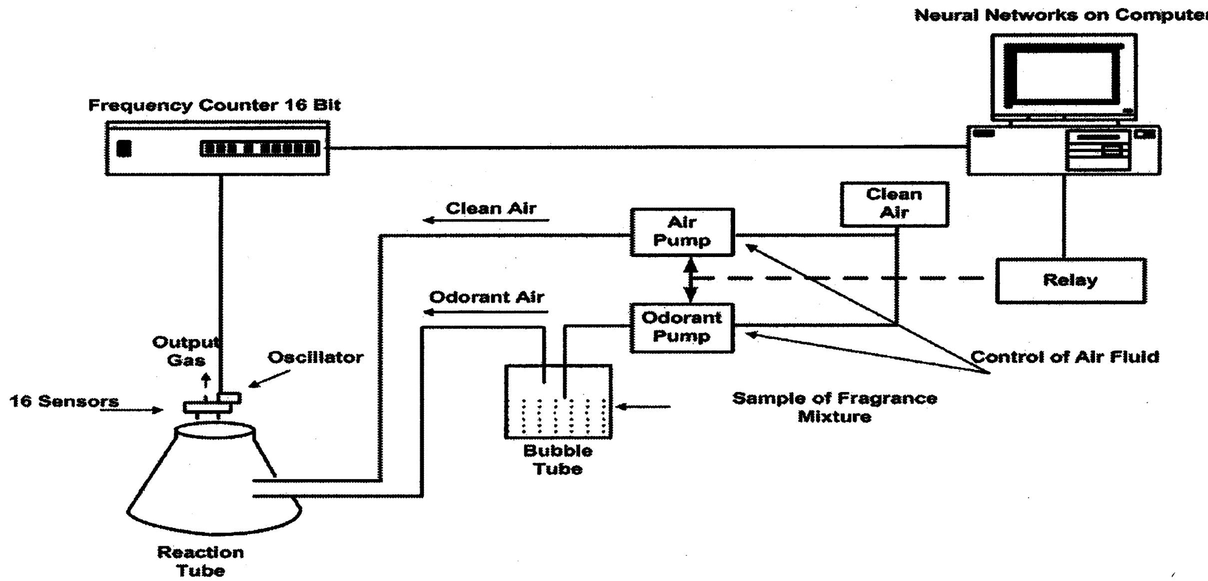

Fig. 2. Schematic diagram of the measurement system.

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 the mass-loading effect [16]. 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 [16]

$$\Delta F = -2.3 \times 10^6 F^2 \frac{\Delta M}{A} \tag{1}$$

where F denotes the characteristics frequency (in megahertz), 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 $(< 50\ ^\circ\mathrm{C})$.

The experimental setup for determining the category of odor uses two small pumps as can be seen in Fig. 2, 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 a 20-MHz base frequency is depicted in Fig. 3. Sixteen chemical vapors were being used as sensors in the experiment. The wide range of different coatings has proven to be useful [1]–[3]. The following is a list of coating materials used by our experiment:

- phosphaticid;
- lecithin;
- cholesterol;
- phospatidyl inositol;

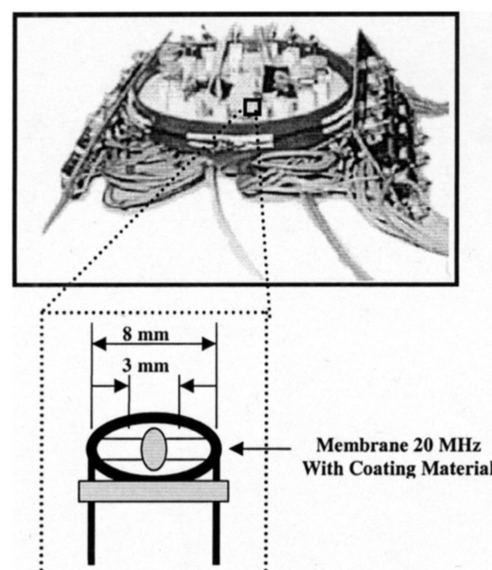

Fig. 3. QCM sensor array with a 20-MHz base frequency.

- phospatidyl serine;
- phospatidyl ethanol amine;
- phospatidy chorine;
- phospatidy choline 63% sphingomyelin 37%;
- sphingomyelin;
- lecithin 63% cholesterol 37%;
- cardioliin;
- ethyl cellulose;
- silicone OV101;
- silicone OV17;
- silicone 50 MB/2.000;
- silicone 75 MB/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

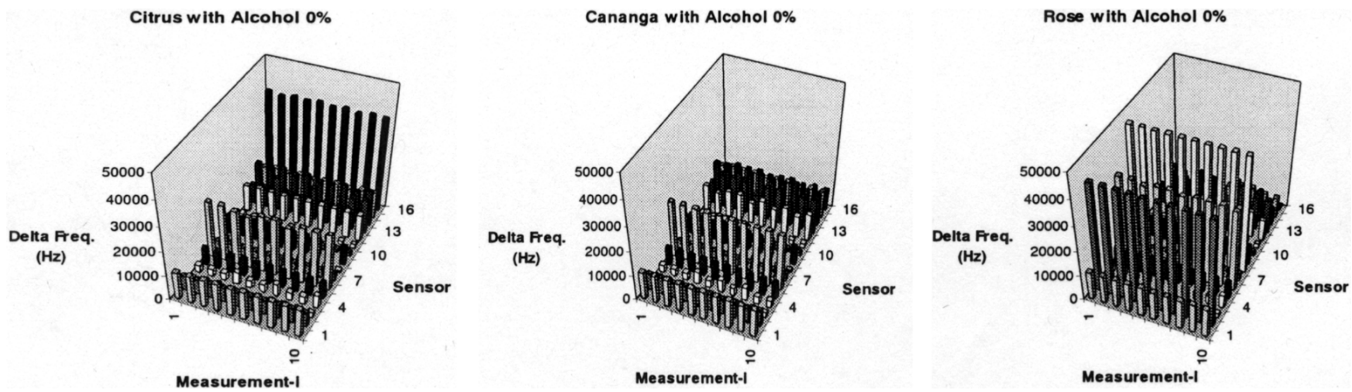

Fig. 4. Signature or pattern characteristic from CiA0% (citrus with alcohol 0%), CnA0% (cananga with alcohol 0%), and RoA0% (rose with alcohol 0%).

of signatures can be built up. This database of labeled signatures is used to train the pattern recognition system. The purpose of the training 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. Fig. 4 is the database of signature from CiA0% (citrus with alcohol 0%), CnA0% (cannagga with alcohol 0%), and RoA0% (rose with alcohol 0%). The patterns were shown overlapping one another for those odors especially in odor mixture; consequently, it was very difficult to discriminate between the odors in conventional way. The popular advance techniques for analyzing this pattern include principal component analysis, cluster analysis, discrimination function analysis, and artificial neural networks (ANNs) [4], [17], [18].

III. Fuzzy-Neuro Learning Vector Quantization With Matrix Similarity Analysis

The output pattern recognition methods that are applied in the artificial odor discrimination are cluster analysis, discrimination of functions analysis, and NNs [1], [2], [4]. The NN method is generally used because it has easier recognizing process algorithm and better odor recognizing result than the other methods [4], [17]. There are several reports on the use of ANNs in gas/odor identification. Many reports are available in the literature on the application of different NN architectures in processing sensor array data, i.e., BP-trained NN and its variance [19]–[23], radial basis function NN [11], probabilistic neural network (PNN) [17], genetically trained ANN [25], adaptive resonance theory [17], self-organizing network [17], and learning vector quantization (LVQ) [7], [26].

From the best of our knowledge, to classify the problem with very similar data, like discrimination odor mixture, LVQ proposed by Kohonen is a powerful method for realizing an alternative NN, since the neuron in LVQ learning is nonlinear, localized updated and the network does not take much time to converge [17], [18], [26]. It has been proved that the LVQ together with fuzzy theory shows high recognition capability compared with other NNs [9], [13]. Other features from FNLVQ can also be used for recognizing the unknown fragrance [13]. Matrix similarity analysis (MSA) is then proposed to increase the accuracy of the FNLVQ, became FNLVQ-MSA neural system in determining the best exemplar vector, for speeding up its convergence [15].

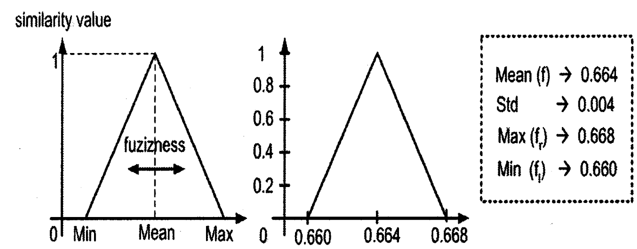

Fig. 5. Fuzziness of CiA0% fragrance taken from sensor 1 of the recognition system.

A. Fuzzy-Neuro Learning Vector Quantization

FNLVQ is developed based on LVQ and extended by using fuzzy theory. In this FNLVQ, 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, the value is equal to 1. A normalized triangular fuzzy number F is designated as [27]–[30]

$$F = (f, f_l, f_r) \tag{2}$$

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. Fig. 5 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 100 frequency data taken from one measurement. 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 [31], [32].

As the neuron of FNLVQ 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 [33]–[36].

The architectural network of FNLVQ is depicted in Fig. 6, which consists of one input layer, one cluster layer as a hidden

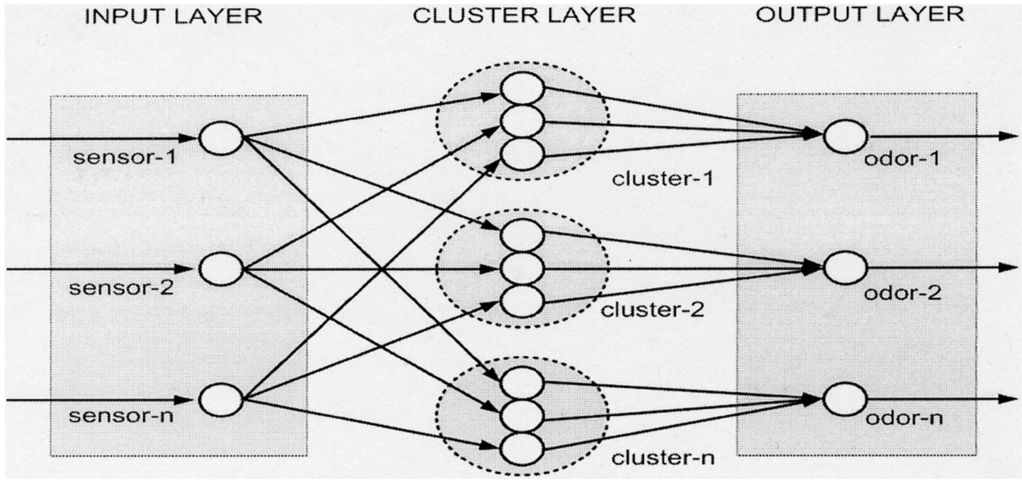

Fig. 6. Architecture of the FNLVQ that is used as the discrimination system in the artificial odor discrimination system.

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 min 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 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

$$x(t) = (x_1(t), x_2(t), \ldots, x_n(t)) \tag{3}$$

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. 5). The membership function of $x(t)$ can be expressed by

$$hx(t) = (hx_1(t), hx_2(t), \ldots, hx_n(t)). \tag{4}$$

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

$$w_i(t) = (w_{i1}(t), w_{i2}(t), \ldots, w_{in}(t)) \tag{5}$$

and the membership functions of w_i can be expressed by

$$hw_i(t) = (hw_{i1}(t), hw_{i2}(t), \ldots, hw_{in}(t)). \tag{6}$$

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

$$\mu_i(t) = \max(h_x(t), h_{wi}(t)) \tag{7}$$

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

A schematic diagram of fuzzy similarity calculation between inputs vectors with a reference vector in each cluster is depicted in Fig. 7.

The 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

$$\mu(t) = \min(\mu_i(t)) \tag{8}$$

which is the output from the ith 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 FNLVQ is accomplished by presenting a sequence of training vector with its known category, and the similarity value between the training 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 nonwinning reference vectors are updated repeatedly for reducing the difference between the output and the target. During learning, two steps of the 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

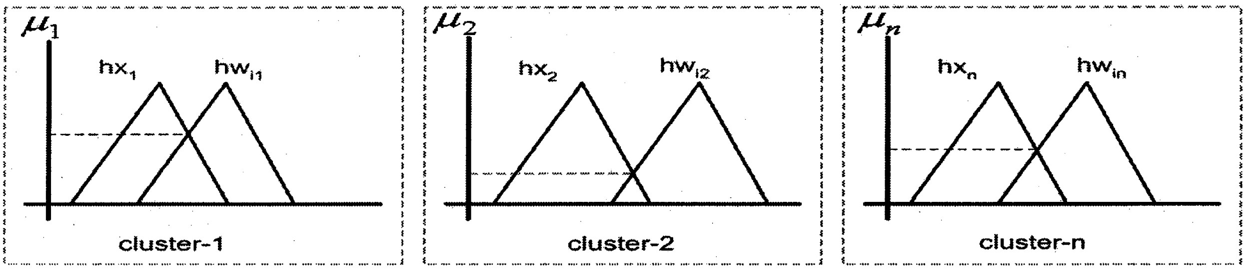

Fig. 7. Fuzzy similarity calculation in the cluster neuron between the input vector and the reference vector in respect to its sensor number.

factor [35], [36], while the second is by multiplying it with a variable factor [37].

By using these procedures, FNLVQ has three cases that can possibly occur. 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 training vector Cx is the same as the target category T, the reference vector of the winning cluster is updated according to [35]–[37].

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

$$w_i(t+1) = w_i(t) + \alpha(t)\left\{(1-\mu_i(t))^*(x(t) - w_i(t))\right\}. \quad (9)$$

- Step 2. Increase the fuzziness of the reference vector for the next training step.

a) Modification by constant factor

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

b) Modification by a variable factor

$$\begin{aligned} f_l(t+1) &= f_l(t) - (1-\mu) * \{(1+\eta)\} * \{f(t) - f_l(t)\} \\ f_r(t+1) &= f_l(t) - (1+\mu) * \{(1+\eta)\} * \{f_r(t) - f(t)\} \\ f(t+1) &= w_i(t+1). \end{aligned} \quad (11)$$

For the second case, when the network outputs the category of the training 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 the following.

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

$$\omega_i(t=1) = \omega_i(t) - \alpha(t)\left\{(1-\mu_i(t)) * (x(t) - \omega_i(t))\right\}. \quad (12)$$

- Step 2. Decrease the fuzziness of the reference vector for the next training step.

a) Modification by constant factor

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

b) Modification by a variable factor

$$\begin{aligned} f_l(t+1) &= f_l(t) + (1-\mu) * \{(1-k)\} * \{f(t) - f_l(t)\} \\ f_r(t+1) &= f_r(t) - (1-\mu) * \{(1-k)\} * \{f_r(t) - f(t)\} \\ f(t+1) &= w_i(t+1). \end{aligned} \quad (14)$$

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

$$\omega_i(t+1) = \xi(t) * \omega_i(t). \quad (15)$$

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

$$\begin{aligned} \alpha(t+1) &= 0.9999\alpha(t) \\ \alpha(0) &= 0.05. \end{aligned} \quad (16)$$

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

$$\begin{aligned} \eta(t+1) &= \frac{1}{100}\{1-\alpha(t+1)\} \\ k(t+1) &= 1 - \alpha(t+1). \end{aligned} \quad (17)$$

ξ constant value of 1.1.

B. Improving FNLVQ Using Matrix Similarity Analysis

The weakness of the conventional FNLVQ algorithm is in selecting the best codebook vector that will influence the result of recognition. This problem can be anticipated by adding the matrix of similarity method to select the best codebook vector. The matrix of similarity is the $n \times n$ matrix element with the average training vector similarity value from the category toward the all reference vector, and n denotes number category of learning process. The mathematics notation of matrix of similarity M within m_{mj} matrix element is given [15]

$$m_{mj} = \frac{1}{N}\sum_{k=1}^{N} \max\min \mu_{ij}(k) \quad (18)$$

TABLE I
MATRIX SIMILARITY ANALYSIS OF THE CODEBOOK VECTORS OF THE FNLVQ NEURAL SYSTEM THAT PERFORMED THE BEST APPROACH TO AN IDENTITY MATRIX

Row \ Column	I	II	III	IV	V	VI
I	0.74	0.20	0	0	0	0
II	0	0.73	0.13	0	0	0
III	0	0.11	0.70	0	0	0
IV	0	0	0	0.79	0.21	0
V	0	0	0	0.01	0.76	0
VI	0	0.01	0	0	0	0.66

where i denotes the sensor's number, j denotes the reference vector of odor category, m denotes the training vector of odor category, N denotes the number of training vector, and $k = 1, 2, 3 \ldots N$.

The recognition rate accuracy of the neural system is heavily dependent on the codebook vectors, which can be written as a matrix. If this matrix is not optimal, then the codebook vectors are not in general corresponding to the best solution of the neural system, and, as a consequence, the recognition rate is lower than it could be achieved. The ideal type of the similarity matrix is similar to the identity matrix, which in turn will produce higher recognition rate. The experimental result of matrix similarity analysis of the FNLVQ is shown in Table I, showing the fourth epoch of the three-mixture of odor, which produced 86% of recognition rate.

The first column of the matrix is the average of reference vector similarity value category of i toward training vector category I, II, III, IV, V, and VI, showing the value: 0.74, 0, 0, 0, 0, and 0. It means that reference vector of odor category I has been represented.

IV. EXPERIMENT AND ITS RESULT

The experiments are designed to elaborate the capability of the developed odor discrimination system to recognize and determine mixture odors. Five types of neural classifiers namely BP neural system, back propagation-self organize map (BP-SOM) [22], fuzzy neuro-back propagation (FN-BP) [23], PNNs, and standard FNLVQ are conducted and compared to recognize the odor mixture. FNLVQ with matrix similarity analysis (FNLVQ-MSA) is also used for recognizing the fragrance mixture and the unknown fragrance mixtures.

Two groups of odor mixture are prepared such as depicted in Tables II and III, respectively. In the two-mixture odors, each odor mixture is prepared by mixing a 50% of odor and 50% of alcohol with various gradient concentrations from 0% to 70%. While in 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%.

A. Comparison Between a Four-Sensor 10-MHz System With a 16-Sensor 20-MHz System Using BP

The odor mixtures (Sample I) are classified all at once. The experiment used the Processor Pentium II 300-MHz and BP neural system program that is constructed by C++ Linux *software*. BP is a standard tool for establishing relationships between data in many real world problems, in the absence of a parametric model [18], [20]. The architectural network of BP like PNN and FNVLQ, which consists of one input layer, one cluster layer as a hidden layer and one output layer. The number of neurons in the input layer depends on the number of sensors and the number of neurons in the output layer depends on the number of odor that will be classified, but number of neurons in hidden layer can be chosen by cross validation experiment [17], [18]. In experiments with BP, we used eight neurons in hidden layer, sigmoid activation function, learning rate 0.01 and error convergence 0.1, which was the best parameter in BP from our previous experiment [8], [9]. The treatment of each type of odor mixture has been done five times.

The result of artificial odor recognition within four sensors with fundamental resonance frequency at 10 MHz cannot recognize the odor mixture (citrus and alcohol). Its recognition probability was only 55%, as depicted in Table IV. However, the artificial odor recognition within 16 sensors and fundamental resonance frequency at 20 MHz can obtain recognition probability 75%, as can be seen in Table V. The improvement of system

TABLE II
SAMPLE OF TWO-MIXTURE ODOR WITH VARIOUS GRADIENT ALCOHOL CONCENTRATIONS

No	Sample I	
	Type of odor-mixture	Odor-mixture with various gradient alcohol concentration
1	**CiAlch** Citrus based Alcohol	CiA0%, CiA15%, CiA25%, CiA35%, CiA45%, CiA70%,
2	**CnAlch** Cananga based Alcohol	CnA0%, CnA15%, CnA25%, CnA35%, CnA45%, CnA70%
3	**RoAlch** Rose based Alcohol	RoA0%, RoA15%, RoA25% RoA35%, RoA45%, RoA70%

TABLE III
SAMPLE OF THREE-MIXTURE ODOR WITH VARIOUS GRADIENT ALCOHOL CONCENTRATIONS

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

TABLE IV
RESULT OF SYSTEM WITHIN FOUR SENSORS AND FUNDAMENTALS RESONANCE FREQUENCY OF 10 MHz

Sample I	Recognition Probability (%)					
	4 Sensors					
	1	2	3	4	5	Average
CiA0%	70	65	60	60	75	69
CiA15%	80	85	75	90	85	85.5
CiA25%	0	0	5	0	0	1
CiA35%	45	45	50	55	45	46
CiA45%	25	10	20	15	20	17.5
CiA70%	95	90	95	100	85	93
Average	52	49	50	53	51	52.75

TABLE V
RESULT OF SYSTEM WITHIN 16 SENSORS AND FUNDAMENTALS RESONANCE FREQUENCY OF 20 MHz

Sample I	Recognition Probability (%)					
	16 Sensors					
	1	2	3	4	5	Average
CiA0%	100	100	100	100	98	99.5
CiA15%	80	65	65	70	85	75
CiA25%	95	100	90	95	90	95
CiA35%	50	30	60	40	45	41
CiA45%	50	60	45	65	45	51.5
CiA70%	100	100	100	100	100	100
Average	79	75	76	78	77	76.83

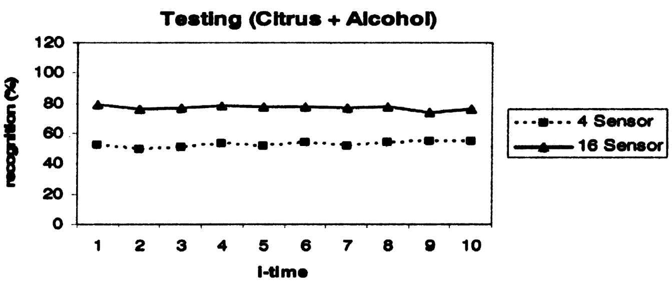

Fig. 8. Comparison of recognition probability CiAlch.

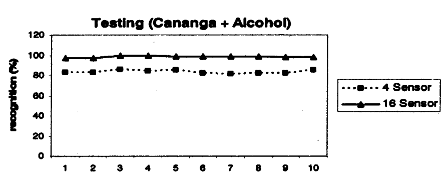

Fig. 9. Comparison of recognition probability CnAlch.

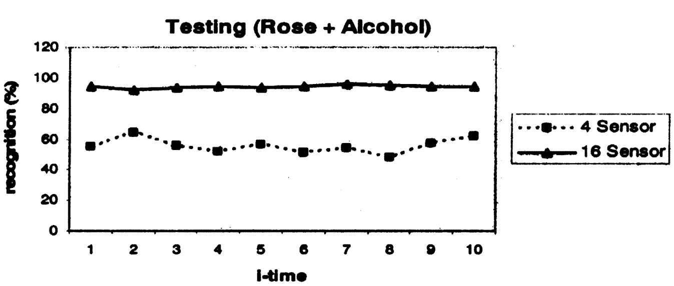

Fig. 10. Comparison of recognition probability RoAlch.

by adding the number of sensors can enhance the odor-mixture recognition.

The comparison results of the artificial odor discrimination with four sensors and fundamental resonance frequency at 10 MHz and with 16 sensors and fundamental resonance frequency at 20 MHz can be seen in Fig. 8 for citrus odor, Fig. 9 for cananga odor, and Fig. 10 for rose odor.

From these figures, it can be concluded that the artificial odor discrimination using 16 sensors and fundamental resonance frequency at 20 MHz has higher recognition probability than the artificial odor discrimination using four sensors and fundamental resonance frequency at 10 MHz.

TABLE VI
RECOGNITION RATE OF THE ODOR RECOGNITION SYSTEM USING VARIOUS NNS AS THE PATTERN CLASSIFIER FOR TWO MIXTURES OF FRAGANCE

Sample I	Neural Networks as the Classifier					
	BP	BP-SOM	FN-BP	PNN	FNLVQ	Average
CiAlch	76.80%	83%	95%	93.70%	95.00%	88.10%
CnAlch	99.00%	95%	95%	100.00%	96.00%	97.00%
RoAlch	94.10%	95%	100%	100.00%	100.00%	97.82%
Average	89.97%	91%	97%	97.90%	97.00%	

TABLE VII
RECOGNITION RATE OF THE ODOR RECOGNITION SYSTEM USING VARIOUS NNS AS THE PATTERN CLASSIFIER FOR THREE MIXTURES OF FRAGANCE

Sample II	Neural Networks as the Classifier					
	BP	BP-SOM	FN-BP	PNN	FNLVQ	Average
CiCnAlch	50.00%	60%	75%	74.20%	76.00%	67.04%
CiRoAlch	56.00%	70%	80%	80.00%	85.00%	74.20%
CnRoAlch	66.00%	70%	75%	70.00%	76.00%	71.40%
Average	57.33%	67%	77%	74.73%	79.00%	

B. Comparison Among BP, BP-SOM, FN-BP, PNN, and FNLVQ as Classifiers

In experiments Sections IV-B and C, various well known NNs have been implemented. Two type variance of BP which are BP-SOM and FN-BP will be discussed. BP-SOM is a combination of BP with competitive learning paradigm. BP-SOM architecture and parameter are exactly similar with BP standard, except that BP-SOM have cluster competitive parameter which in our experiment we used 0.9 [22]. While FN-BP is a type of BP standard with a basic difference in which FN-BP is employing fuzzy theory for its sum ($\sum$) operation [23].

For a more comprehensive study, PNN and FNLVQ, which have different basic concepts than BP, will also be discussed. Although architectural network of BP a like PNN and FNVLQ, the concept of learning process is different [17], [18]. The basic concept of BP is gradient descent, PNN is probabilistic while FNLVQ is winner take all [18]. The important parameter in experiment with PNN is a smoothing parameter (σ), because the σ value will influence the width of Gaussian curve constructed on each training example (in our experiment we used the σ value range between 0.03 and 5 within trial and error in the sample training set) [9]. In a previous report, authors [13] had proved and developed the LVQ cooperating with fuzzy theory showing high recognition capability for single odor compared with other NNs [9], [13]. In this paper our concern is to solve the odor-mixture problem.

Results of experiment on recognizing various odor-mixtures are depicted in Tables VI and VII, respectively. Table VI shows that the recognition rate of BP to determine two-mixture of odors is about 89.9 6% in average. This recognition rate is high enough, even though it is still lower than that of variance of BP, PNN, and FNLVQ, which show recognition rate of more than 90%, respectively. Experimental results also show that the average recognition rates by all of the neural classifiers to each mixture odors are nearly the same. However, the recognition rate of citrus + alcohol (with various gradient concentrations) mixture is rather low compared with that of two other mixtures of odors.

TABLE VIII
COMPARSION OF CLASSIFYING AND RECOGNIZING TWO MIXTURES OF ODOR BY BP, BP-SOM, FN-BP, PNN, AND FNLVQ USING DIFFERENT OUTPUT PATTERNS (SIX, 12, AND 18 OUTPUT PATTERNS)

Classifier	Sample I						
	6 output pattern			12 output pattern			18 output pattern
	CiAlch	CnAlch	RoAlch	CiAlch + CnAlch	CiAlch + RoAlch	CnAlch + RoAlch	CiAlch + CnAlch + RoAlch
BP	76.8%	99%	94.1%	83.6%	76.7%	86.6%	69.86%
BP-SOM	83%	95%	95%	85%	80%	90%	75%
FN-BP	95%	95%	100%	90.7%	92.9%	89%	90%
PNN	93.7 %	100%	100%	97.5%	91.9%	98.3%	92.6%
FNLVQ	95%	96%	100%	93.8%	93.8%	100%	96.5%

TABLE IX
COMPARISON OF CLASSIFYING AND RECOGNIZING THREE MIXTURES OF ODOR BY BP, BP-SOM, FN-BP, PNN, AND FNLVQ USING DIFFERENT OUTPUT PATTERNS (SIX, 12, AND 18 OUTPUT PATTERNS)

Classifier	Sample II						
	6 output pattern			12 output pattern			18 output pattern
	CiCnAlch	Ci RoAlch	CnRoAlch	CiCnAlch + CiRoAlch	CiCnAlch + CnRoAlch	CiRoAlch + CnRoAlch	CiCnAlch + CiRoAlch + CnRoAlch
BP	50%	56%	66%	46.7%	45%	46.6%	39.86%
BP-SOM	60%	70%	70%	50%	50%	55%	40%
FN-BP	75%	80%	75%	60%	70%	70%	45%
PNN	74.2%	80%	70%	65%	70%	70%	40%
FNLVQ	76%	85%	76%	73.8%	73.8%	80%	52%

Table VII shows the recognition rates of using various neural classifiers to determine and recognize three-mixture of odors. It is shown that the recognition rate of using BP to this three-mixture odor (57.33%) is lower than when it is used to recognize the two-mixture odor (90%), showing the difficulties of recognizing three-mixture of odors. FN-BP, PNN, and FNLVQ, however, show higher recognition rate of about 77%, 74.70%, and 79.00%, respectively.

C. Comparison Among BP, BP-SOM, FN-BP, PNN, and FNLVQ for RecognitionWithin Different Output Patterns

To know the capability and performance of the system, in the following experiments, the classification of sample odor has been conducted in three phases of the odor pattern classifiers. First, the experiment is done using the six-fragrance odor of pattern classifiers, then using the 12-fragrance odor of pattern classifiers, and, finally, using the 18-fragrance odor of pattern classifiers. The steps of classifying have been conducted to compare the recognition capability of the systems that based on BP, BP-SOM, FN-BP, PNN, and FNLVQ.

The result of the experiments can be seen in Tables VIII and IX. Table VIII shows that by using the FN-BP, PNN, and FNLVQ algorithms, the average recognition probability to recognize the two-mixture odor is more than 90%, while the using of BP and BP-SOM algorithms, the recognition ability is less than 85%, for example, recognized by 18 patterns.

Recognizing for the three-mixture odor used BP, BP-SOM, FN-BP, and PNN algorithm producing low recognition probability. In these cases, using more pattern classifier will decrease recognition probability. For 18-pattern classifiers, using the BP, BP-SOM, FN-BP, and PNN algorithms, we obtain an average recognition probability less than 50%. From those tables, it can be concluded that the more output patterns being used, recognition probability of the system, it will reduce.

D. Result of FNVLQ-MSA Experiment

The experiment shows that FNLVQ-MSA being applied in artificial odor discrimination system can improve the capability of conventional FNLVQ. The aim of using the Matrix of Similarity in FNLVQ is to select the best codebook vector from the target vector. The comparison result between the FNLVQ and FNLVQ-MSA in recognizing the odor mixture can be seen in Table X. It can be concluded that FNLVQ-MSA being applied in artificial odor discrimination system can improve odor recognizing.

TABLE X
COMPARSION OF CLASSIFYING AND RECOGNIZING THREE MIXTURES OF ODOR BY FNLVQ AND FNLVQ-MSA USING DIFFERENT OUTPUT PATTERNS (SIX, 12, AND 18 OUTPUT PATTERNS)

Classifier	Sample II						
	6 output pattern			12 output pattern			18 output pattern
	CiCnAlch	Ci RoAlch	CnRoAlch	CiCnAlch + CiRoAlch	CiCnAlch + CnRoAlch	CiRoAlch + CnRoAlch	CiCnAlch + CiRoAlch + CnRoAlch
FNLVQ	76%	85%	76%	73.8%	73.8%	80%	52%
FNLVQ-MSA	78%	86%	76%	74%	74%	82%	64%

FNLVQ can also be used for recognizing the unknown fragrance mixtures. To recognize and classify the unknown odor samples, we have treated the odor samples with eight patterns classifier. The result of the recognition can be shown in Table XI. We can observe the CiAlch35% that is unknown, only three cases that are classified in invalid classifications (CiAlch0%). While the RoAlch35% that is unknown, has been classified as new odor types with zero similarity, although two cases (CiAlch35% and RoAlch15%) has been classified as new odor types.

The capability of FNLVQ algorithm in recognizing various outputs of unknown odor samples is depicted in Table XII. In this table, we can see that the FNLVQ has recognition probability of more than 85% to the unknown odor samples. The comparison between FNLVQ and FLVQ-MSA for recognizing the various outputs of unknown odor samples is indifferent as the result of not conducting the analysis of the probability recognition in this paper.

V. CONCLUSION

Improving the hardware and changing the software of pattern classifiers, we have developed a new artificial odor discrimination system. In the experiment, the improvement is done not only by replacing the last hardware system from four quartz resonator-basic resonance frequencies at 10 MHz with new 16 quartz resonator-basic resonance frequencies at 20 MHz, but also by replacing the pattern classifier from BP NNs with variance of BP, PNN, and FNLVQ. MSA is then proposed to increase the accuracy of the FNLVQ, become FNLVQ-MSA neural system in determining the best exemplar vector, for speeding up its convergence. The experiment found out that the using of new sensing system and FNLVQ-MSA produces higher capability compared to the conventional system

Using FNLVQ as the neural classifier, the developed system could be used to recognize mixtures of odors that could not be performed by using system based on lower number of sensors. FNLVQ neural system shows its high ability compared with that of PNN and BP neural system, especially when they are used as the neural classifier in determining the three-mixture of odors. FNLVQ NN can also recognize the unknown fragrance mixtures. Incorporating FNLVQ-MSA could increase slightly the recognition of the result.

TABLE XI
RECOGNIZING AND CLASSIFYING RESULTS OF UNKNOWN ODOR SAMPLE I (TWO MIXTURES) BY FNLVQ

CnAlch35% unknown category of odor samples

Target	Output	Similarity
CiAlch0%	CiAlch0%	0.507
CiAlch0%	CiAlch0%	0.794
CiAlch0%	CiAlch0%	0.586
CiAlch15%	CiAlch15%	0.806
CiAlch15%	CiAlch15%	0.913
CiAlch15%	CiAlch15%	0.782
CiAlch25%	CiAlch25%	0.683
CiAlch25%	CiAlch25%	0.806
CiAlch25%	CiAlch25%	0.874
CiAlch35%	CiAlch35%	0.829
CiAlch35%	CiAlch35%	0.829
CiAlch35%	CiAlch35%	0.804
CnAlch0%	CnAlch0%	0.612
CnAlch0%	CnAlch0%	0.829
CnAlch0%	CnAlch0%	0.697
CnAlch15%	CnAlch15%	0.801
CnAlch15%	CnAlch15%	0.851
CnAlch15%	CnAlch15%	0.851
CnAlch25%	CnAlch25%	0.714
CnAlch25%	CnAlch25%	0.774
CnAlch25%	CnAlch25%	0.721
CnAlch35%	New	0
CnAlch35%	New	0
CnAlch35%	CnAlch0% [WR]	0.098
CnAlch35%	CnAlch0% [WR]	0.121
CnAlch35%	CnAlch0% [WR]	0.142
CnAlch35%	New	0
CnAlch35%	New	0
CnAlch35%	New	0
CnAlch35%	New	0
CnAlch35%	New	0

RoAlch35% unknown category of odor samples

Target	Output	Similarity
CiAlch0%	CiAlch0%	0.507
CiAlch0%	CiAlch0%	0.794
CiAlch0%	CiAlch0%	0.586
CiAlch15%	CiAlch15%	0.806
CiAlch15%	CiAlch15%	0.913
CiAlch15%	CiAlch15%	0.782
CiAlch25%	CiAlch25%	0.683
CiAlch25%	CiAlch25%	0.806
CiAlch25%	CiAlch25%	0.874
CiAlch35%	CiAlch35%	0.829
CiAlch35%	New [WR]	0
CiAlch35%	J35%	0.804
RoAlch0%	RoAlch0%	0.618
RoAlch0%	RoAlch0%	0.618
RoAlch0%	RoAlch0%	0.859
RoAlch15%	RoAlch15%	0.953
RoAlch15%	RoAlch15%	0.944
RoAlch15%	New [WR]	0
RoAlch25%	RoAlch25%	0.818
RoAlch25%	RoAlch25%	0.869
RoAlch25%	RoAlch25%	0.861
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0
RoAlch35%	New	0

[WR] = Wrong Recognition

TABLE XII
RECOGNIZING AND CLASSIFYING RESULTS OF UNKNOWN ODOR SAMPLES BY FNLVQ WITHIN DIFFERENT OUTPUT PATTERNS

Classifier	Sample I						
	6 output pattern			12 output pattern			18 output pattern
	CiAlch	CnAlch	RoAlch	CiAlch + CnAlch	CiAlch + RoAlch	CnAlch + RoAlch	CiAlch + CnAlch + RoAlch
FNLVQ	87%	92%	86%	87%	88%	88%	92%

To increase further the recognition rate of the developed recognition system, to recognize three-mixture odors, and to recognize unknown fragrance mixtures, more rigorous studies on the applications of genetic algorithms on the optimization of fuzzy-NNs is under consideration.

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Wisnu Jatmiko (S'05) received the B.Sc. degree in electrical engineering and the M.E. degree in computer science from the University of Indonesia, Jakarta, in 1997 and 2000, respectively. He is currently pursuing the Ph.D. degree at the Department of Micro-Nano Systems Engineering, Nagoya University, Nagoya, Japan.

After receiving the M.S. degree, he joined the Faculty of Computer Science, University of Indonesia, as a Researcher and Assistant Lecturer. His research interests include artificial intelligence and sensory and integrated systems.

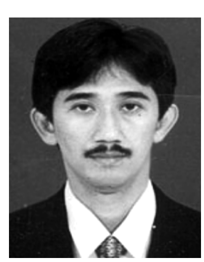
Toshio Fukuda (M'83–SM'93–F'95) graduated from Waseda University, Tokyo, Japan, in 1971, and received the M.S. and Dr.Eng. degrees from the University of Tokyo in 1973 and 1977, respectively. He also studied at the Graduate School of Yale University, New Haven, CT, from 1973 to 1975

In 1977, he joined the National Mechanical Engineering Laboratory in Japan. From 1979 to 1980, he was a Visiting Research Fellow at the University of Stuttgart, Stuttgart, Germany. He joined the Science University of Tokyo in 1981 and then joined the Department of Mechanical Engineering, Nagoya University, Nagoya, Japan, in 1989. At present, he is a Professor with the Department of Micro System Engineering and the Department of Mechano-Informatics and Systems, Nagoya University. He is mainly engaged in the research fields of intelligent robotic systems, self-organizing systems, microrobotics, robotic systems under hostile environments, bio-robotic systems, neuromorphic intelligent control, fuzzy control, control of mechanical systems, and technical diagnosis.

Dr. Fukuda was the President of IEEE Robotics and Automation Society from 1998 to 1999. He was elected Director of the IEEE Division X, Systems and Control. Since 2002, he has been the IEEE Nanotechnology Council President.

Fumihito Arai (M'91) graduated from the Science University of Tokyo, Tokyo, Japan, in 1986 and received the M.Eng. degree from the Science University of Tokyo in 1988 and the Dr.Eng. degree from Nagoya University, Nagoya, Japan, in 1993.

From 1988 to 1989, he was a Research Fellow with Fuji Photo Film Company, Ltd., Japan. He joined Nagoya University in 1989 as Research Associate. Since 1998, he has been an Associate Professor with the Department of Micro System Engineering, Nagoya University, mainly engaged in the research fields of micro/nano robotics and their applications to the micro/nano-assembly and bio automation, bio-MEMS, bio-chips, medical robotics, microsensors and microactuators, carbon nano tubes and nano dovices, intelligent robotic systems, and intelligent human machine interfaces.



Benyamin Kusumoputro received the B.Sc. degree in physics from the Bandung Institute of Technology, Indonesia, and the M.E. degree in optoelectronics from the University of Indonesia, Jakarta, in 1981 and 1984, respectively, and the Ph.D. degree in electronic and electrical engineering from the Tokyo Institute of Technology, Tokyo, Japan, in 1993.

During 1996 and from 1998 to 1990, he was a Research Fellow at the Tokyo Institute of Technology. After finishing his doctoral research, he joined the Faculty of Computer Science, University of Indonesia, as Academic Staff, where he is now Head of Computational Intelligence Research Laboratory and where he has been a Full Professor since March 2005. His research interests include the development of neural networks for 3-D recognition systems, voice recognition systems using higher order spectra analysis, and human-machine interaction.