Neural Network Architectures for Artificial Noses

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Abstract— **The paper presents a review of electronic noses with emphasis of the usage of live olfactory receptor neurons as detectors interfaced with electronics. The paper focuses on the pattern recognition issue using artificial neural networks. The proposed architecture seems to be very simple and powerful at the same time. The architecture was verified in recognition of noisy images with characters where pixels are represented by analog values in the range 0 to 1. In the case of odor recondition instead of analog values only discrete 0 or 1 values were given to neural network inputs and the system proved to be equally reliable.**

I. INTRODUCTION

Electronic noses are becoming realities and they are entering out daily life. They are being used to recognize honey [1], tea [2][3][4], fruits [5], wine [6][7], food [8], beef [9], or infection [10]. These noses are becoming so sophisticated that they can even recognize the direction where smell is coming from [11]. Currently, several techniques are being used [12-16]. Gardner and Bartlett defined the electronic nose as "an instrument which comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system, capable of recognizing simple or complex odors" [17]. There are several types of electronic noses which are using sensors implementing different physical phenomena. In most cases the electronic nose uses arrays of sensors which react differently to odor stimulus thus generating different patterns which are changing with time.

The purpose of this research is to develop a device which is inspired by the dog's sense of smell. The proposed approach is different from that used in the area of gas sensors based on man made polymers or semiconductors. We intend to use live olfactory receptor neurons as detectors interfaced with electronics.

History of electronic noses is well described [17-20]; however an artificial system that matches sensitivity and selectivity of the dog's nose does not yet exist [21]. The fine properties of the dog's olfactory system results from physical and biochemical events that occur at the olfactory epithelium of the nasal cavity where olfactory receptor neurons interact with odorants. Then the information received from the sensory neurons is transferred to the secondary neurons in olfactory bulb, and it is further sent to the cortex where the information is used for the discrimination of many odors [22]. Olfaction begins with sniffing that transports odorant molecules into the nose and delivers them to the mucus layer covering the olfactory epithelium. The binding of the odorant by a receptor protein initiates an intracellular cascade of signal transduction events, including the G-protein-dependent production of second messenger molecules, leading to opening of ion channels and passing of ion currents. This process triggers an action potential in the axon of olfactory receptor neuron that projects directly to the olfactory bulb where they synapse on mitral and tufted cell dendrites in the spherical neuropils called glomeruli [23]. From the olfactory bulb the information is further sent to the cortex for recognition of the signal. Finally, the odorant is cleared from mucus and the process begins again [24].

Table 1. Olfaction in Numbers [25][26]

	Human	*Dog*
area [cm^2]	2-4	170
neuron diameter [μm]	2.5	3
number of neurons	50×10^6	$2x10^9$
density of neurons [mm^{-2}]	170,000	120,000

The olfactory receptors cannot function if they do not preserve their structure and orientation. A long-lived culture system composed of olfactory epithelium and olfactory bulb tissues was viable and functional up to 98 days [27][28]. Cocultured neurons in this system have preserved all major elements of signal transduction and therefore reporting of binding events can be achieved by measuring electrical activity of olfactory receptor or bulb neurons, using high-gain low-noise amplification of olfactory transduction [29]. The most significant advantage of using culturing olfactory neuron system over the olfactory receptors is the unique capability to collect odorant responses from glomerili where signals from several olfactory neurons specialized in defined odorants are combined and amplified [30]. This method provides further increase of the signal-to-nose ratio and selectivity of detection. Organotypic culture of olfactory receptor and bulb neurons can be used as a detector layer grown over the microelectrode array for monitoring neuronal activity. Such a system has already been tested using various organotypic cocultures including rat entorhinal cortexes and dentate gyrus, hippocampus slices, retina segments from newly hatched chickens, and olfactory receptor and bulb neurons [31-35].

Suitable microelectrode arrays were designed and fabricated for these purposes. Extracellular contacts and communications with cells were carried out by galvanic connections [31][32][36] or addressable by light [37]. Patch-

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clamping of cells through micro-openings in substrate was also demonstrated [38].

II Pattern Recognitions

In order to retrieve electrical signals from live tissue two approaches can be used intracellular and extracellular. The intracellular methodology follows the patch clamp technique to read cell membrane current. In the case of extracellular methodology the outside set of electrodes are detecting electrical activities of cells/neurons. The extracellular methodology requires more sophisticated electronics and only passive measurement is possible. With extracellular approach it is more difficult to separate signals from noise and multiple signals have to be processed at the same time. The intracellular methodology allows for selective stimulation cells to be read so the useful information can be read on one by one basis.

Several methods are used in the process of recognizing odors by electronic nose. The most common methods are implementing PCA – Principal Component Analysis, DFA - Discriminant Function Analysis, or ANN – Artificial Neural Networks [10], [39]. PCA is being used primarily to reduce the size of the problem and DFA is used as classifier. Both PCA and DFA are linear methods and as such have significant limitation for recognizing patterns from sensors, which in most cases have a nonlinear nature. ANN can handle both linear and nonlinear problems. I was shown by Oja [40] [41] that Hebbian type of ANN architectures can work as PCA systems. Also, simple artificial neurons with linear activation function can work as DFA Discriminant function classifier [42]. Therefore both PCA and DFA can be considered as simple cases of linear neural network architectures. Many other more complex ANN architectures were already developed such as: EBP – Error Back Propagation Networks, WTA- Winner Take All networks, ART- Adaptive Resonant Theory networks, Counterpropagation networks, LVQ – Learning Vector Quantization networks, Polynomial networks, Functional Link networks, CC- Cascade Correlation networks, Recurrent networks, FC - Fully Connected networks, and many others [42-44]. Depending on network architectures a different number of artificial neurons must be used to obtain the similar classification abilities. In other words, depending on the architecture ANN can be more or less complex to perform the same function. Also, some ANN are easier to train than another [44].

The most well known and most commonly used are the EBP networks. The most popular EBP networks, known also as MLP – Multi Layer Perceptrons [42], are unfortunately not very powerful and they are difficult to train. The most powerful neural networks are CN - Cascade Networks, but it is relatively difficult to train them. Cascade Correlation Networks are subset of CN and they can be easily trained but the training process has to be done with a fixed set of patterns and they may not adapt their weights to changing patterns. Fully Connected networks can be almost as powerful as Cascade Networks, but because they can be wider instead of being deeper (signal can propagate through less number of neurons in cascade); thus, learning algorithms may converge much faster. The FC networks are not only more powerful than EBP networks; they are easier to be trained [44]. Unfortunately most of ANN training software (like Neural Network Toolbox of MATLAB) are not capable of training FC networks. At Auburn University we developed the NBN software by modifying the second order LM - Levenberg-Marquardt algorithm for arbitrary connected neural networks (including EBP, CN, and FC networks). The training time for our software is over 100 times shorter than the traditional EBP learning scheme [44]. Moreover, our software converges to several orders of magnitude smaller errors than
EBP.

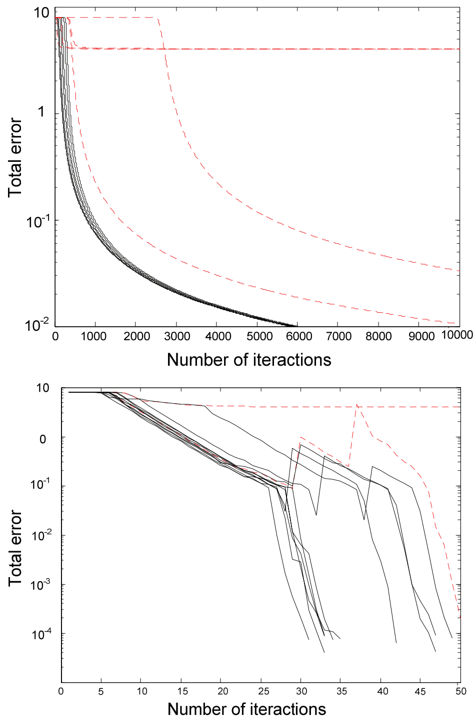

Fig. 1. Comparison of learning methods: (a) with EBP - Error Back Propagation and (b) with LM algorithms. Solid red dashed lines indicate cases where method convergence was not reached to the required errors (0.01 for EBP and 0.0001 for NBN)

Fig. 1 shows comparison of training resulting in relatively simple FC network for the parity-3 problem. As one may see, our algorithm converges in about 30-40 interactions to the error of 10^{-4} while commonly used EBP algorithm has difficulty to reach error of 0.01 with 10,000 iterations. Due to the asymptotic characteristics of the EBP training there is no practical way of reaching a solution for EBP algorithm with errors significantly smaller than 0.01.

III. Proposed ANN Architecture

There are many methods to reduce the size of array with large number of inputs such as PCA - Principle Component Analysis, FT - Fourier Transformation, WT- Wavelet Transformation, etc. These methods of dimensionality reduction are very computational intensive and often it is more difficult to classify compressed data so sometimes it is much easier to recognize patterns without dimensionality reduction if an efficient classification method is used. One such simple method used relatively simple neural network architecture shown in Fig. 2. The main advantage of this architecture is its computational simplicity.

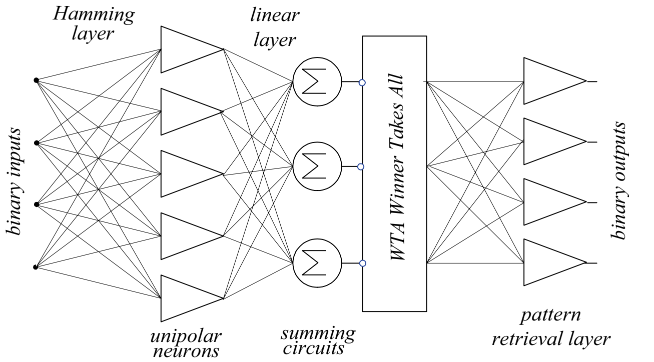

Fig 2. Artificial Neural Network architecture for classification of patterns.

This network is an enhanced version of the conterpropagation network proposed by Hecht-Nielsen [42] with Kohonen/Hamming input layer and with Grosberg/linear output layer. First layer computes Euclidean distances between input pattern and stored patterns. If inputs are binaries, for example **X**=[1, -1, 1, -1, -1] then the maximum value of *net*

$$net = \sum_{i=1}^{n} x_i w_i = \mathbf{X}\mathbf{W}^T = n = 5 \tag{1}$$

is when weights **W**=[1, -1, 1, -1, -1] are identical to the input pattern **X. I**f input signal is different, for example **X**=[1, 1, 1, -1, -1] then

$$net = \sum_{i=1}^{n} x_i w_i = \mathbf{X}\mathbf{W}^T = 3 \tag{2}$$

or

$$net = n - 2 \cdot HD(\mathbf{X}, \mathbf{W}) = 3 \tag{3}$$

Winning "neuron" is with the highest value of net and it is with the minimum of Euclidean distance from the stored pattern. This specific architecture of artificial neural network was selected because it is not computationally intensive because of binary patterns to find the Hamming distance the weight-signal multiplication process can be replaced by a subtraction:

$$\mathbf{D} = abs(\mathbf{X} - \mathbf{W}) \tag{4}$$

and calculate the sum of all elements of **D.** Then

$$net = n - 2 \cdot sum \tag{5}$$

Such neural network can be easily implemented on very simple ($1 worth) microcontrollers [46]

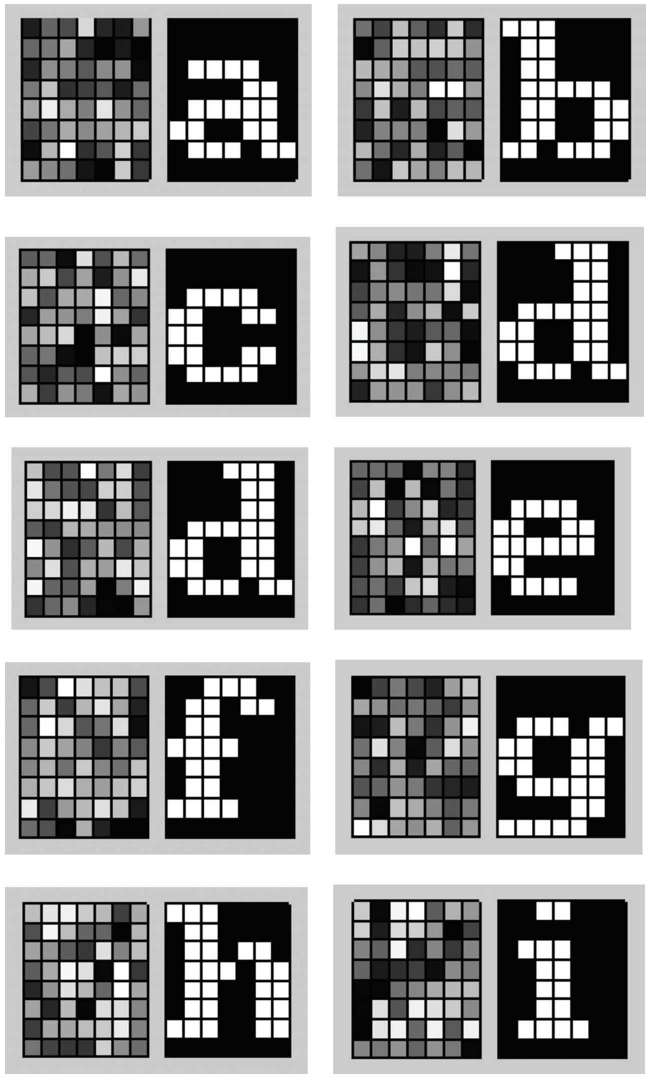

Fig. 3. Recognition of noisy characters by the neural network of Fig. 2.

IV. CASE STUDY WITH CHARACTER RECOGNITION

The process of odor recognition can be compared to recognition of optical images where intensities of pixels are time dependent. Depending on the sensor types temporal changes may carry more or less information. Recognizing time dependent patterns is a very complex issue and often the time sequence is discretized (sampled) leading to larger (more dimensional) patterns, which are time invariant.

In this experiment, 256 characters used in CGI displays were selected for the experiment. The CGI characters are organized in 8*7 arrays. (Fig. 3). One may notice that the artificial neural network of Fig 2 was able to correctly recognize noisy characters while humans may have difficulties to fulfill the same task.

The experiment of character recognition was carried on in the following scheme. Original characters (left columns on Figs. 4,5,6 were distorted by six levels of noise. Then the neural network with the architecture of Fig. 1 was asked to recognize characters (left side of the architecture) and to retrieve the original character (right side of the architecture). For the experiment shown in Fig. 4 the neural network was trained to 9 patterns only and as result on the output only 9 characters were recognized (letters from a to i). The correct character retrieval was done for noise level 1, 2, and 3. For higher level of noise, the system had difficulty to recognize letter “e”, recognizing it depends on the noise level as “b”, “a”, or “h”. For the highest level of noise, also, only one character “b” was misclassified.

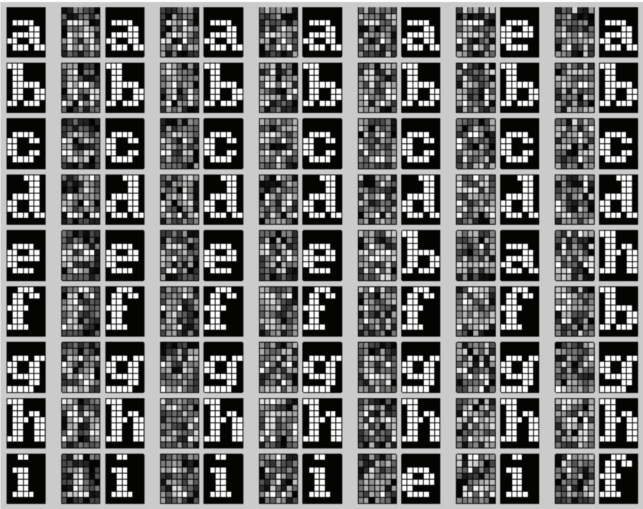

Fig. 5. Result of pattern retrieval for neural network architecture from Fig. 2 trained to recognize 9 patterns.

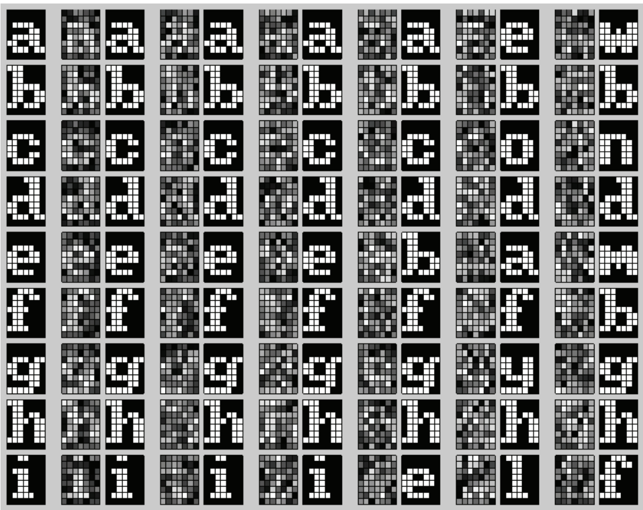

Fig. 6. Result of pattern retrieval for neural network architecture from Fig. 2 trained to recognize 26 patterns.

In the case of the experiment of Fig. 5 the neural network was trained to recognize 26 characters (small letters). Again correct classifications were done for noise levels 1, 2, and 3. For the highest level of noise (level 6) only four out of nine characters (“b”, “d”, “g”, and “h”) were classified correctly.

In the case of the experiment of Fig. 6 the neural network was trained to recognize 256 characters (all ASCII code). In this case the system failed for all 9 letters at the highest level of noise (levels 5 and 6). At the level 4 five out of nine characters were classified correctly, while at the level 3, seven out of nine characters were classified correctly.

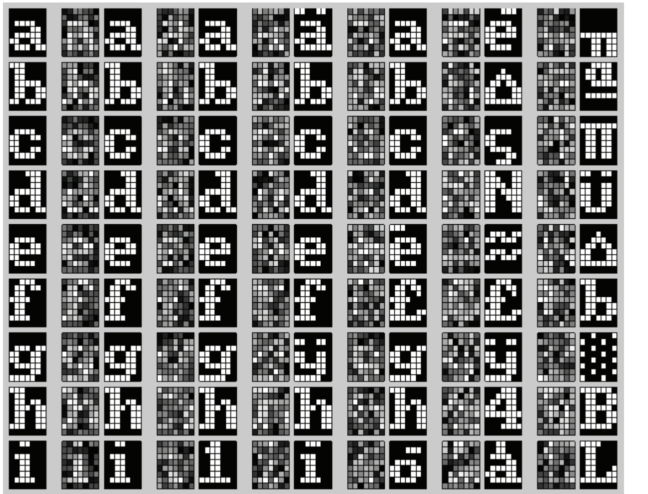

Fig. 7. Result of pattern retrieval for neural network architecture from Fig. 2 trained to recognize 256 patterns.

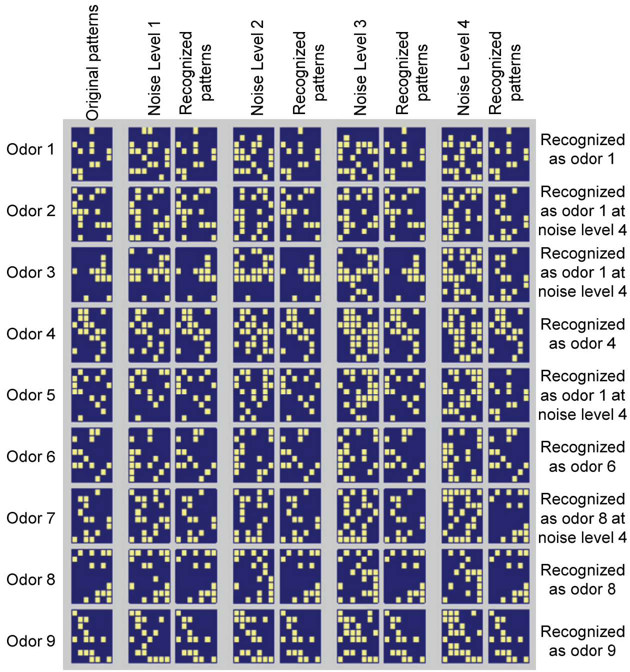

Fig 8. Retrieval of odors with introduced 4 levels of noise using ANN for Fig 2 when only 9 known odors are considered.

V. RECOGNITION OF ODORS

In the case of recognizing odors by live olfactory receptor neurons the electronic interface is sensitive only to binary signals: receptors were activated or not. Therefore, instead of noisy patterns (gray scale on Figs. 3 to 7) only binary (o or 1) information is received. Each odor represents a different pattern as is shown in the first columns of Figs 8 and 9. For nine odors, a different group of receptors is being activated. Unfortunately usually many different odors are present at the same time and receptors are responding to many existing odors; as result we are obtaining distorted patterns. In the case of distorted patterns some receptors were activated by the background odors so the system sees distorted images (columns 2, 4, 6, and 8 on Figs. 8 and 9). The level of these distortions could be different. The purpose of the Artificial Neural Network of Fig. 2 is performing an attempt of restoration of original odor patterns (columns 3, 5, 7, and 9) in Figures 8 and 9.

Figure 9. Retrieval of odors with introduced 4 levels of noise using ANN for Fig 2 when 9 known and 18 unknown odors are considered.

For the example shown in Fig 8, the input pattern is significantly distorted by introducing four different levels of noise and then the Artificial Neural Network has to retrieve odorants with four different levels of noise. In the case of Fig. 8 the artificial neural network is enforced to select one of 9 possible options. Only in three cases of nine there was misclassification and only for the largest level of noise. All other classifications were done correctly.

For the example shown in Fig 9 the same number of 9 odors has to be recognized, but ANN was previously trained to 27 odors, 9 of them are known and 18 odors are unknown. In this case for the highest level of noise (level 4), only two odors were classified correctly. For noise level 3, only two odors were misclassified. For level 1 and level 2 noises, all odors were correctly recognized. It is worthy of notice that level 2 of noise is so significant that humans may not be able to provide proper classification, while ANNs are handling properly these very distorted patterns. Despite very simple ANN architecture of Fig. 2, the obtained results surpass human ability of recognizing patterns.

If patterns need not to be retrieved, then the architecture of Fig. 2 can be further simplified by elimination of WTA and retrieval layer. Notice that output values from sumators would be proportional to the probability of a given odor. Of course, the largest value selects the winner, but at the same time there is information there about runner up, second runner up, etc. In other words this ANN gives information not only about the winner but about probability of different odors.

V. Conclusion

The proposed architecture proved to be y simple and powerful at the same time. The neural network architecture was very reliable in recognition analog patterns (letters) and digital patterns (odors). With the increased number of odors to be recognized the complexity of the pattern recognition system increases significantly for several reasons:

(1) Practically the number of ANN must be equal to the number of odors to be recognized. Benefits of merging these networks are minimal in comparison to difficulties which we can face
(2) If more odors have to be classified then more different sensors have to be used in order to distinguish odors. From practical point this would require larger arrays of sensor. This leads to large number of inputs and large sizes of artificial neural networks
(3) If more odors have to be recognized (with the presence of other odors) then patterns become noisier and the recognition process is more difficult.

VI. References

[1] S. Denedetti, S. Mannino, A.G. Sabatini, and G. Lugi, Marcazzan, “Electronic nose and neural network use for the clacification of honey,” *Apidologie*, vol 35, pp. 1-6, 2004.

[2] R. Dutta, E.L. Hines, J.W. Gardner, K.R. Kashwan, and M. Bhuyan, “Determination of Tea Quality by using a Neural Network Based Electronic Nose,” in *Proc. International Joint Conference on Neural Networks*, 2003, vol. 1, pp. 404-409.

[3] K.R. Kashwan, and M. Bhuyan, "Robust electronic-nose system with temperature and humidity drift compensation for tea and spice flavour discrimination," in *Proc. International Conference on new Techniques in Pharmaceutical and Biomedical Research*, 2005, pp. 154 – 158

[4] N. Bhattacharyya, B. Tudu, R. Bandyopadhyay, M. Bhuyan, and R. Mudi,"Aroma “Characterization of orthodox black tea with electronic nose," in *Proc. IEEE Region 10 Conference*, 2004, pp. 427-430.

[5] J. Brezmes, M. L.L. Fructuoso, E. Llobet, X. Vilanova, I. Recasens, J. Orts, G. Saiz, and X. Correig, "Evaluation of an electronic nose to assess fruit ripeness," *IEEE Sensors Journal*, vol. 5, pp. 97-108, Feb. 2005

[6] J. P. Santos, J. Lozano, M. Aleixandre, T. Arroyo, J.M. Cabellos, M. Gil, and M. del Carmen Horrillo, "Comparison between an electronic nose and a human sensory panel for wine compound detection," in *Proc. of IEEE Sensors*, 2004, pp. 341-344.

[7] J. Lozano, J.P. Santos, M. Aleixandre, I. Sayago, J. Gutierrez, and M.C. Horrillo, "Identification of typical wine aromas by means of an electronic nose," *IEEE Sensors Journal,* vol. 6, pp. 173-178, Feb. 2006.

[8] C. Di Natale, A. Macagnano, A. Mantini, F. Davide, A. D'Amico, R. Paolesse, T. Boschi, M. Faccio, and G. Ferri, "Advances in food analysis by electronic nose," in *Proc. IEEE International Symposium on Industrial Electronics*, 1997, pp. SS122-SS127.

[9] Chen Cunshe, Li Xiaojuan, and Yuan Huimei, "Quality Assessment of Beef Based of Computer Vision and Electronic Nose," in *Proc. ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing,* 2007, vol. 2, pp. 627-631

[10] R. Fend, R. Geddes, S. Lesellier, H.M. Vordermeier, L.A.L. Corner, E. Gormley, E., Costello, R.G. Hewinson, D.J. Marlin, A.C. Woodman,

and M.A. Chambers, "Use of an electronic nose to diagnose Mycobacterium bovis infection in badgers and cattle," *Journal of Clinical Microbiology,* vol. 43, pp. 1745-1751, 2005.

[11] J. Cai and D.C. Levy, "Using Stationary Electronic Noses Network to Locate Dynamic Odour Source Position," in *Proc. IEEE International Conference on Integration Technology*, 2007, pp. 793-798.

[12] R.M. Dowdeswell "Odour measurement using conduction polymer gas sensor and artificial neural networks," *Engineering Science and Education Journal*, pp.129-134, June 1999.

[13] A. Depari, P. Ferrari, A Flammini, D. Marioli, S. Rosa, and A. Taroni, " A New Modular Approach for Low-Cost Electronic Noses," in *Proc. Instrumentation and Measurement Technology Conference*, 2006, pp. 578-583.

[14] E. T. Jang and W. Y. Chung, "Electronic nose module with system on chip," in *Proc. IEEE Sensors Conference*, 2002, pp.1335-1338.

[15] V. Ferrari, D. Marioli, and A. Taroni, "Theory, Modeling and Characterization of PZT-on-alumina resonant piezo-layers as acoustic-wave mass sensors," *Sensors and Actuators A*, vol. 92, pp 182-190, Aug. 2001.

[16] E. Commini, V. Guidi, M. Ferroni, and G. Sberveglieri, "Detection of landfill gases by chemosensitive sensors based on titanium, molybdenum, tungsten oxides," *IEEE Sensor Journal*, vol. 1, pp. 4-11, Feb. 2005.

[17] J.W. Gardner and P.N. Bartlett "A Brief-History of Electronic Noses," *Sensors and Actuators B-Chemical,* vol. 18, pp. 211-220, 1994.

[18] J.W. Gardner and P.N. Bartlett. "Electronic Noses Principles and Applications," *Oxford University Press*: New York, 1999.

[19] C. Ziegler, W. Gopel, H. Hammerle, H. Hatt, G. Jung, L. Laxhuber, H.L. Schmidt, S. Schutz, F. Vogtle, and A. Zell, "Bioelectronic noses: A status report. Part II," *Biosensors & Bioelectronics,* vol *.13*, pp. 539-571, 1998.

[20] W. Gopel, "From electronic to bioelectronic olfaction, or: from artificial "moses" to real noses," *Sensors and Actuators B-Chemical,* vol. 65, pp. 70-72, 2000.

[21] E.J. Staples, S. Viswanathan, "Homeland security, olfactory images, and virtual chemical sensors," *in Proc. AIChE Annual Meeting*, 2004, pp. 41-49.

[22] G. M. Shepherd, "Discrimination of Molecular Signals by the Olfactory Receptor Neuron," *Neuron,* vol. 13, pp. 771-790, 1994

[23] D. Harel, L. Carmel, and D. Lancet, "Towards an odor communication system," *Computational Biology and Chemistry,* vol. *27*, pp. 121-133, 2003.

[24] T.V. Getchell, F.L. Margolis, and M.L. Getchell, "Perireceptor and receptor events in vertebrate olfaction," *Progress in neurobiology*, vol 23, pp. 317-345, 1984.

[25] D. Lancet, "Vertebrate Olfactory Reception," *Annual Review of Neuroscience*, vol. 9, pp. 329-355, 1986.

[26] D. Schild and D. Restrepo, "Transduction mechanisms in vertebrate olfactory receptor cells," *Physiological Reviews*, vol. 78, pp. 429-466, 1998.

[27] E.M. Josephson, S. Yilma, V. Vodyanoy, and E.E. Morrison, "Structure and function of long-lived olfactory organotypic cultures from postnatal mice," *Journal of Neuroscience Research*, vol. 75, pp. 642-653, 2004.

[28] N. Viswaprakash, E.M. Josephson, and V.J. Vodyanoy, "Cultured olfactory receptor neurons show summation, adaptation, and age-related differences in EOG response kinetics," *Chemical Senses,* vol. 31, pp. A14-A15, 2006.

[29] S.J. Kleene, "High-gain, low-noise amplification in olfactory transduction," *Biophysical Journal,* vol. 7*3*, pp. 1110-1117, 1997.

[30] S. Firestein, "How the olfactory system makes sense of scents," *Nature,* vol. *413*, pp. 211-218, 2001.

[31] H. Hammerle, U. Egert, A. Mohr, and W. Nisch, "Extracellular Recording in Neuronal Networks with Substrate Integrated Microelectrode Arrays," *Biosensors & Bioelectronics*, vol. 9, pp. 691-696, 1994.

[32] W. Nisch, J. Bock, U. Egert, H. Hammerle, and A. Mohr, "A Thin-Film Microelectrode Array for Monitoring Extracellular Neuronal-Activity in-Vitro," *Biosensors & Bioelectronics*, vol. 9, pp. 737-741, 1994.

[33] U. Egert, B. Schlosshauer, S. Fennrich, W. Nisch, M. Fejtl, T. Knott, T. Muller, and H. Hammerle, "A novel organotypic long-term culture of the rat hippocampus on substrate-integrated multielectrode arrays," *Brain Research Protocols,* vol. 2, pp. 229-242, 1998.

[34] F. Hofmann, E. Guenther, H. Hammerle, C. Leibrock, V. Berezin, E. Bock, and H. Volkmer, "Functional re-establishment of the perforant pathway in organotypic co-cultures on microelectrode arrays," *Brain Research,* vol. 1017, pp. 184-196, 2004.

[35] Q. Liu, H. Cai, Y. Xu, Y. Li, R. Li, and P. Wang, "Olfactory cell-based biosensor: A first step towards a neurochip of bioelectronic nose," *Biosensors & Bioelectronics*, vol. *22*, pp. 318-322, 2006.

[36] S. Bauerdick, C. Burkhardt, D.P. Kern, and W. Nisch, "Substrate-integrated microelectrodes with improved charge transfer capacity by 3-dimensional micro-fabrication," *Biomedical Microdevices*, vol. 5, pp. 93-99, 2003.

[37] V. Bucher, J. Brugger, D. Kern, G.M. Kim, M. Schubert, and W. Nisch, "Electrical properties of light-addressed sub-mu m electrodes fabricated by use of nanostencil-technology," *Microelectronic Engineering,* vol. 61-2, pp. 971-980, 2002.

[38] A. Stett, V. Bucher, C. Burkhardt, U. Weber, and W. Nisch, "Patch-clamping of primary cardiac cells with micro-openings in polyimide films," *Medical & Biological Engineering & Computing,* vol. 41, pp. 233-240, 2003.

[39] J. Fu, G. Li, Y. Qin, and W. Freeman, "A pattern recognition method for electronic noses based on an olfactory neural network," *Sensors and Actuators*, vol. B 125, pp. 489-497, 2007

[40] E. Oja, "Simplified neuron model as a principle component analyzer," *Journal of Mathematical Biology*, vol. 15, pp. 267-273, 1982

[41] E. Oja, "Neural networks, principal component, and subspaces," *International Journal of Neural Systems*, vol. 1, pp 61-68r, 1989 and *Journal of Mathematical Biology*, vol. 15, pp. 267-273.

[42] Jacek Zurada, "Introduction to Artificial Neural Networks," *West Publishing Company*, 1992

[43] Bogdan M. Wilamowski, "Neural Networks and Fuzzy Systems for Nonlinear Applications," in *Proc. 11th INES -International Conference on Intelligent Engineering Systems,* 2007, pp. 13-19

[44] B.M. Wilamowski "Neural Networks and Fuzzy Systems," *The Electronic Handbook,* (Second edition), CRC Press 2005, chapters 124.1 to 124.8, pp. 2039- 2063

[45] B.M. Wilamowski, N. Cotton, J. Hewlett, and O. Kaynak, "Neural Network Trainer with Second Order Learning Algorithms," in *Proc. 11th INES -International Conference on Intelligent Engineering Systems*, 2007, pp. 127-132.

[46] N.J. Cotton, B.M. Wilamowski, and G. Dundar "A Neural Network Implamentation on an Inexpensive Eight Bit Microcontroller" *12th INES 2008 -International Conference on Intelligent Engineering Systems,* Miami,Florida, USA, February 25-29, 2008, pp. 109-114