

An Artificial Neural Networks-Based on-Line Monitoring Odor Sensing System

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Abstract: Problem statement: There have been many works for odor recognition using different sensor arrays and pattern recognition techniques in last decades. **Approach:** Although an odor is usually recorded utilizing language expression, it is too difficult for laymen to associate actual odor with that expression. **Results:** The odor sensing system should be extended to new areas since its standard style where the output pattern from multiple sensors with partially overlapped specificity is recognized by a neural network or multivariate analysis. **Conclusion/Recommendations:** In this study, we have developed odor sensing system with the capability of the discrimination among closely similar 20 different odor patterns and proposed an on-line classification method using a handheld odor meter (OMX-GR sensor) and neural network.

Key words: ANN, Oder sensing, enoses, artificial noses

INTRODUCTION

Models of the olfactory system: The goal of much of the research regarding the olfactory system is to understand how individual odors are identified. Many researchers have produced mathematical models of the olfactory system. These models often include simulations of the neurobiological information processing systems (biological neural networks). The olfactory information is processed in both the olfactory bulb and in the olfactory cortex. Figure 1 shows the main information processing structures within the brain. The olfactory cortex performs pattern classification and recognition of the sensed odors. Once identified, odor information is transmitted to the hippocampus, limbic system and the cerebral cortex. The connection to the hippocampus explains why odor can sub-consciously evoke memories. Conscious perception of the odor and how to act on the odor takes place in the cerebral cortex^[1]. The mammalian olfactory system uses a variety of chemical sensors, known as olfactory receptors, combined with signal processing in the olfactory bulb and automated pattern recognition in the olfactory cortex of the brain.

Electronic/artificial noses: Electronic/artificial noses are being developed as systems for the automated detection and classification of odors, vapors and gases. The two main components of an electronic nose are the sensing system and the automated pattern recognition system. The sensing system can be an array of several different sensing elements (e.g., chemical sensors),

where each element measures a different property of the sensed odor, or it can be a single sensing device (e.g., spectrometer) that produces an array of measurements for each odor, or it can be a combination. Each odor presented to the sensor array produces a signature or pattern characteristic of the odor. By presenting many different odors to the sensor array, a database of signatures is built up. This database of labeled odor signatures is used to train the pattern recognition system. The goal of this training process is to configure the recognition system to produce unique mappings of each odor so that an automated identification can be implemented^[2]. The prototype electronic nose, shown in Fig. 2, identifies odors from several common household chemicals.

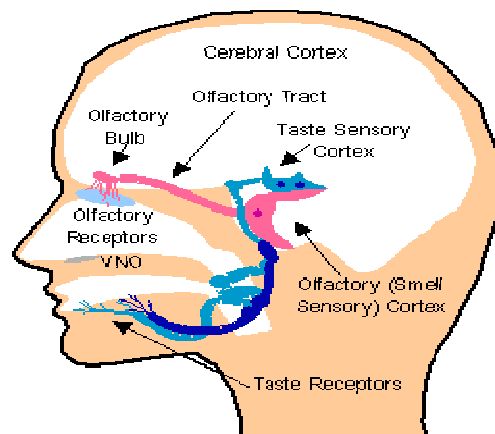


Fig. 1: The major processes of the olfactory system

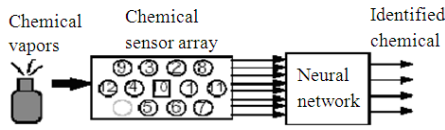


Fig. 2: Prototype of electronic nose

Although each sensor is designed for a specific chemical, each responds to a wide variety of chemical vapors. Collectively, these sensors respond with unique signatures (patterns) to different chemicals. During the training process, various chemicals with known mixtures are presented to the system. Artificial Neural Networks (ANNs), which have been used to analyze complex data and for pattern recognition, are showing promising results in chemical vapor recognition. When an ANN is combined with a sensor array, the number of detectable odors is generally greater than the number of sensors^[3]. Also, less selective sensors which are generally less expensive can be used with this approach. Once the ANN is trained for odor recognition, operation consists of propagating the sensor data through the network. Electronic noses that incorporate ANNs have been demonstrated in the following applications^[4-11]:

- Quality control in the food industry
- Quality control of packaging material
- Medical diagnostics
- Environmental monitoring
- Perfume and aroma industry
- Control of beverages, e.g., wine and beer
- Tobacco industry
- Coffee industry
- Assessment of car interiors

In this study an example shall demonstrate how electronic noses may be used in the cosmetic, perfume and aroma industry.

Artificial neural networks: An Artificial Neural Network (ANN) is an information processing paradigm that was inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. The basic unit of an artificial neural network is the neuron. Each neuron receives a number of inputs, multiplies the inputs by individual weights, sums the weighted inputs and passes the sum through a transfer function, which can be, e.g., linear or sigmoid (linear for values close to zero, flattening out for large positive or negative values).

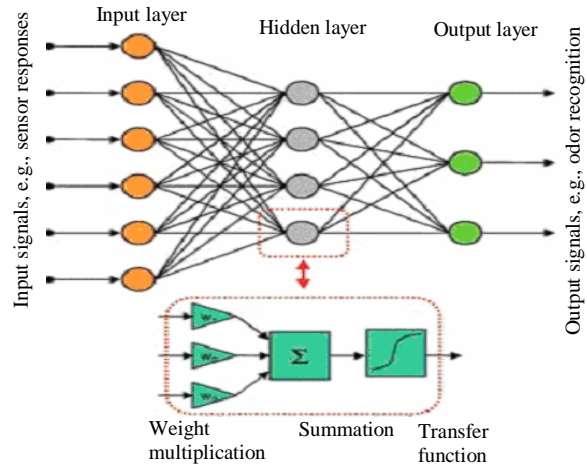


Fig. 3: Schematic of an artificial neural network

An ANN is an interconnected network of neurons. The input layer has one neuron for each of the sensor signals, while the output layer has one neuron for each of the different sample properties that should be predicted. Usually, one hidden layer with a variable number of neurons is placed between the input and output layer. During the ANN training phase, the weights and transfer function parameters in the ANN are adjusted such that the calculated output values for a set of input values are as close as possible to the known true values of the sample properties. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems for this study. It consists of three interconnected layers of neurons (Fig. 3). The computing neurons (hidden and output layers) have a non-linear transfer function. In this study sigmoid function was used.

The parameters of the neurons are chosen through a minimization of the output error for a known training set. ANNs, like people, learn by example. An ANN is configured for an application such identifying chemical vapors through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. For the electronic nose, the ANN learns to identify the various chemicals or odors by example. Another advantage of the parallel processing nature of the ANN is the speed performance. During development, ANNs are configured in a training mode. This involves a repetitive process of presenting data from known diagnoses to the training algorithm. This training mode often takes many hours. The payback occurs in the field where the actual odor identification is accomplished by propagating the data through the

system which takes only a fraction of a second. Since the identification time is similar to the response times of many sensor arrays, this approach permits real-time odor identification.

Several ANN configurations have been used in electronic noses including back propagation-trained, feed-forward networks; Kohonen's self-organizing maps (SOMs); Learning Vector Quantizers (LVQs); Hamming networks; Boltzmann machines and Hopfield networks^[1-11]. In this study a Multi-Layered neural network with back-propagation training algorithm, which has generalized delta rule learning is used.

MATERIALS AND METHODS

The monitoring system: While the inclusion of visual, aural and tactile senses into virtual reality systems is widespread, the sense of smell has been largely ignored. We have studied a chemical vapor sensing system for the automated identification of chemical vapors. Our prototype chemical vapor sensing system is composed of an array of chemical sensors (usually gas sensors) coupled to an artificial neural network. The artificial neural network is used in the recognition and classification of different odors and is constructed as a standard multilayer feed-forward network trained with the back-propagation algorithm. When a chemical sensor array is combined with an automated pattern identifier, it is often referred to as an electronic or artificial nose. It can be shown in Fig. 4, our prototype electronic nose system has been used to identify odors from common household odorants (Perfumes).

The prototyped ANN was constructed as a multilayer feed-forward network and was trained with the back-propagation of error algorithm by using a training set from the sensor database. This prototype was initially trained to identify odors of 20 different perfumes. This system allows users to obtain the desired data from a particular odorant (perfumes). There are two ways to obtain data by using a handheld odor meter (OMX-GR sensor):

- Real time sampling data
- Memory sampling data

The system mainly contains three forms:

- The first form, shown in Fig. 5, allows user to choose among two buttons in which when the user clicks on any one of the buttons an open dialog box well appears (Fig. 6), asking the user to enter the name of the file

- Real Time sampling form (the second form) shown in Figure 7. It appears when the user chooses the real time sampling data button from the first form

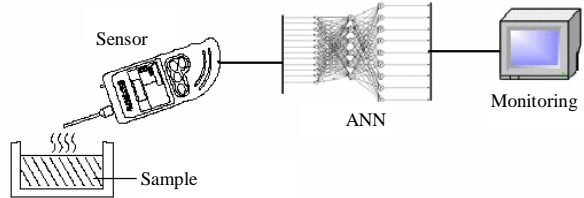


Fig. 4: On-line monitoring odor sensing system

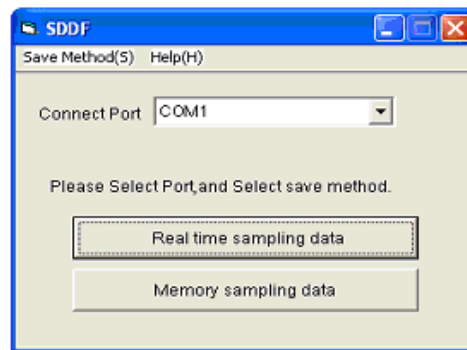


Fig. 5: The main form in the sensor program

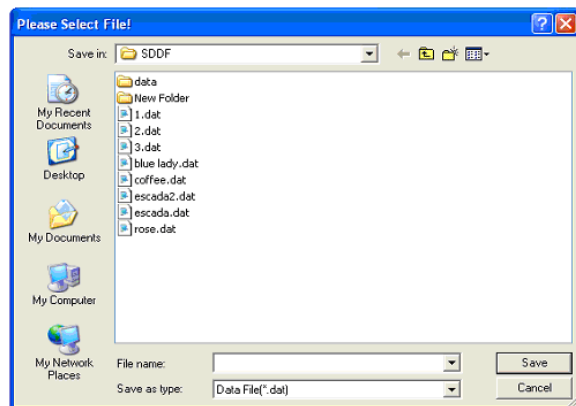


Fig. 6: Open dialog box

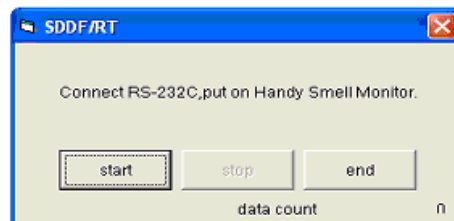


Fig. 7: The Real time sampling form

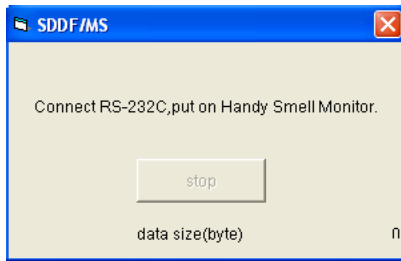


Fig. 8: The Memory sampling data form

- Memory sampling data form (the third form) shown in Figure 8. It appears when the user chooses the Memory sampling data button from the first form

Finally this is the Artificial Neural Network System, which classifies the data and tests them. The system asks the user to enter some values and input file name, after learning session the system will create four new files, assume that the input file name is first_learning.dat, then it will create the following files:

- first_learning_w.dat: this file contains the weights
- first_learning_v.dat: this file contains the value
- first_learningy.cns: this file contains the
- first_learning.err: this file contains the error

And for the output generation it will create:

first_learninght.dat: This file contains the output of the testing session

RESULTS AND DISCUSSION

At the beginning the program will ask the user to enter L for learning, O for output generation or 1 to continue from old weights file:

- If the user chooses learning, the program will ask you to enter the task name that contains data
 - Then the user should enter the number of features in each input pattern, which in our case are 30 (each odor contains 30 numbers)
 - Then the user should enter the number of output units which in our case is 20 output (20 odor samples)
 - Continued by entering the number of input samples, which are also 20 in our case
 - The program will search for the file that the user entered and if it found it then it will ask the user if he/she wants to take a look of the data in the file, just to read by entering yes or no

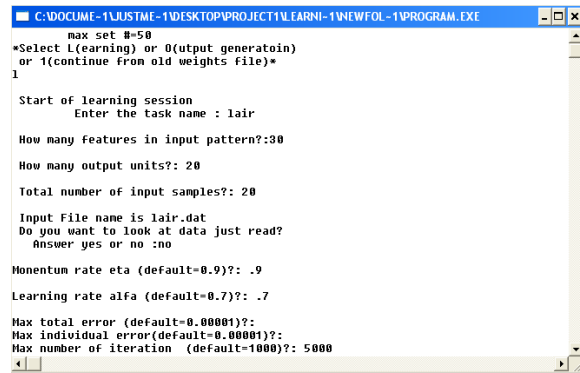


Fig. 9 The ANN program in the learning session

- Then the user should enter the momentum rate value and it's by default 0.9 and followed by the learning rate Alfa, which is by default 0.7
- Enter the maximum number or iteration, by default its 1000, but its better to enter a number that is greater than 1000
- Then the program will ask the user to put the number of hidden layers and a number of layer units for each layer
- The last thing before starting the learning session, the program will ask the user if she/he wants to create an error file or not, if yes press 1 if no press 0

The learning phase will start and the program will ask the user to wait until it finishes the training (Fig. 9):

If the user chooses the testing, the program will ask the user if she/he wants to work on a different learning task or not

After that it will ask the user for the testing input file name, if the user enters a correct file name it will ask the user to enter the number of patterns for processing.

CONCLUSION

Due to the limitations of current technology, many ANN based electronic noses have less than 20 sensing elements and less than 100 neurons. These systems are designed for specific applications with a limited range of odors. Systems that mimic more of the functionality of the human olfactory system will require a much larger set of sensing elements and a larger ANN. During operation, the sensor array "smells" an odor, the sensor signals are digitized and fed into a computer and the ANN (implemented in software) then identifies the

chemical. This identification time is limited only by the response of the chemical sensors, but the complete process can be completed within seconds. The proposed ANN program is very useful for on-line odor recognition system, which has a various types of odor samples. The identified odors can then be transmitted to an odor regeneration system in the future.

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