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THREE NEURAL NETWORK BASED SENSOR SYSTEMS FOR ENVIRONMENTAL MONITORING

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Three Neural Network Based Sensor Systems for Environmental Monitoring

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ABSTRACT

Compact, portable systems capable of quickly identifying contaminants in the field are of great importance when monitoring the environment. One of the missions of the Pacific Northwest Laboratory is to examine and develop new technologies for environmental restoration and waste management at the Hanford Site (a former plutonium production facility). In this paper, three prototype sensing systems are discussed. These prototypes are composed of sensing elements, data acquisition system, computer, and neural network implemented in software, and are capable of automatically identifying contaminants. The first system employs an array of tin-oxide gas sensors and is used to identify chemical vapors. The second system employs an array of optical sensors and is used to identify the composition of chemical dyes in liquids. The third system contains a portable gamma-ray spectrometer and is used to identify radioactive isotopes. In these systems, the neural network is used to identify the composition of the sensed contaminant. With a neural network, the intense computation takes place during the training process. Once the network is trained, operation consists of propagating the data through the network. Since the computation involved during operation consists of vector-matrix multiplication and application of look-up tables (activation function), unknown samples can be rapidly identified in the field.

1. INTRODUCTION TO THE PROBLEM

Enormous amounts of hazardous waste were generated by more than 40 years of plutonium production at the Hanford Site. There are an estimated 1700 waste sites distributed around the 560 square miles of southeastern Washington that comprise the Hanford Site.[1] This waste includes nuclear waste (e.g., fission products), toxic chemical waste (e.g., carbon tetrachloride, ferrocyanide, nitrates, etc.), and mixed waste (combined radioactive and chemical waste). The current mission at the Hanford Site is environmental restoration and waste management.

As part of this mission, the Pacific Northwest Laboratory is exploring the technologies required to perform environmental restoration and waste management in a cost effective manner. This effort includes the development of portable, inexpensive systems capable of real-time identification of contaminants in the field. The objective of our research is to demonstrate the potential information processing capabilities of the neural network paradigm in sensor analysis. The initial portion of this effort involves the development of three prototype systems, where each prototype combines a sensor array with a neural network. These prototypes are discussed in this paper.

Artificial neural networks (ANNs) are used in a wide variety of data processing applications where real-time data analysis and information extraction are required. One advantage of the neural network approach is that most of the intense computation takes place during the training process. Once the ANN is trained for a particular task, operation is relatively fast and unknown samples can be rapidly identified in the field.

2. SENSOR DATA ANALYSIS

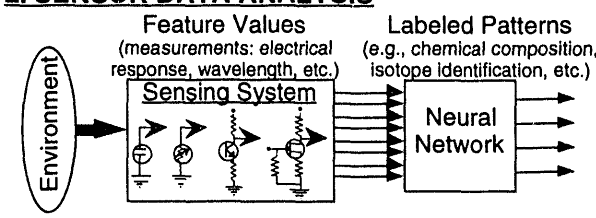

Figure 1. Sensor system combined with an ANN.

There are many real-time (rapid response) and remote sensing applications that require an inexpensive, compact, and automated system for identifying an object (e.g., target, chemical, isotope). Such a system can be built by combining a sensor array with an ANN. A generic system is shown in Figure 1.

The quantity and complexity of the data collected by sensor arrays can make conventional analysis of data difficult. ANNs, which have been used to analyze complex data and for pattern

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recognition, could be a better choice for sensor data analysis. A common approach in sensor analysis is to build an array of sensors, where each sensor in the array is designed to respond to a specific analyte. With this approach, the number of sensors must be at least as great as the number of analytes being monitored. When an ANN is combined with a sensor array, the number of detectable analytes is generally greater than the number of sensors.[2]

A sensor array is composed of several sensing elements, where each element measures a different property of the sensed sample. Each object (e.g., target, chemical, isotope) presented to the sensor array produces a signature or pattern characteristic of the object. By presenting many different objects to the sensor array, a database of signatures can be built up. From this database, training sets and test sets are generated. These sets are collections of labeled patterns (signatures) representative of the desired identification mapping. The training sets are used to configure the ANNs. The goal of this training is to learn an association between the sensor array patterns and the labels representing the data.

When a chemical sensor array is combined with an automated data analysis system (such as an ANN) to identify vapors, it is often referred to as an artificial nose. Several researchers have developed artificial noses that incorporate ANNs for use in applications including monitoring food and beverage odors,[3] automated flavor control,[4] analyzing fuel mixtures,[5] and quantifying individual components in gas mixtures.[6] Several ANN configurations have been used in artificial noses including backpropagation-trained, feed-forward networks; Kohonen's self-organizing networks; Hamming networks; Boltzmann machines; and Hopfield networks.

3. CHEMICAL VAPOR SENSOR SYSTEM

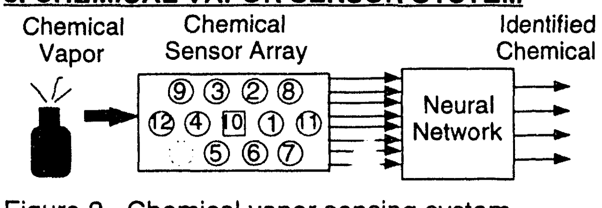

Figure 2. Chemical vapor sensing system.

The first prototype system, shown in Figure 2, identifies and quantifies chemicals vapors. It employs an array of nine tin-oxide gas sensors, a humidity sensor, and two temperature sensors to examine the environment. 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. In the initial studies, the backpropagation algorithm was used to train the ANN to provide the correct analysis of the presented chemicals.

The nine tin-oxide sensors are commercially available Taguchi-type gas sensors obtained from Figaro Co. Ltd. (Sensor 1, TGS 109; Sensors 2 and 3, TGS 822; Sensor 4, TGS 813; Sensor 5, TGS 821; Sensor 6, TGS 824; Sensor 7, TGS 825; Sensor 8, TGS 842; and Sensor 9, TGS 880). Exposure of a tin-oxide sensor to a vapor produces a large change in its electrical resistance.[7] The humidity sensor (Sensor 10: NH-02) and the temperature sensors (Sensors 11 and 12: 5KD-5) are used to monitor the conditions of the experiment and are also fed into the ANN.

The prototyped ANN was constructed as a multilayer feedforward network and was trained with the backpropagation of error algorithm by using a training set from the sensor database.[8] The parameters used to train this ANN are listed in Table 1. This prototype was initially trained to identify eight household chemicals: acetone, correction fluid, contact cement, glass cleaner, isoproponal alcohol, lighter fluid, rubber cement (Naphtha and Hexane), and vinegar. Another category, "none", was used denote the absence of all chemicals except those normally found in the air. This resulted in nine output categories from the ANN. Figure 3 illustrates the network layout.

Table 1. ANN Training Parameters

Type:	Backpropagation in batch mode
Architecture:	12-6-9 feedforward
Activation:	Logistic
Learning Rate:	0.01
Momentum:	0.9
No. of Epochs:	15000

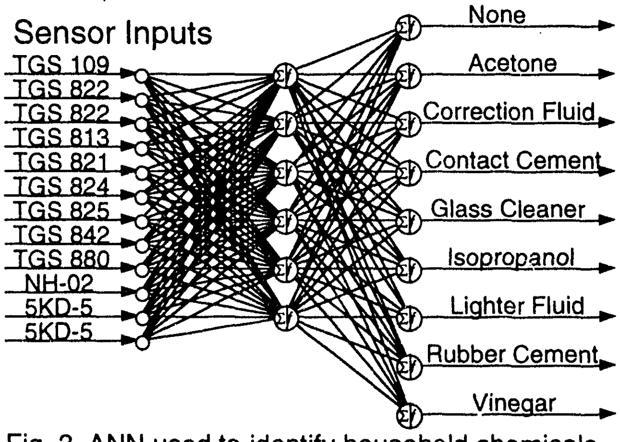

Fig. 3. ANN used to identify household chemicals.

During operation, the sensor array "smells" a vapor, 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 a few seconds. Figure 4 illustrates both the sensor response and the ANN classification of the system for a variety of test chemicals presented to the prototype.

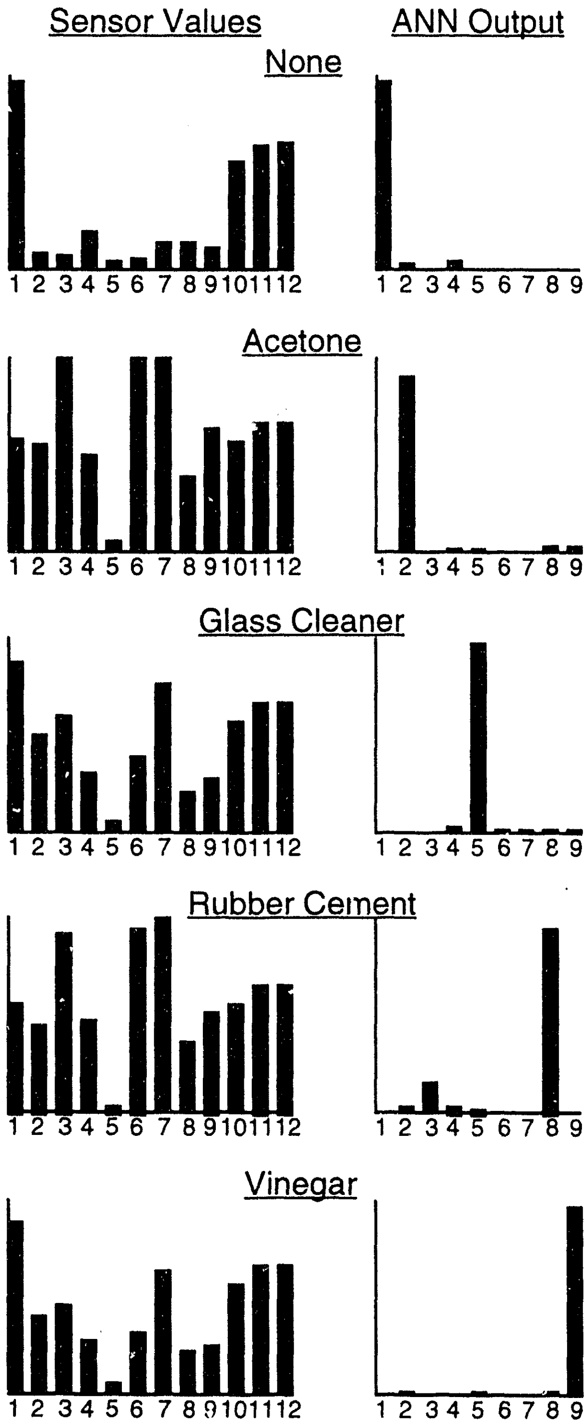

Figure. 4. Sample responses and ANN classifications. The numbers correspond to sensors and ANN outputs that are shown in Figure 3.

4. OPTICAL SENSOR SYSTEM

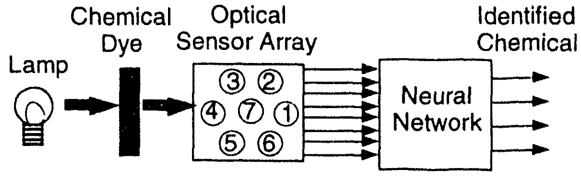

Figure 5. Optical sensor array system.

The second prototype system, shown in Figure 5, employs an array of optical sensors and identifies the composition of chemical dyes in solution. Light is passed through the dye solution and into an array of seven optical sensors. Each optical sensor consists of a silicon detector covered by a narrow bandpass interference filter and is sensitive to a specific wavelength of light in the visible and near-infrared spectrum. The output of each sensor provides an input to the ANN. By examining the absorption of the liquid at different wavelengths, the ANN is able to identify and quantify the dyes. Initial tests with this system have just begun.

5. RADIATION SENSOR SYSTEM

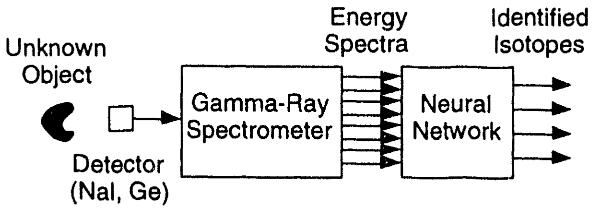

Figure 6. Gamma-ray spectrometer with ANN.

The third prototype system, shown in Figure 6, contains a portable gamma-ray spectrometer and is used to identify and quantify radioactive isotopes. The gamma-ray spectrometer consists of a sodium iodide (NaI) crystal, photomultiplier, pulse height analysis circuit, and multichannel analyzer. There are 512 channels of data produced by the spectrometer. All 512 channels are fed into the ANN. The ANN is configured as an optimal linear associative memory[9] where each neuron implements a linear activation function. There is a single processing layer in the ANN where the number of output neurons is equal to the number of isotopes being identified (eight in this case). This ANN is shown in Figure 7 and described in Table 2.

One feature of this approach to gamma-ray spectral analysis is that the whole spectrum is used in the identification process instead of individual peaks in the spectrum. For this reason, it is potentially more useful for processing data from lower resolution gamma-ray spectrometers (like those employing NaI detectors).[10]

Table 2. ANN Training Parameters

Type:	Optimal Linear Associative Memory
Architecture:	512-8 feedforward network
Activation:	Linear

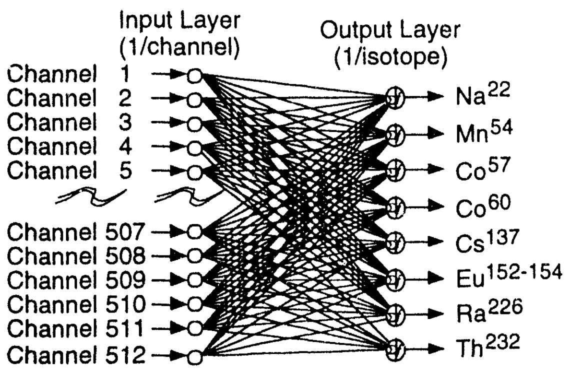

Fig. 7. ANN used to identify radioactive isotopes.

This system was trained with the spectra of eight radioactive isotopes: sodium (Na^{22}), manganese (Mn^{54}), cobalt (Co^{57}), cobalt (Co^{60}), cesium (Cs^{137}), europium ($Eu^{152-154}$), radium (Ra^{226}), and thorium (Th^{232}). The spectra of these isotopes are illustrated in Figure 8. Operation consists of presenting an unknown sample to the system, generating a gamma-ray spectrum, and passing the spectrum to the ANN which produces a classification of the unknown sample. The values on the output neurons are proportional to the quantities of each radioactive isotope found in the sample. Figure 9 illustrates an example of the classification and quantification of a sample composed of equal amounts of $Cobalt^{60}$ and $Cesium^{137}$. The resulting classification by the ANN correctly identifies the composition of the sample as being composed of equal quantities of both isotopes.

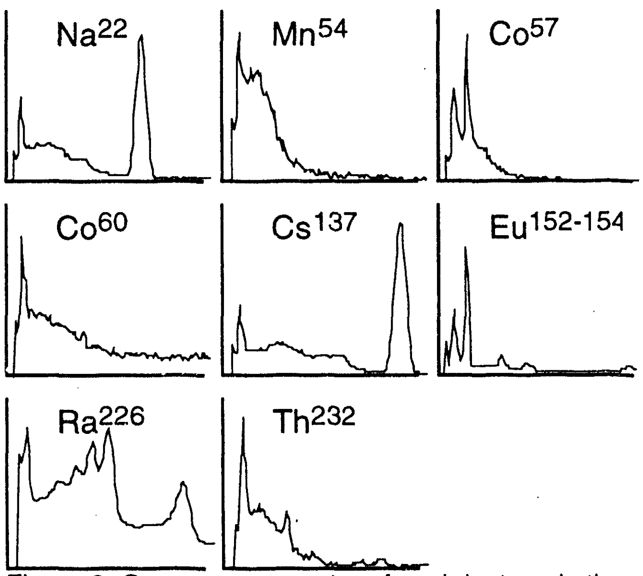

Figure 8. Gamma-ray spectra of each isotope in the training set. There are 512 channels per spectrum.

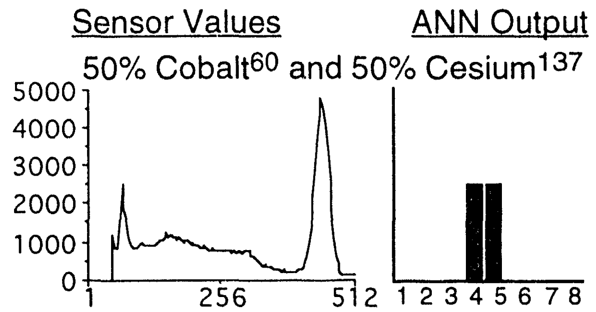

Figure 9. Sampie spectra and ANN classification.

6. DISCUSSION

Three prototype systems that employ neural networks for sensor analysis were presented. The first prototype combined an array of tin-oxide gas sensors with a neural network and was used to identify common household chemicals. The second prototype combined an array of optical sensors and was used to identify chemical dyes in solution. The third prototype combined a gamma-ray spectrometer with a neural network and was used to identify radioactive isotopes.

Initial results demonstrated the pattern recognition capabilities of the neural network paradigm in sensor analysis. These prototypes also demonstrated several advantages of this approach over conventional analytical techniques including compactness, portability, real-time analysis, and automation. Further work will involve comparing neural network sensor analysis to more conventional techniques, exploring other neural network paradigms, and evolving the preliminary prototypes to field systems.

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