Enhancing the Classification Efficiency of a Neural Model

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Abstract
Neural networks are used to handle complex issues such as pattern identification (pattern classification), computer vision, voice and image recognition, and others. An intelligent gas sensor application is shown, which employs pattern categorization by neural networks with backpropagation and error correction (by comparing two errors). The published data from a thick film tin oxide sensor array is utilized to train a classifier. Its superior categorization and learning skills are shown by its capacity to discriminate between various forms of alcohol and alcoholic drinks. The novel model proposed in this paper improves classification accuracy.
Keywords: B.P Algo, output error, Neural Network Classifier, Training Phase, Testing Phase are some key concepts.

1. Introduction

Scientists and engineers developed the Artificial Neural Net model, sometimes known as "Neural Nets," in order to attain human-like performance in speech and picture identification (Pattern recognition/classification). The human brain's cerebral cortex serves as the prototype for the "natural" neural network that "thinks," "feels," "learns," and "remembers." This artificial neural system has grown swiftly, acquiring robust, resilient capacities similar to those of the human brain [1-4]. When presented with information, the neural network responds in parallel. There are two phases: learning, in which the weights are altered according to a predetermined learning rule, and working, in which the weights are fixed and the network is placed into operational mode. Some of the complicated challenges that neural networks are now utilized to tackle include adaptive control in systems such as autonomous cars, pattern identification (Pattern Classification), computer vision, and voice and image recognition.

Recently, researchers have made great efforts to improve the operation of intelligent gas sensors (IGS). The sensors' dependability and sensitivity have greatly improved, but their lack of selectivity limits their ability to discern between gases and scents. Several pattern recognition (PR) approaches have been used to a variety of partly overlapping gas sensor data. Various pattern recognition approaches were investigated in order to establish a basic nonlinear response of individual sensors in an array to changing gas concentrations. Methods such as partial model construction [5, 4], Fourier transform approaches [6, 7], the cluster method [8, 9], transformed cluster analysis [10], and others have all been utilized to evaluate sensor array responses with varying identification capabilities. These public relations tactics have two main downsides. For starters, they can only be employed when transduction properties behave properly, such as when they follow a power law. Second, they are in chronological sequence. Non-linear transduction properties, on the other hand, may be managed by artificial neural networks (ANN). They have a lot of parallelism and can mimic how humans respond to patterns. With varied degrees of effectiveness, artificial neural network (ANN) approaches have been used for gas/odor discrimination [11-16]. In each of these efforts, an Artificial Neural Network (ANN) was trained using sensor array response data to accurately classify gases and scents. The sharp approach used to build divisions ensures that each sensor array response vector belongs to just one class.

The current effort seeks to decrease system error and improve neural network classification efficiency. The supervised back propagation technique is improved to incorporate error correction (by comparing two errors) in order to identify and categorize any existing gases or scents using published data from a thick film tin oxide sensor array [17-18]. This modification results in more error reduction and higher classification performance. The method shown here is helpful for modeling sensor output data.

2. PROBLEM DEFINITION

The response of the tin oxide sensor array reported by Nayak et al. [17] was employed in our present study to evaluate the performance of the modified B.P.Algorithm for gas/odor classification in neural networks to that of the classic B.P.Algorithm. We initially train the neural network (training phase) using 70% of the data (41 samples) using supervised learning (standard B.P.Algorithm) [17]. In the testing phase, a fraction of the data [17] (i.e., the remaining 30% of data, or 14 samples, not utilized in the training phase) is used to evaluate the performance of the neural network classification system. The same data set is utilized for both training and testing, and the results are compared using a modified version of the B.P. Algorithm.

3. NETWORKING IN OUR WORK (4:6:7 Network)

In this study, a three-layer network (4:6:7 topology [18]) with four, six, and seven units (input, hidden, and output) is employed. During the training phase, the system error is computed for a total of 10000 iterations. There have been 41 samples [17] collected, with 7 output faults for each sample.

For the first iteration, the first sample creates 7 outputs, which are propagated back for weight correction, and the second sample generates 7 outputs, which are propagated back for weight correction, and the third sample generates 7 outputs, which are propagated back, and so on. Up to 41 samples are possible. The method is done for the second, third, and fourth times... Up to ten thousand iterations.

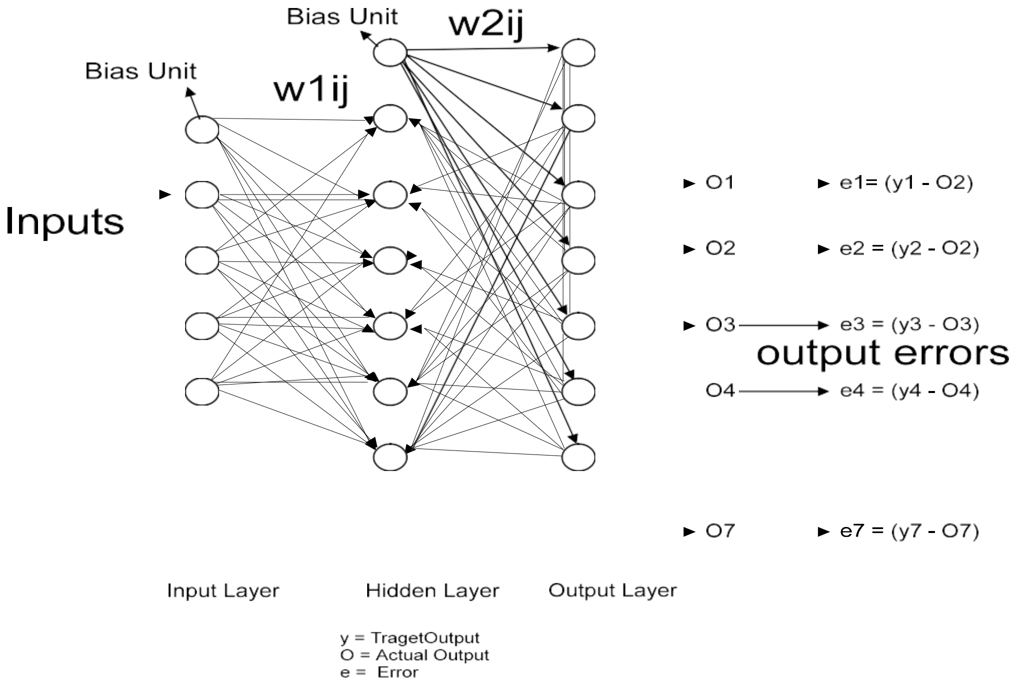


Fig 1

2. MODIFICATION

We compare mistakes from one sample with errors from the next sample and alter the weight correction phase of the B.P. Algo as 70 percent of the data (41 samples) [17] or [18] is utilized for training.

If $E_t[i] > E_{t-1}[i]$ $\Delta wij = 4\eta\delta jOi$ Else

$\Delta wij = (\eta/8)\delta jOi$ (i = 1,2…….7)

Where **E_t** =

e1	e2	e3	e4	e5	e6	e7

Where E is the output error of each sample. t represents the current sample, while (t-1) represents the preceding sample alone. wij = Weight shift from one layer's unit I to another layer's unit j Oi = unit j input (i.e. activation level of unit i)

j = unit j error gradient

Figure 1 shows the output errors for each of the 41 samples.

All seven mistakes in the first sample are compared to zero, and seven errors in the second sample are compared to seven errors in the first sample........so on up to 41 samples, the same procedure is repeated, and one cycle (iteration) is finished. The process is repeated for the remaining cycles.

ERROR IN THE SYSTEM

This neural network was trained 10,000 times.

The values for, and so on are derived from [18]. To evaluate the system error, the following expressions were used: Using Rumelhart's notation, Ep = 12 (ypj - Opj)2 j Error in the system = In such scenario, Ep Ep is the sum square error for the pth pattern. The target is Ypj, the calculated output is Opj, j is the Gas/odor class index, and p is the training pattern index.

3. GRAPHS.

(1) We plot (Graph 1) the system error vs. iteration for the original (conventional) B.P.Algorithm and the modified B.P.Algorithm.

(2) We plot (Graph 2) the percent classification effectiveness vs. test samples for the conventional (original) and modified B.P.Algorithms.

(3) We create a graph (Graph 3) of output values vs test samples using the original (conventional) B.P.Algorithm and the modified B.P.Algorithm.

4. RESULT AND DEBATE

Using the value of input parameters [18] for 10000 iterations, both the original (without change) and modified graphs are presented in Appendix in Graphs 1, 2, and 3. Graph 1 depicts the variance of system error with iteration across 10000 iterations. As we can see, the output error for the amended example is smaller than that of the original case. The system error for 1000 iterations is 0.423867 (original) and 0.497497 (changed), however it is 0.213570 (original) and 0.105577 for 1000 iterations (modified).

Iteration	Original system error	Modified system error	Improved/not improved
1000	0.423867	0.497497	Not improved
10000	0.213570	**0.105577**	Improved

Graph 2 (table 1) shows the change in classification performance with alcohols (test samples). We can observe that in the testing phase, out of 14 samples, 6 are categorized 100% correctly using the traditional B.P.Algorithm and about 9 are classified 100% correctly using the modified B.P.Algorithm. Graph 3 depicts the variance in output values (target, original, and adjusted) for test samples.

ALCO HALS	S A M P L ES	TAR GET Out Put	ORIGINAL output (using conventional B.P.algo)	% classifi -cation efficie -ncy	MODIFIED Output (using modified B.P.algo)	% classifi -cation efficie -ncy

ETHENOL	1	0.9	0.9	100%	0.9	100%
	2	0.9	0.9	100%	0.9	100%
RUM 1	3	0.9	0.9	100%	0.9	100%
	4	0.9	0.9	100%	0.9	100%
RUM 2	5	0.9	0.5	55%	0.9	100%
	6	0.9	0.5	55%	0.4	44%
WHISKEY 1	7	0.9	0.4	44%	0.8	88%
	8	0.9	0.5	55%	0.9	100%
WHISKEY 2	9	0.9	0.4	44%	0.6	66%
	10	0.9	0.4	44%	0.5	55%
WHISKEY 3	11	0.9	0.9	100%	0.9	100%
	12	0.9	0.9	100%	0.9	100%
WHISKEY 4	13	0.9	0.5	55%	0.4	44%
	14	0.9	0.5	55%	0.5	55%

Table 1

As we can see, for the greatest number of samples, the adjusted output approaches the goal output.

In this method, we acquire a better learning curve (graph 1) and improved classification efficiency by comparing mistakes in change of Back Propagation Algorithm parameters (Threshold /Weight). This is a substantial increase in categorization performance.

2. CONCLUSION

The updated version of the B.P. Algorithm offered here demonstrated a better learning curve (i.e., lower system error) after training the neural network, as shown in graph 1. As demonstrated in Graph 2, the success rate for distinguishing between alcohols and alcoholic drinks has risen dramatically, from 42.8 percent (original) to 64.2 percent (modified), and To make it operate better, a stronger training plan is anticipated to be used.

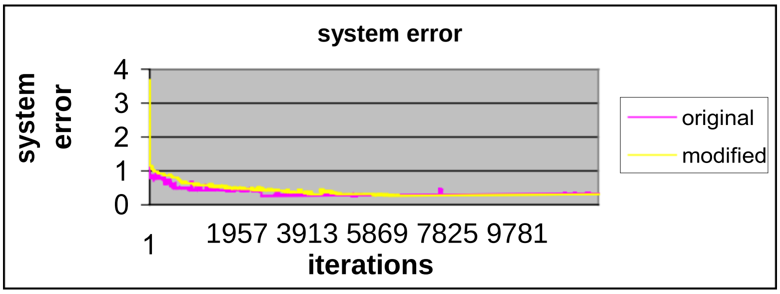
Success rate	Original	Modified
	42.8%	64.2%

The classifier suggested in this article has an advantage in terms of implementation since it makes use of a typical neural network. As a result, it can be quickly implemented using industry-standard DSP or a specially designed VLSI processor.

2. APPENDIX

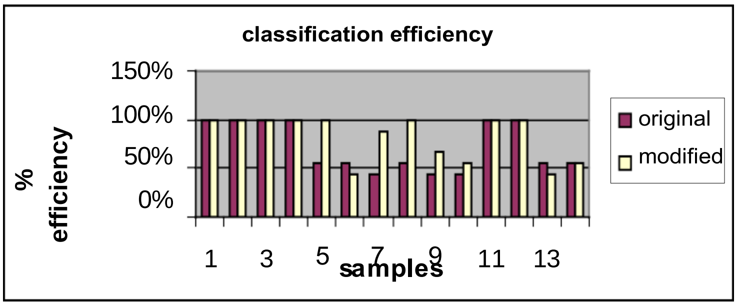
SYSTEM ERROR VS. ITERATION

Graph 1



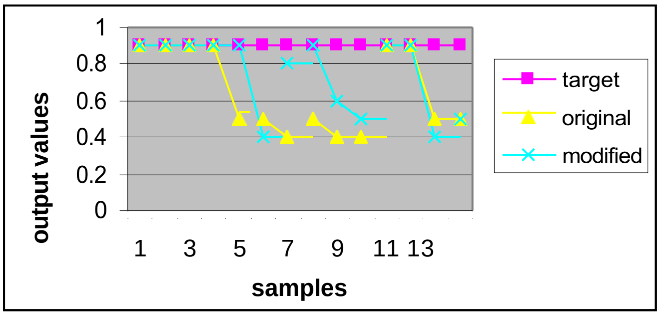
CLASSIFICATION EFFICIENCY VS. TEST SAMPLES

Graph 2



OUTPUT VALUES VS. TEST SAMPLES

Graph 3



REFERENCES

1. V.Vermuri, Ed,Computer Society Press Technology Series : Neural Networks, The Computer Society Press of the IEEE,1998.
2. Jiulin Song,Yansheng Chen, A Study on the Application and the Advancement of Deep Neural Network Algorithm, AICNC 2021, Journal of Physics: Conference Series, 2146 (2022) 012001 doi:10.1088/1742-6596/2146/1/012001
3. MaureenCaudill,Neural Networks Primer, Parts 1 to V, AI Expert, Dec.1987, Feb. 1988, Jun 1988, Aug. 1988, Nov. 1988.
4. Special issue on Artificial Neural Systems, IEEE Computer, Vol. 21, March 1988.
5. 4. G.Horner. C.Hierod.Gas analysis by partial model building, Sensors and Actuators B 2

(1990) 173-174.

6. W.M.Sears,K.Colbow,Selective thermally cycled gas sensing using fast Fourier transform techniques, Sensors and Actuators B 2 (1990) 283-289.
7. H.V.Shurmer, J.W.Gardner,H.T.Chan, The application of discrimination techniques to alcohols and tobaccos using tin oxide sensors and actuators B 18 (1989) 361-371.
8. M.S. Nayak, R.Dwivedi and S.K. Srivastava: Transformation of cluster analysis: ans approach to identification of gases/odors. Using an integrated gas sensor array, Sensors and Actuators B 12 (1993) 103-110.
9. J.C.Legras, et al.: Application of multiple regression method and automatic testing equipment to the characterization of smart sensors. Sensors and Actuators B 12 (1987) 235-243
10. J.W. Gardner,H.V. Shurmer, T.T. Tan: Application of electronic nose to the discrimination of coffees, Sensors and Actuators B (1992) 71-75
11. J.W. Gardner, E.L.Hines, H.C. Tang: Detection of vapors and odors from a multi-sensor array using pattern recognition techniques. Part II: Artificial Neural Network, Sensors and Actuators B 9(1992) 9-15.
12. Kheireddine Lamamra , Djamil Rechem, Artificial neural network modelling of a gas sensor for liquefied petroleum gas detection, 8th International Conference on Modelling, Identification and Control (ICMIC-2016) Algiers, Algeria- November 15- 17, 2016, doi:10.1109/icmic.2016.7804292
13. T. Nakamoto,A.Fakuda, T.Moriizumi: Perfume and flavor identification by odor sensing system using quartz resonator sensor array and neural network pattern recognition, sensors and Actuators B 10 (1993)85-90.
14. P.S. Barker, J.R.Chen, N.E.Agbor, A.B.Monkman, P.Mars, and M.C.Pelty: Vapour recognition using Organic film and Artifitial neural networks, Sensors and Actuators B 17 (1994) 143-147.
15. H.Debeda, D.Rebiere, J.Pistre, F.Menil: Thick film pellistor array with a neural network post treatment, Sensors and Actuators B 26 (1995) 297-300.
16. M.Sehweizer-Berberich.J.Goppert, A Hierlemann, J.Mitrovies. U. Weimer. W. Rosentiel, W. Gopel: Application of neural network Systems to dynamic response of polymer- based sensor arrays, Sensors and Actuators B 26-27 (1995) 232-236
17. M.S Nayak, R.Dwivedi, S.K. Srivastava: Integrated sensor array for detection of alcohols and alcoholic beverages, journal of Institution of Engineers (INDA) - ET 75 (1995) 94-98.
18. R.R.Das, K.K.Shukla, R.Dwivedi, A.R. Srivastava: Discrimination of individual gas/odor using responses of integrated thick film tin oxide sensor array and fuzzy-neuro concept, Microelectronics journal 30 (1999) 793-800.