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PRELIMINARY ANALYSIS OF THE JAPE GROUND VEHICLE TEST DATA WITH AN ARTIFICIAL NEURAL NETWORK CLASSIFIER

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INTRODUCTION

Remotely sensing and classifying military vehicles in a battlefield environment have been the source of much research over the past 20 years. The ability to know where threat vehicles are located is an obvious advantage to military personnel. In the past active methods of ground vehicle detection such as radar have been used, but with the advancement of technology to locate these active sensors, passive sensors are preferred. Passive sensors detect acoustic emissions, seismic movement, electromagnetic radiation, etc., produced by the target and use this information to describe it. Deriving the mathematical models to classify vehicles in this manner has been, and is, quite complex and not always reliable. However, with the resurgence of artificial neural network (ANN) research in the past few years, developing models for this work may be a thing of the past. The purpose of this paper is to present preliminary results from an ANN analysis to the tank signatures recorded at the Joint Acoustic Propagation Experiment (JAPE) at the US Army White Sands Missile Range, NM, in July 1991.

BACKGROUND

Neural Networks

An ANN can be trained to find generalized patterns in data. The ANN is trained by analyzing a series of training examples for which the appropriate response is known. Once the ANN has been sufficiently trained, it can process unknown data and indicate which category or pattern the data most closely fits. The advantages of an ANN over an analytic model are twofold. First, an ANN is a general algorithm. It can be used in countless applications and its basic structure never changes, while a model must be modified for each investigation. The second advantage is speed. Given a sufficient training set and moderate computing power, an ANN can be developed to classify data in a fraction of the time it would take to produce a model to perform the same function.

Acoustic Data Acquisition

The acoustic data were acquired during the JAPE by placing microphones at several distances from the test track. The data used in this paper were measured by a microphone located 10 m from the center of the track. The track was approximately 3.5 km long and was relatively flat and straight. The microphones were placed 1 km from the south end of the track near the south tower. The tank started at either end of the track and passed at a constant velocity, generally about 20 kph. A total of ten runs were acquired for each tank, five in the early morning (0000 to 0600 hours) and five in the late morning (0900- 1100).

Tank Descriptions

The tanks used at JAPE were an M1 and M60, both US vehicles. Both of these tanks were used to train the ANN. The M60 was the United States' main battle tank during the 1960's. It's powered by a 750 hp diesel engine and weighs 52.6 tonnes. The M1 is the current US main battle tank. It uses a 1500 hp gas turbine engine and weighs 57.1 tonnes. The turbine engine in the M1 gives it a unique acoustic signature that is different from most tanks.

PROCEDURE

Neural Network Configuration

An ANN consists of a network of neurons. Each neuron is a crude mathematical equivalent of a biological neuron. It receives multiple inputs, sums them, passes this sum through a transfer function (usually a sigmoid formula), and outputs the result. These neurons are generally placed in layers. The outputs from the neurons in the previous layer neurons are fed into the input of the neurons in the current layer. Each input to a neuron is weighted, and it is these weights that are altered when the ANN undergoes the iterative training process. The greater the weight the greater the influence that input has on the output. By changing these weights, the ANN selects which features in the training set are important for classification.

The ANN program used was freeware obtained over the Internet network and was written in the C programming language. It was tested extensively with simple pattern recognition problems and proved to be robust. The software was compiled to run under DOS using the Intel 32-bit C compiler, as well as on the Cray Y-MP under UNIX.

Three basic ANN configurations were tested. The first two had one hidden layer with 20 and 50 neurons, respectively. The last had two hidden layers with 50 neurons in the first layer and 20 in the second. The output layer consisted of two neurons. The first yielded a one for an M1 and a zero for an M60, while the second produced a zero for an M1 and a one for an M60. All neurons implemented the sigmoid transfer function and were fully connected. All networks were trained by the backpropagation technique.

Training Set

Selection

The primary training set consisted of two complete early morning runs, one of an M60 and one of an M1. Both travelled 1 km south of the closest point of approach (CPA) to the microphones to 2.5 km north of CPA. The first set was selected to determine if this minimum number of runs would be sufficient to train an ANN to recognize tank signatures from other runs. In addition, a second set of four runs was briefly used to determine if one pass in each direction was sufficient for each vehicle. It consisted of the two passes used in the first set plus two passes of the vehicles travelling from north to south.

Processing

The recorded acoustic data were digitized by an 80486 Personal Computer (PC) based 16-bit Analog to Digital (A/D) board at 2048 samples per second. Fast Fourier transforms (FFT's) were performed on each second of this data with only 1 through 100 Hz retained for the training set. Only FFT magnitude information was used. Each FFT was normalized to the largest frequency component within it. Table 1 shows the training sets used.

Training Procedure

The one second FFTs were ordered randomly in the training set without regard to run or time into the run. The ANN program took this random training set and trained itself by sequentially passing through the set. So while the training set was random, the randomness was the same for every iteration. One iteration was defined to be one complete pass through the training set. Several combinations of ANN configurations and training parameters were used (Table 2).

Testing Set

Selection

Two test sets were used. The first consisted of two runs, one each of the M60 and M1. One north to south pass was chosen at random from the early morning passes for each vehicle. The second set also contained two runs, but both were south to north passes. As with the first set, one run was chosen from the early morning passes. This second set was used because it matched the vehicle direction of the first training set. See Table 3 for more information.

Processing

The processing of the testing sets was identical to the training sets, with the exception that both testing sets contained 700 examples.

Testing Procedure

Since randomness in the testing set is not important, the examples were placed in temporal order by run number. The ANN processed this data using the neural weights it calculated during its training phase. Table 2 shows which test sets were tested with each ANN configuration.

RESULTS

The percentages of correct classifications for ANN with 0.9 momentum, 0.7 training rate, and training set 1 are shown in Figure 1. Most of the percentages hovered around 60 percent, with the 50 neuron case classifying the best on test set 1 with an average of 63 percent correct. The two layer ANN (50 and 20 neurons) performed the best on the second test set at 63 percent as well. The same tests using a momentum of 0.7 produced the results illustrated in Figure 2. This decrease in momentum rate improved the performance of the 20 and 50 neuron cases to over 60 percent for the second test set, but slightly decreased the two layer performance.

The responses from the individual vehicle passes in the test sets for the 0.9 momentum and 0.7 training rate configuration are shown in Figure 3. The M1 pass performed better than the M60 pass for test set 1, with the opposite being true for the second set. For the 0.7 momentum case in Figure 4 the ANN predicted the M1 better than the M60 for all cases except for the 20 neuron case using the second test set.

ANN configuration three (Table 2) was trained using the second training set (Table 1). It correctly identified the vehicle 63 percent of the time, an improvement of 5 percent over using the first training set.

CONCLUSIONS

From the training and testing sets used, the average correct prediction rate was between 60 and 70 percent. This prediction accuracy is remarkable considering the small amount of analysis performed. Altering the number of iterations and number of neurons seemed to have little effect on this percentage. However, this percentage can probably be improved significantly by improving the training set. The frequency range used (1 to 100 Hz) was probably too narrow in bandwidth and too low in frequency. Also, the number of passes used in the training set was probably too few.

RECOMMENDATIONS

To improve the prediction accuracy of the ANN several improvements are suggested below.

1. **Improve the training set** - This includes increasing and shifting the frequency range of the FFT and increasing its frequency bin widths. Also, training the ANN only on acoustic data when the tank is relatively close to the microphone may improve the response, because of the capability of an ANN to generalize information.

2. **More training examples** - The one ANN trained on four vehicle passes showed some improvement over the two vehicle pass case. More examples could be obtained by using data gathered from several neighboring microphones and geophones.

3. **Optimize the ANN configuration** - Adjusting the momentum, training rates, hidden layers, and neurons per layer would significantly improve the accuracy. Additional adjustments include changing the neural transfer function and connection configuration.

Table 1. Vehicle runs used in the training set.

Training Set Number	JAPE Run Number	Vehicle	Number of Examples	Total Examples
1	078	M1	375	
	090	M60	375	750
2	078	M1	350	
	079	M1	350	
	090	M60	350	
	091	M60	350	1400

Note: Even numbered runs are south to north
Odd numbered runs are north to south

Table 2. ANN training combinations.

Combination	Momentum	Learning Rate	Number of Layers	Neurons in Layer 1	Neurons in Layer 2	Iterations	Evaluated Using Test Set 1	Test Set 2
1	0.9	0.7	1	20	N/A	500	YES	YES
2	0.9	0.7	1	50	N/A	500	YES	YES
3	0.9	0.7	2	50	20	500	YES	YES
4	0.9	0.7	1	20	N/A	1000	YES	YES
5	0.9	0.7	1	50	N/A	1000	YES	YES
6	0.9	0.7	2	50	20	1000	YES	YES
7	0.7	0.7	1	20	N/A	250	NO	YES
8	0.7	0.7	1	50	N/A	250	NO	YES
9	0.7	0.7	2	50	20	250	NO	YES
10	0.7	0.7	1	20	N/A	500	YES	YES
11	0.7	0.7	1	50	N/A	500	YES	YES
12	0.7	0.7	2	50	20	500	YES	YES

Table 3. Vehicle runs used in the test set.

Test Set Number	JAPE Run Number	Vehicle	Number of Examples	Total Examples
1	077	M1	350	
	091	M60	350	700
2	076	M1	350	
	086	M60	350	700

Note: Odd numbered runs are north to south
Even numbered runs are south to north

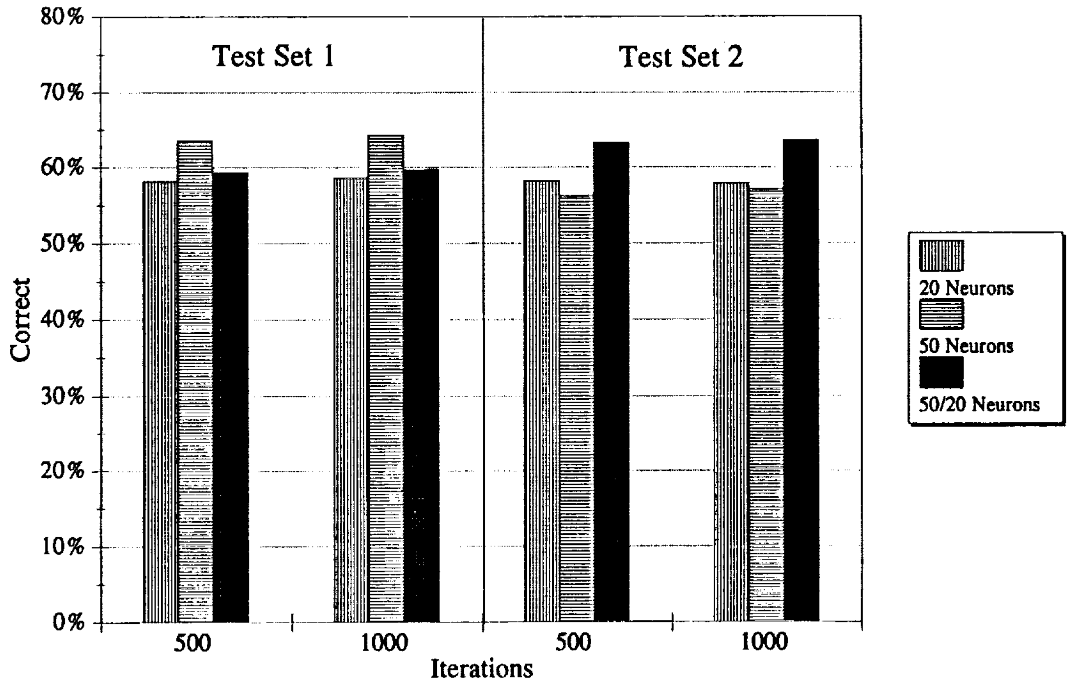

Figure 1. ANN Configuration Comparison
0.9 Momentum, 0.7 Training Rate, Training Set 1

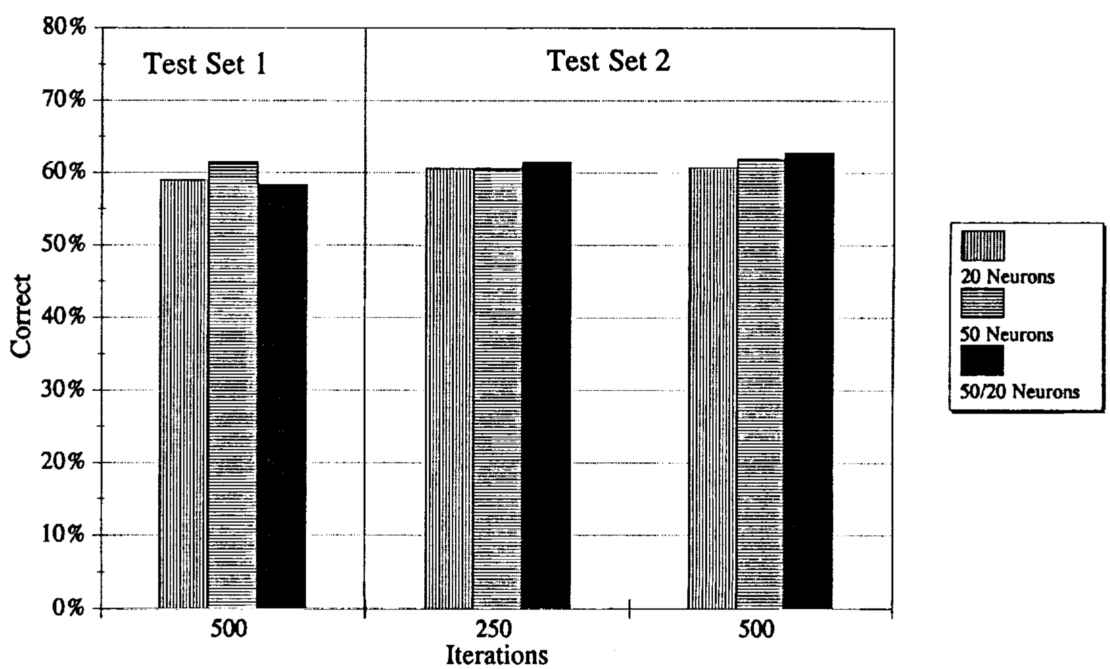

Figure 2. ANN Configuration Comparison
0.7 Momentum, 0.7 Training Rate, Training Set 1

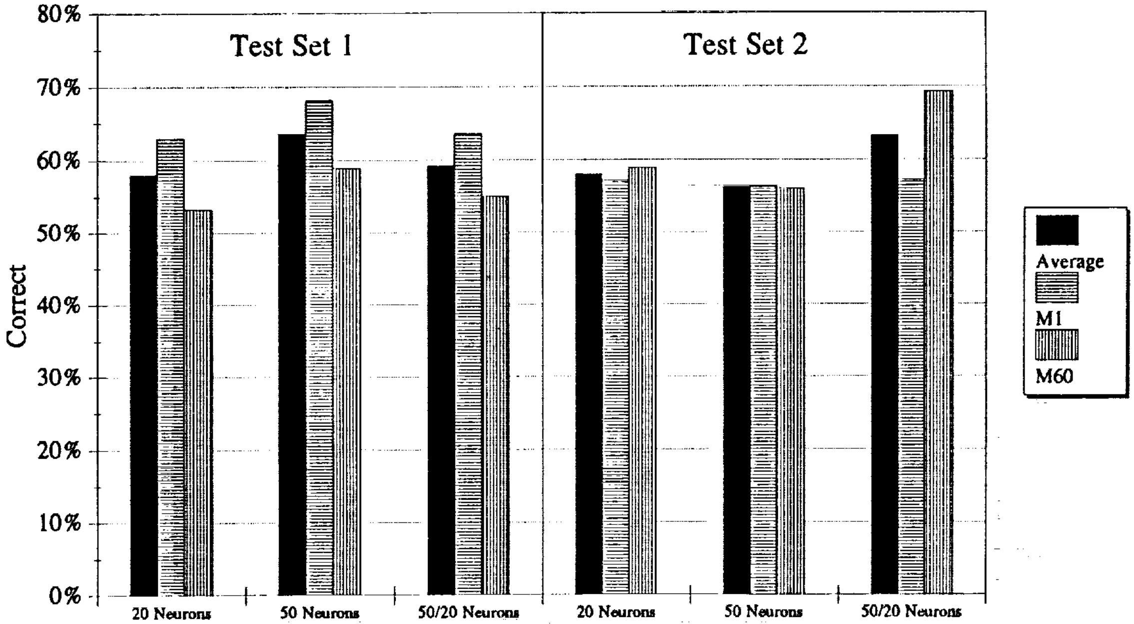

Figure 3. Individual Run Responses
0.9 Momentum, 0.7 Training Rate, 500 Iterations

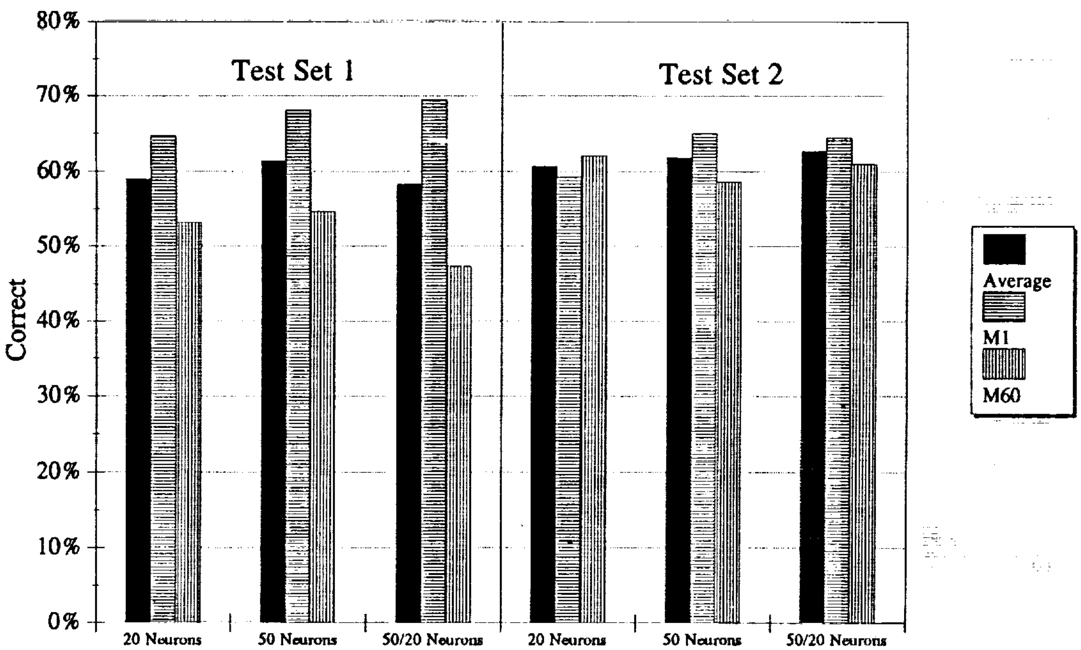

Figure 4. Individual Run Responses
0.7 Momentum, 0.7 Training Rate, 500 Iterations