AD

AD-E402 299

Technical Report ARFSD-TR-91039

INTRODUCTION TO NEURAL NETWORKS

Nanette S. Holder

March 1992

US ARMY
ARMAMENT MUNITIONS
& CHEMICAL COMMAND
ARMAMENT RDE CENTER

U.S. ARMY ARMAMENT RESEARCH, DEVELOPMENT AND ENGINEERING CENTER

Fire Support Armaments Center

Picatinny Arsenal, New Jersey

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. AGENCY USE ONLY (Leave blank)

2. REPORT DATE
March 1992

3. REPORT TYPE AND DATES COVERED

4. TITLE AND SUBTITLE
INTRODUCTION TO NEURAL NETWORKS

5. FUNDING NUMBERS

6. AUTHOR(S)
Nanette S. Holder

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESSES(S)
ARDEC, FSAC
Precision Munitions Division (SMCAR-FSP-E)
Picatinny Arsenal, NJ 07806-5000

8. PERFORMING ORGANIZATION REPORT NUMBER
Technical Report ARFSD-TR-91039

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(S)
ARDEC, IMD
STINFO Br (SMCAR-IMI-I)
Picatinny Arsenal, NJ 07806-5000

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)

There is a great desire for engineers and scientists to model the processing functions of the nervous system. There are some who feel that these models should be directly related to the actual system, so they study the neuron, the primary element of the nervous system. These people model their neural networks after studies performed on the nervous system. Others feel that these networks should be black box models. Neural networks allow for parallel processing of information that can greatly reduce the time required to perform operations which are needed in pattern recognition.

14. SUBJECT TERMS
Neural network Artificial neural network Neural net ANN

15. NUMBER OF PAGES
18

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	SAR

CONTENTS

FIGURES

INTRODUCTION

There is a great desire for engineers and scientists to model the processing functions of the nervous system. Some feel that these models should be directly related to the actual system, so they study the neuron, the primary element of the nervous system. These individuals model their neural networks after studies performed on the nervous system of humans and other organisms. Others feel that since complete knowledge of the nervous system is very far away, the neural networks should be modeled as black boxes, and the transfer functions of these "boxes" are derived mathematically. Either way, neural networks allow for parallel processing of information that can greatly reduce the time required to perform operations. This is very important in pattern recognition.

DISCUSSION

The Neuron

The neuron is the basic component of the nervous system of any organism. The neurons, placed together, form the nerves. A neuron (fig. 1) is a single cell composed of a cell body or soma, dendrites for receiving information, and an axon for transmitting the signal. The dendrites extend out to the other neurons and cells and act as processors of the signals coming from these cells. These dendrites conduct the incoming signals to the soma without any amplification of the signal.

The axon carries the signal out of the soma to the next cell. The signal is transmitted through the axon similar to the fashion in which a signal is conveyed through an electric cable. Just as an electric cable often has an insulative coating, so do the axons. This insulation on the axon is call myelin sheath. The myelin is attached to the axon leaving gaps in the material where the bare axon is exposed. These gaps are called Nodes of Ranvier. The electric signal is transferred from one Node of Ranvier to another which is referred to as saltatory conduction. This transmission is much quicker than on an unmyelinated neuron.

There are two ways that the signal can be transferred from one cell to another-electrically or chemically. An electrical signal can be directly transferred from one cell to another if the cells are very close together. This is called a tight junction. A chemical transfer is a bit me complicated, yet more common. It occurs over a gap between the cells called the synapse. When the electric signal is transmitted down the axon, a chemical is released from the presynaptic side into the gap. This chemical is received on the postsynaptic side of the gap which in turn generates a new signal.

When an action potential reaches the end of a neuron axon, the signal must cross over a small gap, called the synaptic gap, to reach the next neuron dendrite.

There are certain chemicals at the presynaptic side called neurotransmitters. These chemicals are released into the gap and received by neuroreceptors at the postsynaptic side. The type of chemical used as the neurotransmitter is considered either excitatory or inhibitory. The normal resting potential of the neuron is -70 mV. If the transmitter is excitatory, the potential will be raised about 100 mV to +30 mV. However, an inhibitory transmitter will cause a drop in the potential about 10 mV to -80 mV.

The electrical signal that travels through the neuron is generated by concentration gradients between the ions inside and outside of the cell. An ion is a chemical which is either missing or has extra electrons, giving it a positive or negative charge. The major ions of interest in any organism are sodium (Na^+), chloride (Cl^-), and potassium (K^+). If a chemical of one concentration is separated from the same chemical of a different concentration by a thin membrane with pores large enough for the chemical to pass, diffusion will take place. The chemical on the side with the greater concentration will diffuse across the membrane to equalize the concentration between the two sides. This is diffusion by a concentration gradient. If there is a charge gradient (i.e., one side has a more positive charge than the other), diffusion will take place to equalize the charges. To make things more complicated, there is a concentration gradient as well as a charge gradient in the neuron cell. This movement of chemicals, which is also a movement of charges across the cell wall, cause the potential difference between the internal and external fluids.

When a neuron soma receives a signal, there is a threshold voltage that the potential of the neuron must reach in order to fire an action potential or an impulse. This is an all-or-none response in that if this threshold is not met, there will be no signal, but if this limit is reached, there will be a signal to a specific voltage. This action potential is always the same voltage level for each neuron, no matter how high the input voltage is. The input voltage is comprised of all the inputs from the dendrites. However, depending of the lengths of the dendrites, these signals can be delayed from one another.

Neuronal Modeling

As technology advances, engineers are trying to design and improve models of the action potential and the interaction of the neurons. These models are being used to simulate processes that are common in living organisms. When these processes become advanced, they start to be more realistic in terms of modeling the human reasoning operation. These models of neuronal systems are called artificial neural networks (ANN) or neural nets.

There is some controversy between the developers of these neural networks. Some investigators feel that the networks should be modeled after the actual neurons in the human body. This is difficult because although individual neurons can be studied, as often is with the squid giant axon, people do not have a full grasp on how the neurons interact. The other school of thought is to treat the neuronal system as a black box. The input and the output are known, but the inner steps are the question. These neural net developers make their own relationships to correlate the output with the input.

The most important fact about both types of modeling is that many operations can be done at the same time. This parallel processing is the basis for using neural networks. Most artificial computational devices process information in series. For an elementary example, if one were to calculate the mean of 10 numbers (fig. 2), the sum of two numbers would be found, then the sum with the next number, and so on. After nine operations, the sum of all 10 numbers is obtained, then divide by 10. This takes 10 computational steps. In a parallel processor, the first two numbers would be added together at the same time as the second two, and so on (fig. 3). Therefore, five operations would take place during the time it takes to do one computation. The next operation would be again adding the first two and the second two. This would continue until all of the numbers were added which would take four steps; the division would be the fifth step. In this simple example, the series processor took ten steps when the parallel processor only took five. The parallel processor takes fewer steps and therefore less time to perform the desired task. In a much more difficult computation, this difference would have been greater. The use of neural networks can greatly decrease the speed of operation.

Basic Neural Networks

The most basic model of a neuron is the McCulloch-Pitts neuron (fig. 4), named after the creators. This model is similar to the electrical analog operational amplifier or op amp. There is a finite number of inputs (X_i) into each neuron, each with its own weighting coefficient (W_i). In the simple McCulloch-Pitts neuron these weights are +1 for an excitatory neuron and -1 for an inhibitory neuron. These weights are multiplied by the inputs to the neuron. There is one output (y) for each neuron. The neuron is given a threshold value (L). If the sum of all the weighted inputs reaches that threshold value, then the neuron will fire; that is, the output of the neuron will be high. However, if the sum of the weighted inputs does not meet the threshold, the neuron will not fire, or the output will be low. The output of the neuron can be represented by the equation

$$y = g\left(\sum W_i X_i - L\right)$$

where g(p) is the function such that $g(p) = 0$ if $p < 0$ and $g(p) = +1$ if $p > 0$. If a number of neurons are put together in a network, then the output for the j^{th} neuron would be written as

$$y_j = g\left(\sum w_{ij}x_{ij} - L_j\right)$$

Each of the neurons in the network will perform this operation simultaneously at discrete moments in time.

A simple example is the logical AND gate (fig. 5). This neural net has one neuron with two excitatory inputs and a threshold value of two. If both inputs are low or zeros, the sum will be zero and the threshold will not be met. Therefore, the output will be zero. If one of the inputs is zero while the other is one, then the sum will be one, which still is not enough to make the neuron fire. Finally if both inputs are high, the sum will be two. This reaches the threshold value causing the neuron to fire or the output to be one.

A logical OR gate (fig. 6) is very similar to the AND gate. There are again two excitatory inputs, but this time the threshold value is one. A logical NOT or inverter (fig. 7) has a single inhibitory neuron with a threshold of zero. These are all simple neural nets consisting of only one neuron.

The EXCLUSIVE OR gate (fig. 8) consists of five neurons in the network. The two inputs go into inverters where the outputs then go to AND gates. The outputs of these gates go into an OR gate. This is called a three layer network. In a biological system, the first layer, in this case it is the inverters, is called the sensory layer. This layer first processes the information from the outside world. This could be a pressure sensor or a tactile sensor in the body. The final layer, in this case the OR gate, is called the motor layer. This is the motor command to move the part of the body. For example, if a person's finger were to feel something hot, then this hot substance would be recognized in the sensory layer. This would cause the person to move the finger away from that object. This muscle movement comes from the motor layer. All other systems in the body respond this way too. Suppose, for example, that a baroreceptor, or pressure sensor, in an artery measures the blood pressure to be too high. The motor functions that respond this would reduce the heart rate at the sino-atrial (SA) node by decreasing the firing frequency; this would in turn cause an increase in the filtration rate at the kidneys. All of the processing that goes on between the sensing and the movement are in the hidden layers. In the EXCLUSIVE OR gate, there is only one hidden layer, which is the AND gate layer. An artificial neural network has inputs into a sensory layer; goes through any number of hidden layers; and then to the motor layer.

More Advanced Neural Networks

The basic difference between the natural neuronal system and the artificial McCulloch-Pitts neuronal model is that a natural system shows some form of learning.

In visual evoked potential (VEP) experiments conducted by the author on human subjects, an image was shown for 60 sec followed by a rest period. This was continued over 10 cycles. During this time, an electroencephalogram (EEG) was taken at the visual cortex of the brain. The first reading had a peak that was about 20 µV higher than a flat, black image. During each successive viewing of the image, the peak voltage measured was decreased. When a different image was presented at the end of the experiment, the voltage jumped up roughly 20 µV from the previous peak. This peak was higher than the peak of the first image. This shows that the combination of neurons does not always fire at a certain voltage. As the pattern was learned, the response became less because the weights on the neurons decreased. When a new pattern had to be relearned, the weights increased. The weights on a natural neuron are not always +1 or -1. This is how the learning process takes place. In most artificial neural networks, the weights can be changed through feedback techniques.

There are many different methods that people have used to adjust the weights. For example, D. O. Hebb calculates the change in weighting coefficient to be proportional to the output of the neuron*. S. Gossberg uses a relationship where the change in weighting coefficient is proportional to the difference between the output and the weighting coefficient*. Both of these methods are based on biological principles. A nonbiological method of calculating the change in the weighting coefficient is by an amount proportional to the partial derivative of the error with respect to the weight. This error requires that a desired value is known. This model uses back propagation to calculate the partial derivative. This is a truly mathematical method, since neuronal synapses do not reverse direction. There are, however, many different methods used to calculate the weighting coefficient.

Applications of Artificial Neural Networks

The fact that processes performed in parallel with neural networks can greatly reduce the time required to perform the operation is what makes the use of the neural nets so appealing. Neural nets can be used to quickly analyze real-time data that is being collected. An important use of neural computing is in pattern recognition.

The United States Postal Service is beginning to use pattern recognition to read written addresses. In most cases, each address must be personally read and sorted by humans. Now some systems are being developed to find the nine-digit zip code on the address, read it, and sort it accordingly. The difficulty with this is that people do

*Vemuri, V., "Artificial Neural Networks: An Introduction," Artificial Neural Networks: Theoretical Concepts, pp 1-12, 1988.

not always use a nine-digit zip code; they put the zip code in different places on the address (after the state or under the city) and write numbers differently. Therefore, many different forms of each number must be recognized accurately. Parallel processing is used when the number must be compared to all of the stored templates of the different numbers and the different forms of each number.

Another form of pattern recognition that is encountered is by the military. A precision guided munition must somehow be directed to the correct target. Usually this is done simplistically with a series processor. However, as seen in Operation Desert Storm, there was a big problem with friendly fire; that is, our munitions sensing our own vehicles as targets. There is work being performed on neurocomputers to develop an accuracy in identifying types of targets. For example, the TRW Mark IV neurocomputer can identify a type of aircraft with 95% accuracy. The input image of an airplane is taken from directly over the plane with the plane in any angle. These relative intensities throughout the image are digitized into pixels. A neural network takes each pixel and calculates the polar coordinates based on the origin being at the center of the image. This processed image is sent to another neural network that recognizes and classifies the image independent of the angle. This technology is just starting to emerge and there is still a long way to go.

CONCLUSIONS

Artificial neural networks are being used to approximately simulate the processing that takes place in the natural nervous system. Although we are very far from simulating the actual nervous system, certain aspects of the system can be modeled with some degree of accuracy. The visual system is often the system used. For example, the human visual system can sense something and distinguish it very quickly. A person can quickly look at another person from many different angles, in different clothing, and different hair styles, and still be able to determine who that person is. A model of this processing would have to have many different people's images, and different forms of these images stored in memory. The detected image of the person would have to compared to each of the images stored. This would take longer and with less accuracy than the human processing system. Much work has been done in the artificial neural network technology, but we are a long way off from mastering the natural neural network of humans.

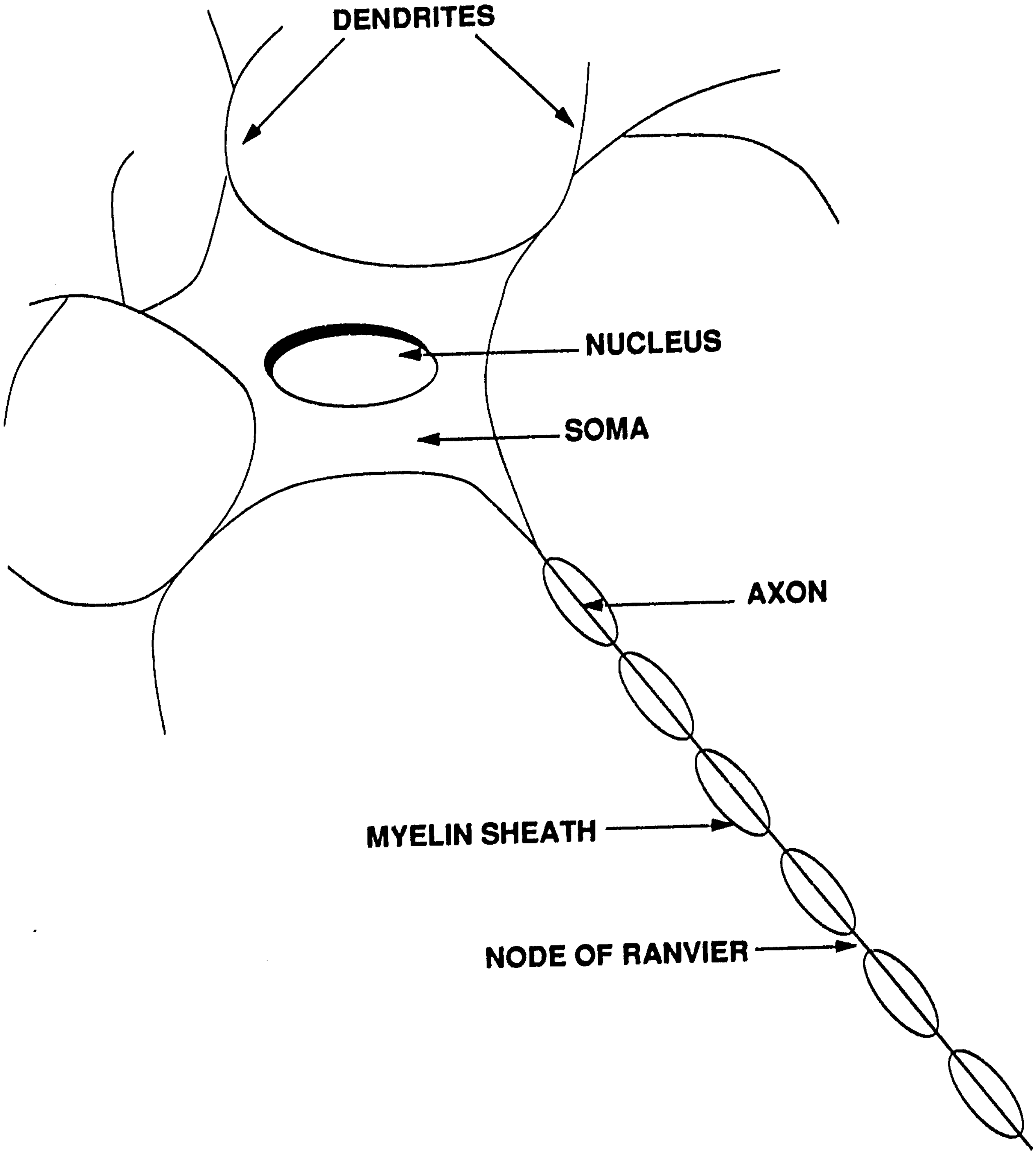


Figure 1. Neuron

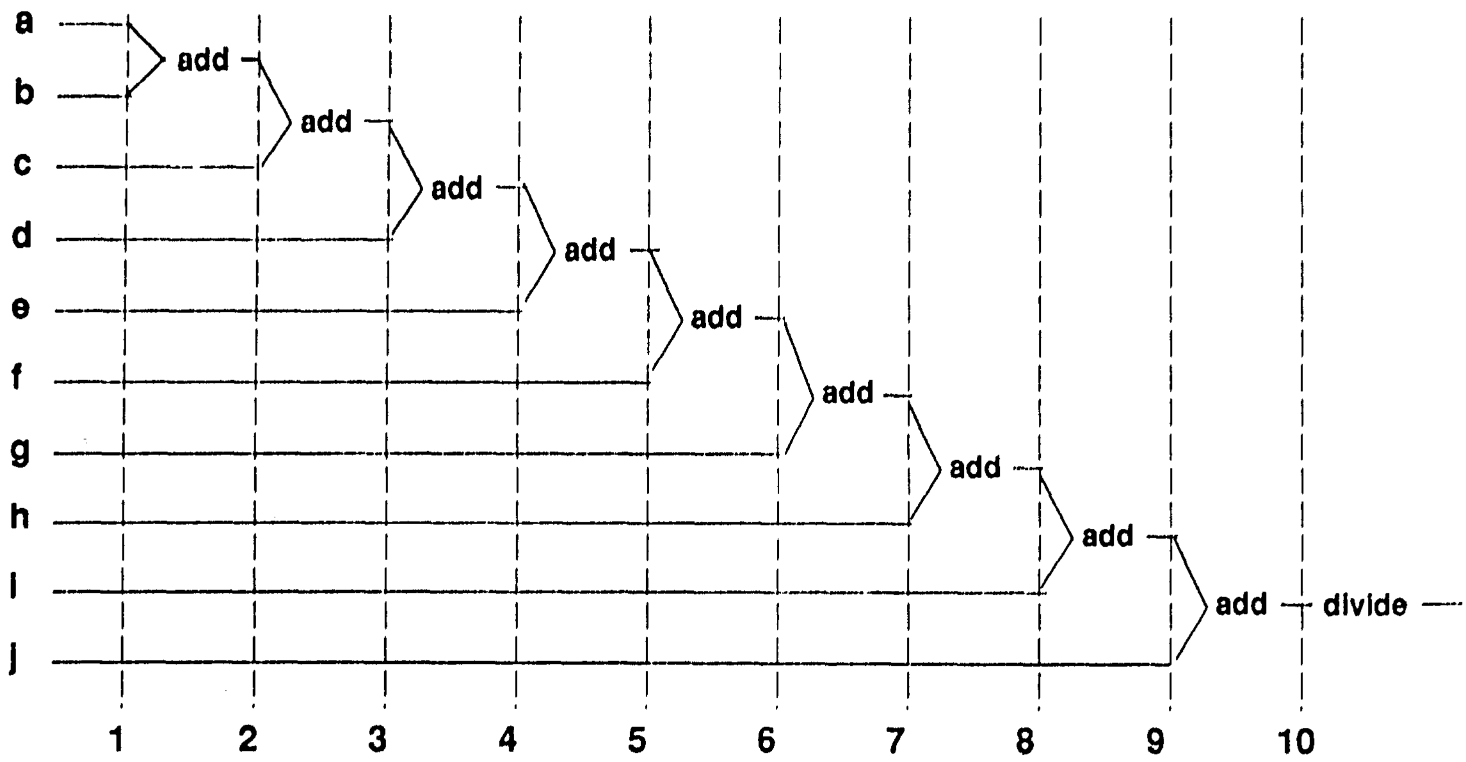


Figure 2. Series calculation of the mean of ten inputs (takes ten steps)

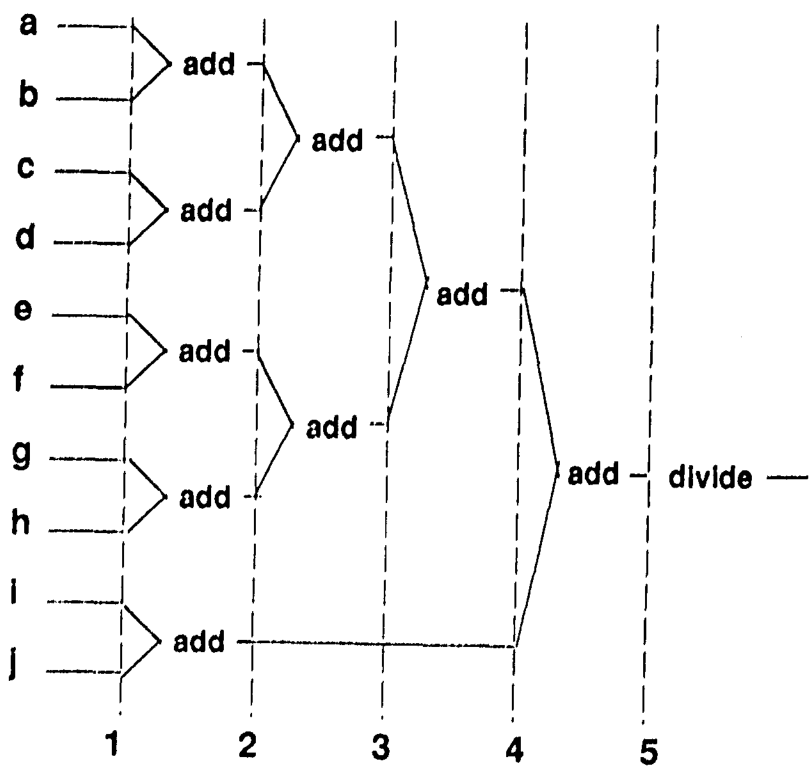
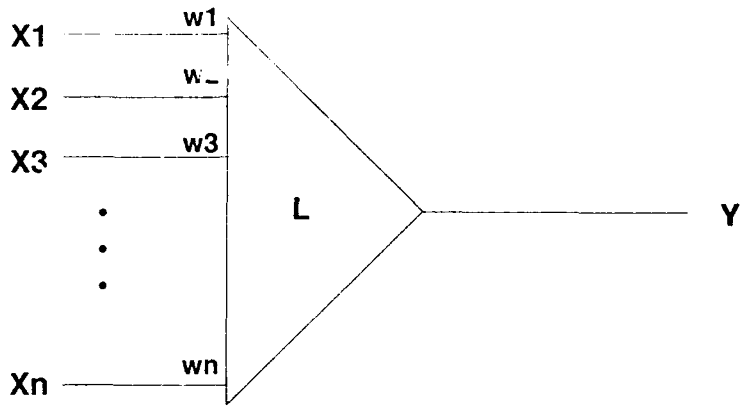
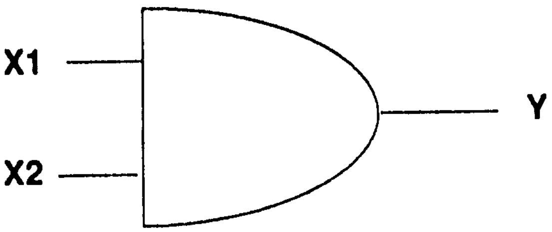


Figure 3. Parallel calculation of mean of ten inputs (takes five steps)

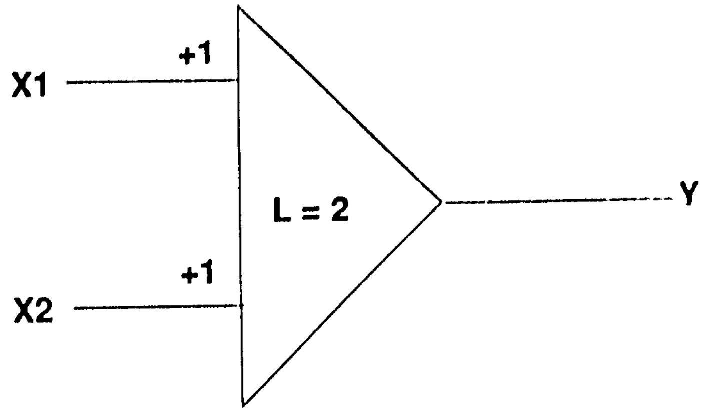


NOTE: There are n inputs (X1, X2, X3...Xn); each with an assigned weighting coefficient (w1, w2, 23...wn); a threshold value of L, and an output Y.

Figure 4. McCulloch-Pitts model of the neuron



a. electronic symbol

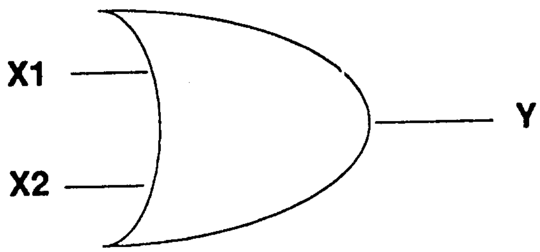


b. neuronal model

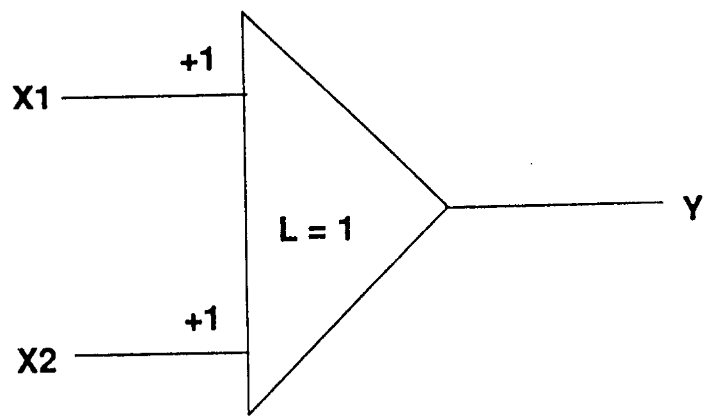
X1	X2	Y
0	0	0
0	1	0
1	0	0
1	1	1

c. truth table

Figure 5. Logical AND gate



a. electronic symbol

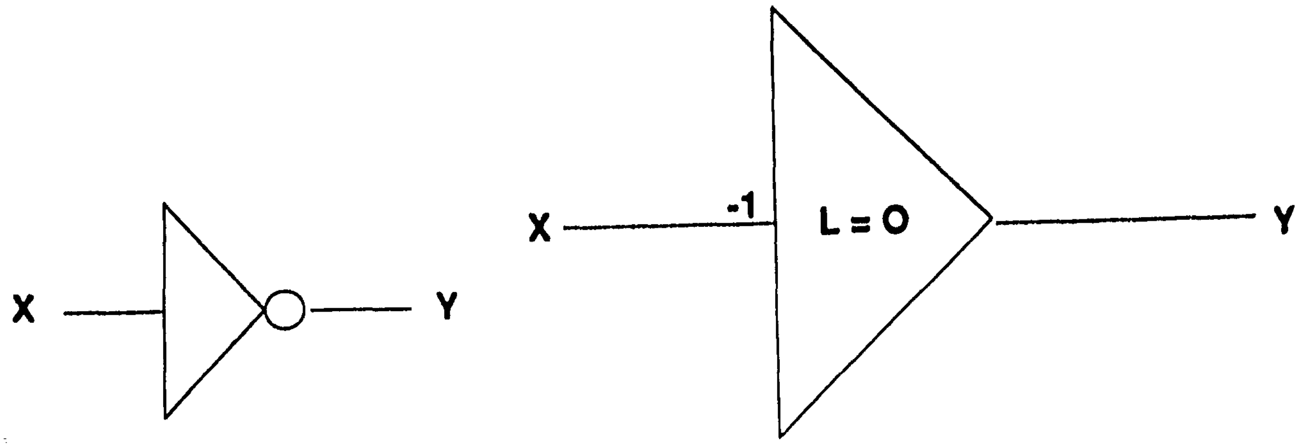


b. neuronal model

X1	X2	Y
0	0	0
0	1	1
1	0	1
1	1	1

c. truth table

Figure 6. Logical OR gate



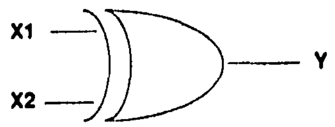
a. electronic symbol

b. neuronal model

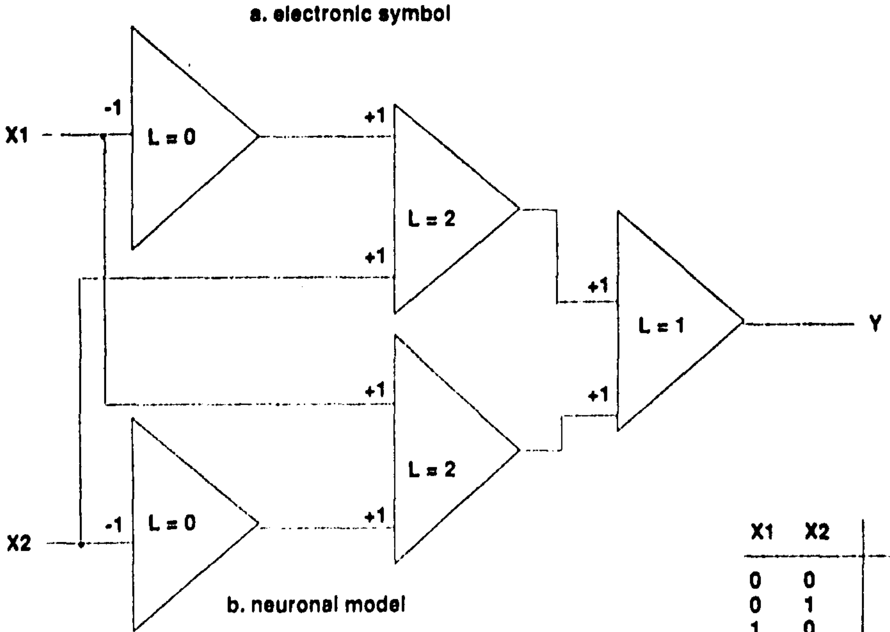
X	Y
0	1
1	0

c. truth table

Figure 7. Inverter



a. electronic symbol



b. neuronal model

X1	X2	Y
0	0	0
0	1	1
1	0	1
1	1	0

c. truth table

Figure 8. Logical exclusive OR gate

BIBLIOGRAPHY

1. Anderson, J. A., "Cognitive and Physiological Computation with Neural Models," IEEE Transactions on Systems, Man, and Cybernetics, vol 13, pp 779-815, September/October 1983.

2. Deutsch, S. and Tranakou, E., Neuroelectric Systems, New York University Press,, 1987.

3. Hecht-Nelson, R., "Neurocomputing: Picking the Human Brain," IEEE Spectrum, vol 25, pp 36-41, March 1988.

4. Lippman, R. P., "An Introduction to Computing with Neural Nets," IEEE ASSP, pp 4-22, April 1987.

5. Ross, M. D., "Bilogical Neural Networks: Models for Future Thinking Machines," NASA Tech Briefs, June 1991.

6. Schmitt, L., "Neural Networks Solve Complex Vision Problems," Automation, pp 38-40, August 1991.

7. Vemuri, V., "Artificial Neural Networks: An Introduction," Artificial Neural Networks: Theoretical Concepts, pp 1-12, 1988.

DISTRIBUTION LIST

Commander
Armament Research, Development and Engineering Center
U.S. Army Armament, Munitions and Chemical Command
ATTN: SMCAR-IMI-I (5)
SMCAR-FSP-E (8)
Picatinny Arsenal, NJ 07806-5000

Commander
U.S. Army Armament, Munitions and Chemical Command
ATTN: AMSMC-GCL (D)
Picatinny Arsenal, NJ 07806-5000

Administrator
Defense Technical Information Center
ATTN: Accessions Division (12)
Cameron Station
Alexandria, VA 22304-6145

Director
U.S. Army Material Systems Analysis Activity
ATTN: AMXSY-MP
Aberdeen Proving Ground, MD 21005-5066

Commander
Chemical Research, Development and Engineering Center
U.S. Army Armament, Munitions and Chemical Command
ATTN: SMCCR-MSI
Aberdeen Proving Ground, MD 21010-5423

Commander
Chemical Research, Development and Engineering Center
U.S. Army Armament, Munitions and Chemical Command
ATTN: SMCCR-RSP-A
Aberdeen Proving Ground, MD 21010-5423

Director
Ballistic Research Laboratory
ATTN: AMXBR-OD-ST
Aberdeen Proving Ground, MD 21005-5066

Chief
Benet Weapons Laboratory, CCAC
Armament Research, Development and Engineering Center
U.S. Army Armament, Munitions and Chemical Command
ATTN: SMCAR-CCB-TL
Watervliet, NY 12189-5000

Commander
U.S. Army Armament, Munitions and Chemical Command
ATTN: AMSMC-IMF-L
Rock Island, IL 61299-6000

Director
U.S. Army TRADOC Systems Analysis Activity
ATTN: ATAA-SL
White Sands Missile Range, NM 88002