International Journal of Engineering Science Invention (IJESI)
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 7 Issue 12 Ver II || Dec 2018 || PP 31-37

Vector Neural Network (RNV), A Processing Similar to The Biological Neural Network.

Prof. Shia Chau Sen
Post-Production Engineering Doctor and Shia, Khaohun, MS in Electrical Eng.

Abstract: *A functioning biological neural network requires the processing of many neurons. Already in a network of artificial neurons during its operation, it requires many calculations and large amount of memories to be executed. In this work the objective is to propose another way to deal with intelligent machine learning by applying a Vector Neural Network (RNV), which is able to process in a similar way to a biological neural network the learning of Intelligent Machine with storage of images and figures of your environment and that is capable of recovery and faster construction of your images.*

Keywords*: Biological Neural Network, Artificial Neural Network, Vector Neural Network, Intelligent Machine Learning.*

Date of Submission: 02-12-2018 Date of acceptance:19-12-2018

I. Introduction

A processing performed by an intelligent machine requires computational resources and lots of memory, in addition to very long machine processing time, often fails to meet human needs in real time. The proposal of this work is to implement an RNV (Vector Neural Network) as an alternative to reduce the processing and storage time in the operation of an intelligent machine.

This work compares the operation of a perceptron type RNA with an RNV. Their results are presented through tables and graphs after the tests and analyzes performed. For future work, it is proposed to demonstrate the creation of other types of figures and images by applying the vector fundamentals in an RNV with their levels of plans.

II. Neural Vector and Biological Network

Complex processing in a biological neural network by a computational machine through algebraic computation would require a large amount of memory and processing of those calculations. This would take a long time to realize and your response would not be able to meet human needs.

The vector processing of a RNV in a practical way replaces the construction of a biological neural network, since it requires less storage space and response time in the construction of images, symbols, planes and ideogram languages. An RNV constructs similarly to the behavior of a biological neuron network. Algebraic calculations are consequences of vector results, contrary to the proposals of an artificial neural network. An RNA relates a biological network with binary information to the construction of that analog information that is collected from its environment. This construction, besides being complex, is represented in its two-dimensional form, while the reality of our space is described in a three-dimensional space.

An RNV creates its space and plane in three-dimensional or two-dimensional form to later build its elements in the plane and space specified. The storage is the result of vector calculations according to the direction the direction and the intensity of its vectors. However, a complete structure of this proposal also involves the foundations of Artificial Intelligence and Artificial Neural Network.

III. Artificial neural networks.

The fundamentals of artificial neural networks and their applications can be found in several disciplines and their main considerations are: learning ability according to their inputs data. It can be considered that an intelligent machine must possess some of the main characteristics of: making inferences for the resolution of rational problems, accumulating knowledge, learning, and interpretation that are similar to human actions. Intelligent systems must at least have the capacity to represent knowledge, learning and logical reasoning.

A knowledge representation is described by a specific set of actions or by recording collections of facts and relationships. An apprenticeship is the generalization sets of skills of the acquired experiences. Already the reasoning is the ability to solve problems through state searches and possible actions to be solved within a finite space of time. It is known that a neural network of a single layer proposed by Rosenblat, is not able to solve simple problems of executing an exclusive (XOR) logical operation and therefore in 1957 Rosemblat proposed a neural network (Perceptron) for the computational simulation for the retina and with that demonstrated how a visual nervous system recognizes patterns.

A neural network is a parallel structure capable of simulating a generalization, since it allows to produce outputs that are not present during its training. Complex learning can not yet be done in a connectionist manner, however a neural network can be designed to modify its synaptic weights in real time. One of the disadvantages of a neural network, it does not formally describe how its results are obtained.

IV. Perceptron Neural Network

A perceptron neural network has an input layer and an output layer. The input layer distributes the received signals and sends them to the output layer which must be equal to the number of outputs. Each neuron has its activation and transfer function. An activation function is responsible for the weighted sum of its input signals, while the transfer function defines the output of its neuron, on which it depends on the weighted sum generated by the weighted sum function.

V. Biological Neural

Each region of the brain has a specific processing function and is performed through networks that are interconnected with each other in parallel. It is known that each region of the brain are formed by a different network architecture, according to the number of neurons and synapses of each neuron. In addition, the values of their synaptic weights are acquired through training, known as memorization.

VI. Mathematical Neural

A mathematical neuron developed and proposed by the authors: Walter Pitts and McCulloch, in the 1940s, created an electronic circuit model that has the ability to simulate synaptic connections.

The mathematical neuron receives signals in its inputs and responds with a single signal in its output to other neurons of the following layers in a parallel processing. A neuron totalises all input products and corresponding synaptic weights and generates the weighted inputs, then applying an activation combination function to then transfer to a transfer function. The purpose of a transfer function is to prevent progressive additions of output values in the network and makes this function important in a neural network is important.

VII. Learning algorithm of a Perceptron

A correct fit for the synaptic weights of a perceptron network causes a set of input data, when processed, to output the desired signal as intended for its training. Values are randomly assigned and at the same time sets of input signals are presented for calculation. The results obtained in these calculations are compared with the values desired for the training of the network during the supervised training. After the analysis the possible errors are verified so that the corrections can be adjusted and carried out by a specialist.

VIII. Extraction of information

The extraction of information by the visual means in an intelligent machine can be considered as intelligent behavior of this machine, because an intelligent machine can not only produce and store images. This machine must interpret and extract its current states and perceptions.

An image or character recognition can be done by recognizing its geometric figures, it does not have to be exactly like the real figure, it only needs to be similar to the symbol using recognition methods of that symbol to which it will be processed.

An intelligent machine must recognize the observed figure of its environment and compare it with the stored symbol that is in the vector form constructed in a two-dimensional or three-dimensional space stored in that machine's memory. In this way it makes the processing and analysis of its image, in addition to understanding its meaning.

IX. Machine Intelligence

An intelligent machine not only restricts the recognition of its images, it has to determine how to use the information obtained, and to form the possible arrangements so that its solution can be found, within a suitable and rational time.

An important concept for the construction and development of this intelligence lies in the application of statistics, probability and biostatistics. The application of statistics defines the structure of this intelligence, the probability of possible behaviors and biostatistics as the way to establish intelligent decisions in the search for a solution. Already the fundamentals of artificial intelligence and neural networks, the search from the starting point for the execution of the intelligence of a machine in a similar way to the biological neural network.

Application Analysis of an RNA (Perceptron) and RNV

The table-01 describes the following results obtained from a classification for two pieces according to their length and width during the learning phase of an RNA. These results are presented in tables and figures below.

Classification							
id	**x1 (cm)**	**x2 (cm)**	**d1 (mm)**	**d2 (mm)**	**s1**	**s2**	**Type**
1	4	3	0,50	-0,49	1	-1	A
2	1	1	-0,57	0,58	-1	1	B
3	2	2	-0,14	0,16	-1	1	B
4	2	3	0,08	-0,03	1	-1	A
5	5	3	0,71	-0,72	1	-1	A
6	3	3	0,29	-0,26	1	-1	A

Table-01. Classification of parts using RNA perceptron during your training. Adapted from Ludwig Jr. Oswaldo and Montgomery, 2007

The table-01, above, describes the values of entries related to the length (in centimeter) and width (in millimeter) of a part. The results generated by the intermediate outputs of the percetrons are presented in d1 and d2, as well as their respective outputs in s1 and s2. The types or classifications of your parts are shown below, depending on the expected results.

Weight			
Perceptron	**w1**	**w2**	**w0**
1	0,21	0,22	-1
2	-0,23	-0,19	1

Table-02. Weights assigned to each of the perceptrons.

The table-02 shows the values of the weights assigned to each of the perceptrons according to the information of a specialist.

d1	0,50
d1	-0,57
d1	-0,14
d1	0,08
d1	0,71
d1	0,29

d2	-0,49
d2	0,58
d2	0,16
d2	-0,03
d2	-0,72
d2	-0,26

Table-03. Information generated by the intermediate outputs of perceptrons 1 and 2.

The results of the intermediate outputs of the perceptrons presented in table-03 show the results generated by the perceptrons 1 and 2 during their training.

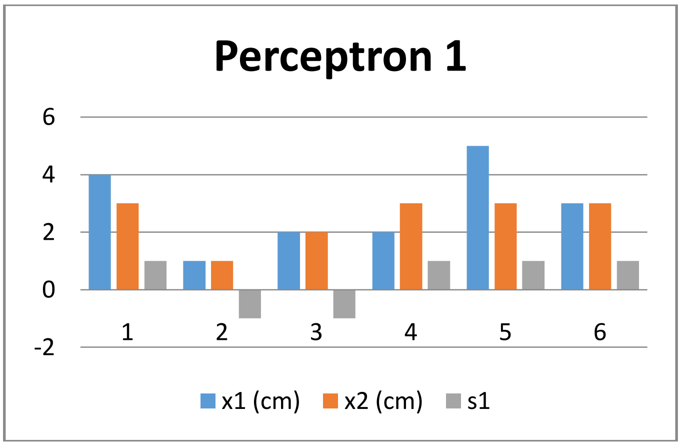

Figure-01. Results generated by perceptron 1.

The figure-01 shows the results of the application according to the input information that are: length and width of each piece, which are realized during the learning of neural perceptron network.

The graph also shows the outputs (s1) for the perceptron 1, generating its desired responses. These outputs can be 1 (positive) or -1 (negative). For output 1 (positive), the part is classified as type A or output -1 (negative) for part of type B. These ratings are assigned according to a specialist.

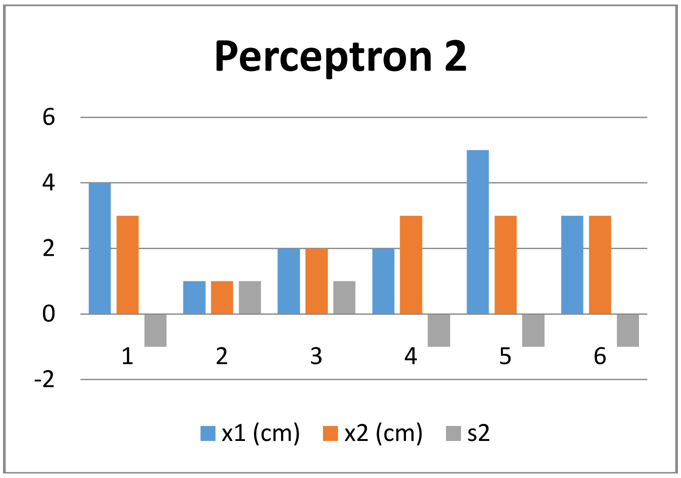

Figure-02. Results generated by perceptron 2.

The figure-02 shows the results of the application according to the input information that are: length and width of each piece, which are realized during the learning of neural perceptron network.

The graph also shows the outputs (s1) for the perceptron 2, generating its desired responses. These outputs can be 1 (positive) or -1 (negative). For output 1 (positive), the part is classified as type A or output -1 (negative) for part of type B. These ratings are assigned according to a specialist.

The tables below represent the results obtained by applying the fundamentals of an RNV in comparison to the results obtained by an RNA.

v=(x,y)	
v1	0,5
v2	-0,57
v3	-0,14
v4	0,08
v5	0,71
v6	0,29

u=(x,y)	
u1	-0,49
u2	0,58
u3	0,16
u4	-0,03
u5	-0,72
u6	-0,26

Table-04 Vector results v and u.

A vector can be described in the form v = (x, y) or u (x, y). Table 4 shows the values generated by vectors (v) and (u). The assigned values are described in tables-01 and table-02. It is observed that the results have the same values generated by percetrons 1 and 2.

Figure-03 shows the results generated by vectors v1, v2, v3, v4, v5 and v6.

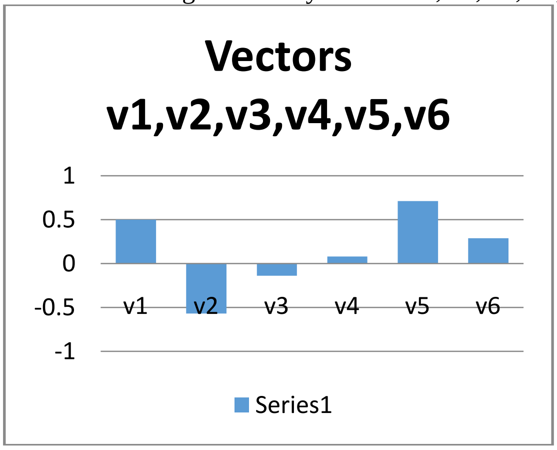

Figure-03 shows the results generated by vectors v1, v2, v3, v4, v5 and v6.

Figure-03 represents the values generated by vector (v) whose values are: The vector v1 = 0.5; v2 = 0.57; v3 = - 0.14; v4 = 0.08; v5 = 0.71; v6 = 0.29. It is observed that the results generated by applying the vector fundamentals present the same results generated by perceptron 1, according to the proposal presented in this paper.

Figure-04 shows the results generated by vectors u1, u2, u3, u4, u5, u6.

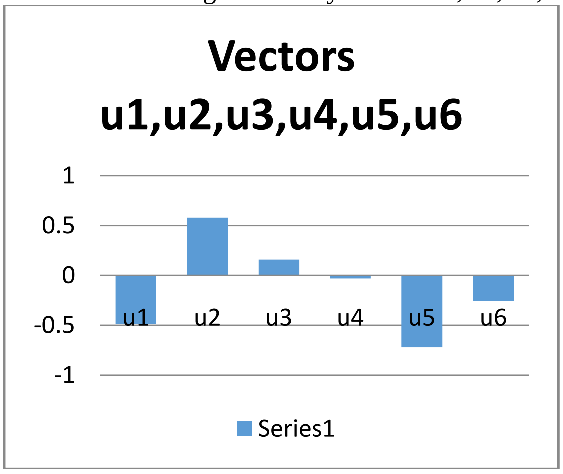

Figure-04. Results generated by the vectors (u).

Figure-04 represents the values generated by vector (v) whose values are: The vector u1 = - 0.49; u2 = 0.58; vmax = 0.16; u4 = -0.03; v5 = - 0.72; v6 = - 0.26. It is observed that the generated results applying the vector fundamentals present the same results generated by the perceptron 2, according to the proposal presented in this work.

Figure-05 shows the results presented by vectors (v) = v1 + v2 + v3 + v4 + v5 + v6, in vector form.

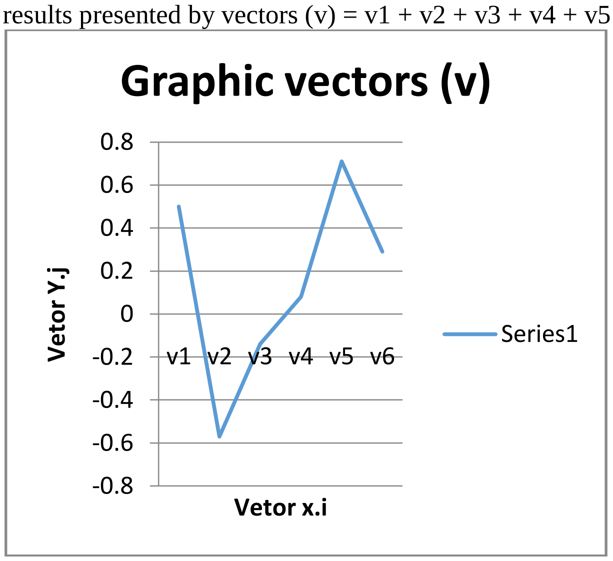

Figure-05. Results generated by the vectors (v), in the representation of vectors.

Figure-05 shows the results of the vector sum of vectors (Vr (v)) and vectors (Ur (u)) generated by vectors (v) and (u). Therefore, the vector (Vr) is the result of the vector sum of vectors v1 + v2 + v3 + v4 + v5 + v6, as shown in table -05.

Figure-06 shows the results presented by vectors (u) = u1 + u2 + u3 + u4 + u5 + u6, in vector form.

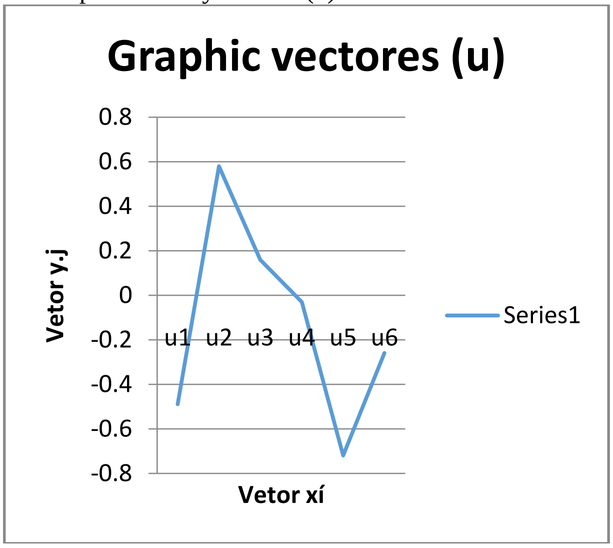

Figure-06. Results generated by the vectors (u), in the representation of vectors.

Figure-06 shows the results of the vector sum of vectors (Vr (v)) and vectors (Ur (u)) generated by vectors (v) and (u). Therefore, the vector (Ur), is the result of the vector sum of vectors u1 + u2 + u3 + u4 + u5 + u6, as shown in table-05.

Table-05 describes the results obtained from the sum of Vr (v) and Vr (u) and also the result vector.

Vector Result (v)	
Vr(v)	0,87

Vector Result (u)	
Ur(u)	-0,76

Vector Result (u)	
Vr	0,11

Table-05 Result of the vector summation for the vectors v and u.

Table-05 shows the results of the vector Vr (u) which are the sum of: v1 + v2 + v3 + v4 + v5 + v6 = 0.87. The sum of Vr (u) is: u1 + u2 + u3 + u4 + u5 + u6 = - 0.76. The resulting vector is given by Vr = Vr (v) + Ur (u) = 0.11.

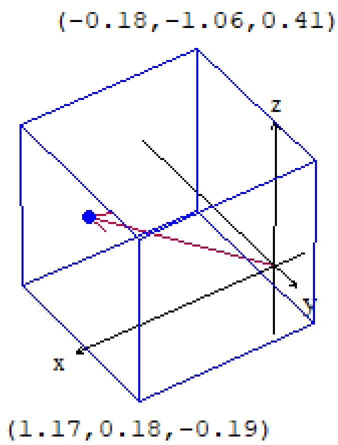

Figure-07. Results generated by the resulting vector (Vr) in the three-dimensional space.

The figure-07 shows the vector result of Vr = Vr (v) + VR (u). This vector result stores the space and the shape of the figure in a three-dimensional plane during the learning of an RNV.

X. Conclusion

A complex processing applied in a biological neural network using computational machine and algebraic calculus requires a large amount of memory and processing of these calculations. Waiting time may not be able to meet human needs.

The vector processing of a RNV in a practical way replaces the construction of a biological neural network, since it requires less storage space and response time in the construction of images, symbols, planes and ideogram languages. Its construction can be performed in a manner similar to the behavior of a biological neuron network. An RNV creates its space and plane in three-dimensional or two-dimensional form to later build its elements in the plane and space specified. The storage is the result of vector calculations according to the direction the direction and the intensity of its vectors.

An intelligent machine must recognize the observed figure of its environment and compare it with the stored symbol that is in the vector form constructed in a two-dimensional or three-dimensional space of that machine. The processing and analysis of its image allows to determine its meaning.

It is known that a vector in the plane determines an orthogonal Cartesian system xOy and its point P (x, y), determine the components of the vector xi + yj, known as canonical basis, as well as in a plane of three dimensions each point P x, y, z) of this space represented by the vector xi + yj + zk, determines the figure of a parallelepiped in three dimensional space with its proper dimensions. It is possible in this way to construct other forms of geometric figures and recognition by intelligent machines, applying the fundamentals of vectors in their construction. Your storage can be accomplished through vector-based results and rebuilding your storage will be faster and more consistent.

The results presented in this work, as presented in figures 01 to 06 and tables 01 to 05, show the possibilities of these representations with the similarity of the functioning of a biological network and an RNV, applying the fundamentals of vectors for the formation of his figures and images. This possibility reduces the need for the application of complex calculations, since the three-dimensional spaces are constructed in vectors in the three-dimensional plane (x, y, z) that is the canonical basis of its Cartesian orthogonal Oxyz system.

Despite the results obtained, another point that could be considered for future work is the realization and demonstration of other forms of figures and languages for storage and learning of intelligent machines. It will also be demonstrated the classification of altitudes for navigation of airspace by applying the proposals of an RNV.

References

[1]. Ludwing Jr. Oswaldo and Montgomery, Eduard. Neural Networks; Editora Ciência Moderna Ltda; Rio de Janeiro - RJ. 2007.
[2]. Russel, Stuart and Norving Peter. Artificial Intelligence; Elsevier Editora Ltda. Brooklin, São Paulo-SP, 2003.
[3]. Winterle, Paulo. Vectors and Analytical Geometry. Person Educatios do Brasil; São Paulo-SP, 2014.

Prof. Shia Chau Sen"Vector Neural Network (RNV), A Processing Similar to The Biological Neural Network."International Journal of Engineering Science Invention (IJESI), vol. 07, no. 12, 2018, pp 31-37