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Application of Neural Network Models in Recognition Field: A Survey

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Abstract— Neural Networks are the manipulated form of human brain nervous system. The working of neural network models is highly inspired by the brain nervous system. In this survey paper we demonstrate different kind of neural network models, their architecture, activation functions and their applications in various fields of recognition. In this paper we present a comparative study of neural network models in different fields of recognition.

Index Terms— Nerual network models, neural singnal function, pattern recognition, character recognition, offline handwritting recognition, online handwriting recognition.

1 Introduction

NEURAL Network is an artificial model of nervous system of human brain [1]. An artificial means 'something which is produced by human rather than natural'. So this artificial network is a mathematical representation of nervous system of human brain. Real neurons in human brain integrate a wide range of temporal signal through dendrites. In human brain the transformation of information is done by neurons. Every neuron has its soma which cell's nucleus and other components exists. Each neurons spread out dendrites by which they receives the input and for processing information between the neurons there is a tubular extension single axon.[1] This architecture of human brain nervous system is manipulated into neural network. The purpose of the survey paper is to study the different kind of neural network models and their application in different fields. A comparative study in field of pattern and character recognition is shown in the table for neural network model which are discussed in the paper.

2 Neuron Signal Functions

The internal activation in neurons is transformed into signal with the help of a signal function. The activation function is used in neurons for calculating the output response of neuron with the weighted input. The output response is produced by sum of weighted input signal applied with activation. The signal functions are as follows:

2.1 Linear Function

The function given by,

$$f(t) = t \text{ for all } t.$$

This is the simplest function. This function is unbounded ($t \in \{-\infty, \infty\}$). This function is unbounded non-differentiable.

2.2 Binary Function

Binary threshold function is given by,

$$f(t) = \begin{cases} 1 & t \geq 0 \\ 0 & t < 0 \end{cases}$$

These functions are non-differentiable and the signal function $f(t) \in \{0, 1\}$. These are some discontinuity around 0 signals, so the function employs "greater than equal to" condition.

2.3 Bipolar Threshold Function

The function is given by,

$$f(t) = \begin{cases} +1 & t \geq 0 \\ -1 & t < 0 \end{cases}$$

To overcome the discontinuity problem bipolar threshold function bipolar threshold function is introduced. It defines that $f(t) = 0$ is ambiguous activation and cannot suitably translate. Now, the signal are $f(t) \in \{-1, 1\}$ instead of $\{0, 1\}$ and behavior of logic neuron extended to bipolar. This function is also known as "signum function, sign(x)".

2.4 Linear Threshold Function

The function is given by,

$$f(t) = \begin{cases} 0 & t \leq 0 \\ \alpha t & 0 \leq t \leq t_m \\ 1 & t \geq t_m \end{cases}$$

Where $\alpha = 1/t_m$ is a slope parameter of function and function is differentiable because of the parameter. The simple linear function is unbounded .This is the bounded version of the linear function.

2.5 Sigmoidal Signal Function

The function is given by,

$$f(t) = 1/\ 1 + e^{\lambda t}$$

Where λ is gain scalar factor. This function is differentiable and $f(t) \in \{0, 1\}$. Function is monotonic means the values if function is either always increase or decrease as x increaes. The sigmoidal function is usually plot shaped curve and commonly used in multi layer network.

2.6 Hyperbolic Tangent function

The function is given by,

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$$f(t) = k \tanh(\lambda t)$$

Where k is constant value greater than 0 (k>0), and λ is a slope factor. This is also a differentiable function. This function is an example of bipolar function where f (t) ∈ {-1, 1}.

2.7 Gaussian Function

The function is given by,

$$f(t) = \exp(-(t-c)^2/2\sigma^2)$$

Where σ is the Gaussian spread factor and c is the center. In radial basic function Gaussian function is employed because it's a center base neural network. It is an example of non-monotonic function which first increase from 0 and then decrease towards 0, i.e. f (t) ∈ {0, 1}.

2.8 Stochastic Function

The function is given by,

$$f(t) = \begin{cases} +1 & \text{with probability } P(t) \\ -1 & \text{with probability } 1-P(t) \end{cases}$$

This function P(x) is the probabilistic activation function. The stochastic neurons are used in reinforcement learning network and the Boltzmann machine. For both either binary or bipolar stochastic neurons, the signal function is f(t) ∈ {0, 1} or {-1, 1}.This neuron function is non-differentiable.

3 Architecture of Neural Network

Neural Network connects to artificial neurons basically with two different type of architecture. These are: Feed Forward and Feed Back.

3.1 Feed Forward Architecture

The feed forward architecture of networks is static in nature where input is directly connected to the output or to the hidden layer neurons. There is no loop in the network because the architecture is forwarded in nature.

3.2 Feed Back Architecture

Feedback networks are opposition to the feed forward networks. These networks have loops in the network because neuron transports a signal back through the network. Recurrent network is also a type of feedback architecture.

4 Neural Network Models

According to the architecture of neural network there are different types of neural network models which are proposed in early time and their application areas are increasing because of their ability. Some of neural networks are discussed which are as follows:

4.1 Perceptron

Perceptron is developed by Frank Rosenblatt [2] in 1958.The perceptron is a single node feed forward neural network model which used binary threshold as an activation function. The root of perceptron model is McCulloch Pitts model [1943]. This was the first neural network model. Perceptron is work on supervised error correction learning approach. In perceptron the training of network will continue till no error occur. The perceptron neural network model is good network for classification with the restriction that classes have to be linearly separable. Perceptron neural network has their application in the fields of recognition like noisy spectra recognition [3], handwritten digit recognition [4] and many more.

4.2 ADALINE

ADALINE neural network is developed by Widrow and Hoff in 1960's. ADALINE abbreviated from Adaptive Linear Neuron. Adaptive behavior is a type of behavior that is adjusts to another type of situation. The neuron is adaptive when its weights are allowed to change in accordance with a well defined learning law [1]. Widrow called this neuron an adaptive linear element (ADALINE). Adaline is a single node feed forward architecture neural network model which works with linear activation function. ADALINE model works on supervised learning algorithm with least mean square or delta rule. The application of ADALINE network is in the domain of regression because of outputs in ADALINE network can take on real values and not restricted like in perceptron and it is also beneficial in adaptive signal field with LMS algorithm [1].

4.3 Multi Layer Perceptron

This neural network is developed by Rumelhart, Hinton and Williams in 1986. The multilayer perceptron is a feed forward network model with layer architecture. This network used nonlinear sigmoidal function as an activation function on hidden layer. The nonlinearity is differentiable everywhere so that it is smooth and not restricted as single node perceptron. Multilayer perceptron model is a supervised learning approach which use delta rule. For multilayer perceptron it is known as 'back propagation learning algorithm. MLP is trained by using back propagation algorithm which is very fast and efficient. The application domains for multilayer perceptron are: prediction of thrombo-embolic stroke [6], emotion recognition [7], and text based image recognition [8], offline character recognition [9] and countless others.

4.4 Reinforcement Learning

Reinforcement Learning is developed by Sutton and Barto in 1998.Reinforcement learning algorithms are based on the principle of reinforcement. If an action of a system is followed by satisfactory response then strengthen the tendency to produce that action [1]. The reinforcement learning networks is based on this approach and evaluates the success/failure signal which is provided by the reviewer. The general purpose of this learning is to maximize success rate of the neural net. This learning is actually a form of supervised learning which use binary threshold activation function. Reinforcement learning has proven itself to be a practical computational tool and it is used in the area of control [1]. This is the main application area of reinforcement learning network. Reinforcement learning network can solve the problem of object recognition [10]. They can solve the problem of recognition of patterns in the input space like 3D object recognition [11]. They therefore have applications that lie within the domain of pattern recognition.

4.5 Support Vector Machine

Support Vector Network is developed by Vapnik and Corinna Cortes [12] in 1990's. This neural network is based on multilayered feed forward neural network architecture. Support vector machine use binary threshold as an activation function. The support vector machine is a supervised learning approach and a kernel based architecture. Although SVM initially used to work on optical character recognition, support vector classifiers but as the good results in the field of recognition it is applied to object recognition tasks. SVM can be used for both classification and regression. Support vector machines are used in the field of forecasting [13] and recognition [14, 15].

4.6 Radial Basis Function

In 1988, Radial Basis Function Networks (RBFN's) are developed by Broom head and Lowe. Radial Basis Function is feed forward neural networks which are enclosed with in a two layer neural network that computes activation at the hidden neurons. Radial basis function is computed using an exponential of a distance measure between input vector and a prototype vectors at hidden layer neurons that characterized the signal function. In the interpolation of data points on a finite training set RBFN's is introduced. For performing interpolation the radial basis function network assumes a set of exactly finite basis functions [1]. RBFNs can be used for both interpolation and function approximation. In optimization problems where there are a large number of possible solutions for a small problem, Hopfield network has found applications. Radial basis function network is a feed forward neural network form but it is slightly different from the standard feed forward neural network. In general form of RBFNs bias weight is added to output linear neuron. The learning in RBFNs can be implemented in a number of ways like supervised learning, random placement of centers, cluster based center placement [1]. RBFNs can be used in the problem of classification, regression as well as interpolation and other different fields like prediction [16], recognition like offline handwriting and pattern recognition[17,18].

4.7 Hopfield Network

In year 1982, John Hopfield proposed a neural network model which is known as Hopfield network. Hopfield network is a neural network which feedback signals to them. Hopfield network is a single layered recurrent network. All the neurons in the network are feedback from all the other neurons present in the network. Hopfield network uses binary threshold/sigmoid as an activation function. Hopfield network have an interesting application in 3-D object recognition [1]. The recognition involves matching an object with the database of object models which is based on the object compression forms from different angles. The recognition is performed with the help of Hopfield networks [19, 20].

4.8 Brain-State-in-a Box Neural Network

Brain-State-in-a Box (BSB) network is developed by J.A. Anderson, J.W. Siwersten, S.A. Ritz; R.S. Jones [21] in 1977.The Brain-State-in-a Box (BSB) [22] is a predecessor of a Hopfield network. BSB neural network is also a single layer feedback neural network. The generalized Brain-State-in-a-Box (gBSB) neural network is a generalized version of the Brain-State-in-a-Box (BSB) neural network [21]. The BSB model is different from all other models because of the use of the linear threshold signal function. BSB model is basically applied to clustering. Apart from clustering BSB model application areas are in speech perception and probability learning [22] and also in radar signal classification. In radar signal applications BSB network is first train on a set of samples which is helpful in creating internal clusters [1].

4.9 Boltzmann Machine

In 1985, David H. Ackley, Hinton and T.J. Sejnowski [23] proposed a model which is named as Boltzmann machine. Boltzmann machine is a neural network model that employs stochastic methods in its operation. Boltzmann learning is implemented with the complex combination of stochastic search method called simulated annealing and gradient descent. So, the Boltzmann learning is stochastic supervised learning. This neural network model is a two layered architecture with binary threshold unit. The architecture of Boltzmann machines are used in optimization techniques. In which the stochastic neurons change their states depending on a probability that is computed from the energy change, which result from the neuron flipping its signal [1]. The probability distribution in the network is produced by using procedure based on the correlations. Robust Boltzmann Machines (RBM) is used for recognition [24].

4.10 Bidirectional Associative Memory

Bidirectional Associative Memory (BAM) is developed by Bart Kosko in 1988. Bidirectional Associative Memories (BAM) [25] is the extension of Hopfield networks to a two field architecture results. In bidirectional associative memory algorithms fields are updated once at a time. The error correction capability of BAM is much more in the comparison of Hopfield network because of its two layered architecture. The bidirectional associative memory is use binary threshold as an activation unit in the network. Other application area of BAM is in the field of authentication where these networks are more powerful because of high error correction capability as in the password authentication [26]. In the field of authentication BAM shows promising result as compare of other neural network models. It's also work in the field of character recognition [27].

4.11 Adaptive Resonance Theory

Adaptive Resonance Theory (ART) is developed by Grossberg and Carpenter from 1987 to 1990. Different type of versions of ART is proposed by Grossberg and Carpenter. Adaptive resonance architecture is a two layered neural network system that make by use of instars and outstars in a bidirectional network. An outstars which downloads spatial pattern information into its weight vectors, when the neurons are activated in the network. In other hand instars tunes its weight vector to better match to the impinging input vector at the time of learning. ART use the 'faster than linear' activation function which results winner takes all type of behavior. In adaptive resonance theory this function performs hard competition between the network neurons, in application fields like classification and clustering. The application of ART1 is binary pattern classification [1]. This model extended to ART2, which introduced for analog input patterns handling. Then ART3 model for sophisticated neuro transmitter based parallel search of distributed recognition codes in multilayered network is introduced. ART modules have their applications in various fields such as mobile robots [28], target recognition, face recognition, 3-D visual object recognition, character recognition, online handwritten symbol recognition [29, 30].

4.11 Vector Quantization

Tuevo Kohonen developed a neural network model which is known as Vector Quantization. Vector quantization is a single layer feedback neural network. Vector quantization is basically introduced for compressing information, store and transmit speech or version form data. It used the competitive learning approach. The application field of vector quantization is in clustering. Vector quantization work on supervised and unsupervised both competitive learning approach. Kohonen introduced supervised version of vector quantization known as 'Learning Vector Quantization [31]', which works on winner takes all approach. The Vector Quantization uses 'faster than linear' activation function. There is no network which works on soft competition. This hard competition which works with learning vector quantization (LVQ) reduced the possibility of misclassification as compared to unsupervised vector quantization. The clustering and quantization have an application area for the vector quantization. Vector Quantization is also work in the field of recognition like character recognition [32, 33].

4.12 Mexican Hat Network

The Mexican hat neural network is based on competition. This neural network overcomes the hard competition approach with soft competition; where in the network a cluster of neurons which are around the winner neuron became the winner. In this network, there are no learning algorithms and the weights used in the network are fixed. This network use linear threshold as an activation unit. This is a single layer feedback architecture network. Mexican hat networks model employs a complex web of connectivity involving short range excitatory feedback and long range low level excitation. This network is basically used in activity clustering means a group level competition where neighborhood neurons of maximum input switches on and all the other neurons have activates suppressed and instead of a single neuron a cluster of neurons wins. The model with a Mexican-hat type interaction, modeled after the hyper-column of the primary visual cortex and the frontal cortex during the memory-guided saccade, has continuously distributed fixed-point attractors [34].

4.13 Kohonen Self Organizing Features Maps

Kohonen Self Organizing Features Maps (SOFM) is developed by Tuevo Kohonen in 1972. The SOFM is single layer neural networks which are capable of reproducing important aspects of architecture of human neurons system. Topological maps are used to represent the data and SOFM preserve important topological information which can be obtained by an unsupervised learning process. SOFM algorithms are a competitive vector quantization in which clusters of neurons are win the competition rather than single neuron. This approach is the soft competition. This topological structure property is only found in the self organizing maps (SOM) rather than any other neural network. The original purpose for development of this neural network is in the field of signal analysis, pattern classification and data clustering. In clustering neurons in the field undergo normal competition based on a distance metric. SOFM are also work well for prediction of long term as well as short term of data [35] and also work in the field of recognition like offline handwriting and character recognition [36, 37, 38, 39, 40].

4.14 Spiking Neuron Networks

As we have seen the past neural network model which are based on first generation McCulloch-Pitts model and second generation of neural network model employed smooth sigmoid because these function increase firing rate of neuron with net input. They all can only deal with spatial signals such as image. When it comes to deal with temporal signals means the signals of time, no network model present .Hodgkin and Huxley conductance based neuron models is become the father of spiking neurons [1]. Networks of biological neurons compute with the help of fast travelling pulses called action potentials as in spiking neuron model [41]. Spiking neurons are powerful computing elements. These neurons use the timing of signals action potential or spikes which use to encode the information. The spiking neuron model is innately embedded in the time and these time and spatial information of spiking neurons gain fast computational power. In hardware it is showing promising result in many cases [41]. In character recognition this network is used [42]. Spiking neural networks promising results in the field of online, offline handwriting recognition [43, 44] and many other like spiking neural network shows a mixed platform of hardware /software in its application [45].

TABLE 1

COMPARATIVE STUDY TABLE OF NEURAL NETWORK MODEL IN THE FIELD OF RECOGNITION

Neural Network Model	Recognition Fields			
	Pattern Recognition	Character Recognition	Offline Handwritting Recognition	Online Handwritting Recognition
Perceptron	*	*		
ADALINE				
Multi-Layer Perceptron	*	*	*	*
Reinforcement Learning	*		*	
Support Vector Machine	*	*	*	*
Radial Basis Function	*	*	*	
Hopfield Network	*	*	*	
Brain-State-in-a-Box Network				
Boltzmann Machine	*	*	*	
Bidirectional Associative Memory	*	*	*	
Adaptive Resonance Theory	*	*	*	*
Vector Quantization	*	*	*	
Mexican Hat Networks				
KSOFM	*	*	*	*
Spiking Neural Network	*	*	*	*

5 CONCLUSION

In the above survey, we observed that all neural network models have neuro-biological concepts in their behavior and working. A more biologically realistic neuron model has been discussed like spiking neuron model. Comparative study of models in the field of recognition and pattern classification is discussed in the table.

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