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Artificial Neural Network – An Overview

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Abstract: *Today, we are living in the exciting time where technology is changing day by day.The purpose of paper is to study the recent trends emerging in the field of artificial neural over Digital Computer and Human Brain.Artificial Neural Networks are electronic models based on the neural structure of the brain.Neural networks are attractive since they consist of many neurons, each of the neurons processes information separately and simultaneously. Artificial neural network is most popular in the field of pattern classification or recognition, linear filtering problems, system identification, process control, optimization, robotics, and so on.Even by using the feedback network type architecture of neural network can be employed on time-variant systems, such as time series prediction, system identification and optimization and process control as in this network , the outputs of the neurons are used as feedback inputs for other neurons. The paper focuses on four basic types of artificial neural network type including Single-Layer Feed forward, Multilayerd Feed forword, Recurrent/Feedback and Mesh Architecture. Also it focuses on Training Processes and properties of learning.*
Keywords: *Artificial Neural Networks, Hybrid Neural Network, Mesh Architecture*

I. Introduction

The Neural Networks

The study of the neural networks is generated by the study of human brain, that how the brain works to make the decision, to store the patterns and how a brain learns for the recognition of objects? The study defines that a human brain contains an average of 3×10^{10} neurons [23] of various types, which are basically known as decision elements, with each neuron connecting to up to 10^4 synapses [24]. Artificial Neural Networks are electronic models based on the neural structure of the brain [25-27]. Neural networks are attractive since they consist of many neurons, each of the neurons processes information separately and simultaneously. All the neurons are connected by synapses with variable weights.

Artificial neural networks referred as to connectionist systems or neurocomputing, are a recent generation of information processing systems that are deliberately constructed to make use of some organizational principles that characterize the human brain. The main theme of neural network research focuses on modelling of the brain as a parallel computational device for various computational tasks which have traditionally been difficult to solve using traditional serial computers [Mehrotra et al., 1997].

Brain versus Digital Computer

The human brain can be seen as a flexible analog processor with enormous memory capacity that has been engineered and fine-tuned by evolution through several millions of years to execute tasks that are important for survival in our particular world. The human nervous system and the brain is a particular good example ofthis.

We are very good at recognizing faces and understand speech, very rapidly and accurately and far better than any digital computer, probably because it was very important to our survival to differentiate between friends and enemies and to communicate with each other. We can perform such tasks so effortlessly that we do not realize how hard they are until we try to program a digital computer to perform them.
Artificial Neural Networks provide possible methods for trying to solve some of the problems that are not suitable for digital computation.

Artificial Neural Networks:

The great majority of digital computers in use today are based around the principle of using one very powerful processor through which all computations are channeled. This is the so called *von Neumann architecture*, after John von Neumann, one of the pioneers of modern computing. The power of such a processor can be measured in terms of its speed (number of instructions that it can execute in a unit of time) and complexity (the number of different instructions that it can execute). The traditional way to use such computers has been to write a precise sequence of steps (a computer program or an algorithm) to be executed by the computer. This is the *algorithmic approach*. Such programs can be written in different computer languages, where higher level languages will have commands that when translated to the machine level will correspond to several instructions at the processor level. Researchers in Artificial Intelligence (AI) follow the algorithmic approach and try to capture the knowledge of an expert in some specific domain as a set of rules to create so called *expert systems*. This is based on the hypothesis that the expert's thought process can be modelled by using a set of symbols and a set of logical rules which manipulate such symbols. This is the *symbolic approach*. It is still necessary to have someone that understands the process (the expert) and someone to program thecomputer.

Artificial Neural Networks (ANN), also called *neurocomputing*, *connectionism*, or *parallel distributed processing* (PDP), provide an alternative approach to be applied to problems where the algorithmic and symbolic approaches are not well suited.Artificial NeuralNetworks are *inspired* by our present knowledge of biological nervous systems, although they do not try to be realistic in every detail (the area of ANN is not concerned with *biological modelling*, a different field). Some ANN models may therefore be totally unrealistic from a biological modelling point of view[HKP91].

In contrast to the conventional digital computer, ANN perform their computation using a large number of very simple and highly interconnected processors operating in parallel. The representation of knowledge is distributed over these connections and "learning" is performed by changing certain values associated with such connections.

Current ANN models are so crude approximations of biological nervous systems that it is hard to justify the use of the word *neural*. The word is used today more because of historical reasons since most of the earlier researchers came from biological or psychological backgrounds, not engineering or computer science. It is generally believed that knowledge about *real* biological neural networks can help by providing insights about how to improve the *artificial* neural network models and clarifying their limitations and weaknesses. The next section presents a simplified introduction to the human nervous system and human brain. The human brain is the most complex organ we have and is a structure still poorly understood, despite intense research and much progress since Santiago Ramon y Cajal showed that the human nervous system is made of an assembly of well-definedcells.

Main Architectures of Artificial Neural Networks

In general, an artificial neural network can be divided into three partswhich are knownas:

(a) Inputlayer

This layer is responsible for receiving information (data), signals, features, or measurements from the external environment. These inputs (samples or patterns) are usually normalized within the limit values produced by activation functions. This normalization results in better numerical precision for the mathematical operations performed by the network.

(b) Hidden, intermediate, or invisiblelayers

These layers are composed of neurons which are responsible for extracting patterns associated with the process or system being analyzed. These layers perform most of the internal processing from anetwork.

(c) Outputlayer

This layer is also composed of neurons, and thus is responsible for producing and presenting the final network outputs, which result from the processing performed by the neurons in the previous layers.

The main architectures of artificial neural networks, considering the neuron disposition, as well as how they are interconnected and how its layers are composed, can be divided as follows: (i) single-layer feedforward network, (ii) multilayer feedforward networks, (iii) recurrent networks and (iv) meshnetworks.

Single-Layer Feedforward Architecture

This artificial neural network has just one input layer and a single neural layer, which is also the output layer. Figure 1illustrates a simple-layer feedforward network composed of n inputs and m outputs.The information always flows in a single direction (thus, unidirectional), which is from the input layer to the output layer. From Fig. 1, it is possible to see that in networks belonging to this architecture, the number of network outputs will always coincide with its amount of neurons. These networks are usually employed in pattern classification and linear filteringproblems.

Among the main network types belonging to feedforward architecture are the Perceptron and the ADALINE, whose learning algorithms used in their training processes are based respectively on Hebb"s rule and Deltarule

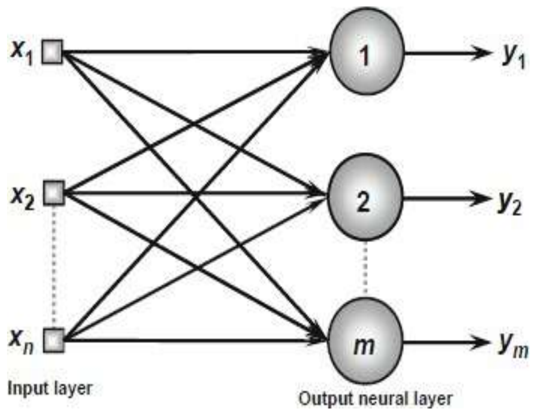

Figure 1: Example of a single-layer feedforward network

Multiple-Layer Feedforward Architectures

Differently from networks belonging to the previous architecture, feedforward networks with multiple layers are composed of one or more hidden neural layers (Fig.2). They are employed in the solution of diverse problems, like those related to function approximation, pattern classification, system identification, process control, optimization, robotics, and so on. Figure 2 shows a feedforward network with multiple layers composed of one input layer with n sample signals, two hidden neural layers consisting of n1 and n2 neurons respectively, and, finally, one output neural layer composed of m neurons representing the respective output values of the problem being analyzed.

Among the main networks using multiple-layer feedforward architectures are the Multilayer Perceptron (MLP) and the Radial Basis Function (RBF), whoselearning algorithms used in their training processes are respectively based on the generalized delta rule and the competitive/delta rule. From Fig. 2, it is possible to understand that the amount of neurons composing the first hidden layer is usually different from the number of signals composing the input layer of the network. In fact, the number of hidden layers and their respective amount of neurons depend on the nature and complexity of the problem being mapped by the network, as well as the quantity and quality of the available data about the problem. Nonetheless, likewise for simple-layer feedforward networks, the amount of output signals will always coincide with the number of neurons from that respectivelayer.

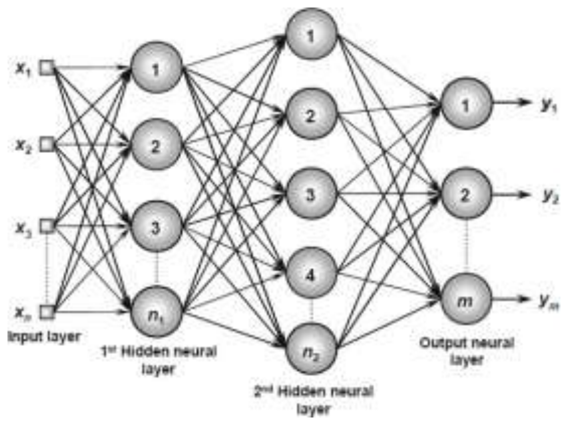

Figure 2: Example of a feedforward network with multiple layers

Recurrent or Feedback Architecture

In these networks, the outputs of the neurons are used as feedback inputs for other neurons. The feedback feature qualifies these networks for dynamic information processing, meaning that they can be employed on time-variant systems, such as time series prediction, system identification and optimization, process control, and so forth.

Among the main feedback networks are the Hopfield and the Perceptron with feedback between neurons from distinct layers, whose learning algorithms used in their training processes are respectively based on energy function minimization and generalized deltarule.

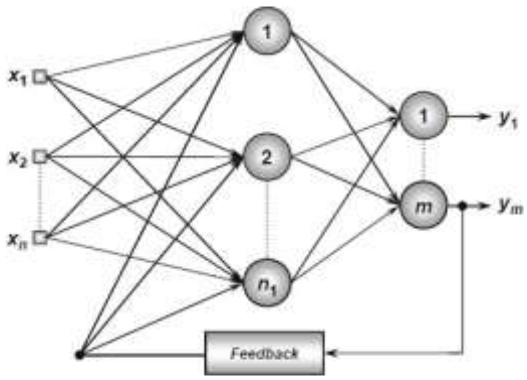

Figure 3: Example of a recurrent network

Figure 3 illustrates an example of a Perceptron network with feedback, where one of its output signals is fed back to the middle layer.
Thus, using the feedback process, the networks with this architecture produce current outputs also taking into consideration the previous output values.

Mesh Architectures

The main features of networks with mesh structures reside in considering the spatial arrangement of neurons for pattern extraction purposes, that is, the spatial localization of the neurons is directly related to the process of adjusting their synaptic weights and thresholds. These networks serve a wide range of applications and are used in problems involving data clustering, pattern recognition, system optimization, graphs, and soforth.

The Kohonen network is the main representative of mesh architectures, and its training is performed through a competitive process.From Fig.4, it is possible to verify that in this network category, the several input signals are read by all neurons within thenetwork.

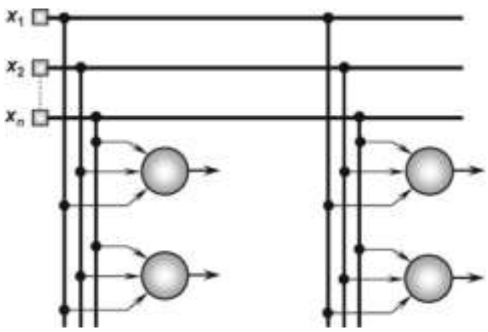

Figure 4: An example of the Kohonen network where its neurons are arranged within a two-dimensional space

Training Processes and Properties ofLearning

One of the most relevant features of artificial neural networks is their capability of learning from the presentation of samples (patterns), which expresses the system behavior. Hence, after the network has learned the relationship between inputs andoutputs, it can generalize solutions, meaning that the network can produce an output which is close to the expected (or desired) output of any given input values.

Therefore, the training process of a neural network consists of applying the required ordinated steps for tuning the synaptic weights and thresholds of its neurons, in order to generalize the solutions produced by its outputs.

Usually, the complete set containing all available samples of the system behavior is divided into two subsets, which are called training subset and test subset. The training subset, composed of 60–90 % of random samples from the complete set, will be used essentially in the learning process. On the other hand, the test subset, which is composed of 10–40 % from the complete sample set, will be used to verify if the network capabilities of generalizing solutions are within acceptable levels, thus allowing the validation of a given topology. Nonetheless, when dimensioning these subsets, statistical features of the data must also be considered. During the training process of artificial neural networks, each complete presentation of all the samples belonging to the training set, in order to adjust the synaptic weights and thresholds, will be called trainingepoch.

II. Conclusion

It is ironic to realize that today's achievements in ANN research are a direct consequence of the vast progress in the areas of hardware and software for digital computers in the recent decades. The majority of ANN models in use today are simulated in digital computers since specific hardware for ANN is not yet easily available or affordable. The current digital computers provide a suitable framework that is used by researchers to carry out experiments with their ANNmodels.

The important point is to realize that certain problems are suitable to be solved by the conventional algorithmic procedure implemented in digital computers while other problems are not. Artificial Neural Networks provide possible methods for trying to solve some of the problems that are not suitable for digital computation.

It is conclude that, the Mesh architecture type of Artificial neural network is the best method for digitization of character and comparison of algorithm for recognition of character

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