NEURAL NETWORK AND INTELLIGENT CONTROL —PART II

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We should be careful to get out of an experience only the Wisdom that is in it—and stop there; lest we be like the cat that sits down on a hot stove lid. She will never sit down on a hot stove lid again—and that is well; but also she will never sit down on a cold one any more. Mark Twain, Pudd'nhead Wilson's New Calender.

Artificial neural networks (ANN) are biologically inspired and their design loosely follows neural structure of human brain. Human brain excels the conventional computers in three broad areas: pattern recognition, associative recall, and learning. Biological neural networks consist of as many as ten billion nerve cells of neurons.

Signals coming into the receptive part (dendrites, dendritic tree or field) can stimulate the neuron cell body (soma) to send action potential down along the axon (single long fibre extending from soma), out along synapses (specialised interconnection and communication between neurons) to the end feet, to excite or inhibit those neurons. Once a neuron is fired, there is an absolute refractory period of 10^{-2} second before it can fire again.

A single neuron can receive thousands of inputs, and in turn send outputs to equal number of neurons. According to M. Singer, "Almost any type of connection scheme that can be imagined can be found in the brain." McCulloch and Pitts in 1943 proposed a simple model of a neuron as a binary threshold unit, which outputs a one or zero depending on the weighted sum of its inputs ($\Sigma_j x_i x_j$) above or below a certain threshold μi.

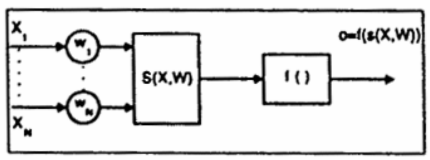

Fig. 8: A generalised neutron model.

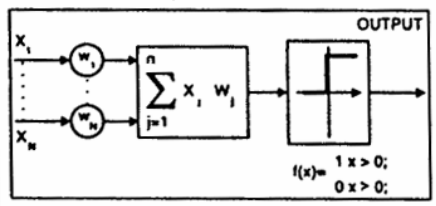

Fig. 9(a): McCultoch-Pitts neuron.

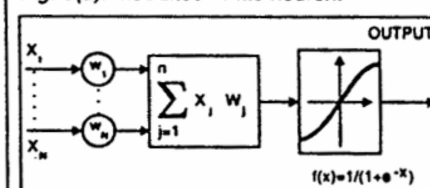

Fig. 9(b): Backpropagation neuron.

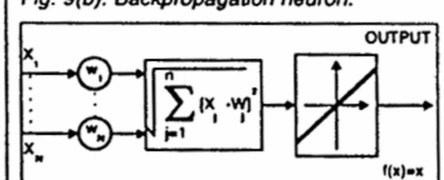

Fig. 9(c): Kohonen neuron.

As biological neurons give continuous output instead of binary, McCulloch and Pitts (MP) neuron is modified for continuous output with a general nonlinear function known as activation function, transfer function, squashing function or gain function.

A generalised model of a neuron is shown in Fig. 8. In this neuron model, S(.) is some rule for combining input (X_i) and weights (W_i) in the form of a scalar function of a pair of vector inputs, and f(.) is the activation function. For backpropagation (to be discussed later) neuron model this activation function must be a semilinear function.

Fig. 9 represents three different neuron models mostly used for neural analysis. Real and artificial neurons do differ in forms of S(.) and f(.), and bidirectional links unlike unidirectional inputs, and intricate dependencies between weights. Research in the field of neurology can give light to the development of more sophisticated neuron model.

A grouping of slabs in a network is a layer where a slab is grouping of artificial neurons (units). A 3-layer net with three outputs is shown in Fig. 10. The units in intermediate layers are often called hidden units as they do not have direct outside world connections, i.e. the inputs and outputs. These layered feedforward structures are called perceptrons.

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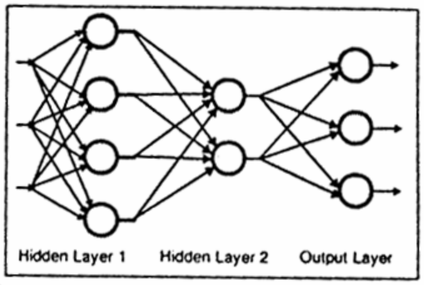

Fig. 10: 3 layered, 3-input, 3output with two hidden-layer feed-forward neural network.

Network models may be consisting of single layer such as Hopfield, Kohonen etc, or cascading of similar layers such as backpropagation or interconnection of dissimilar layers such as counter propagation network. Each network has advantages in its own domain of application. Backpropagation networks are feed-forward networks, and Hopfield networks are fully connected dynamic networks.

The design of the neural networks can be done at both network and unit level. In unit level one should concentrate on unit types and activation function combination method, whereas in network level the important points to be focused on are the number of layers and slabs, number and type of units, and connectivity.

Each neural network is to be trained for the job to be handled. For training, the input data selection and preparation gains utmost importance. Preparation does mean to transform the inputs to some proper form and data types (binary, continuous or bipolar), normalisation and scaling of input data, and preprocessing (filtering, data compression or data expansion etc) the input data.

Learning, which is the core part of the neural network operation, can be broadly classified into the following types:

1. Learning with weight changes only: (a) Supervised learning. Needs a teacher to specify the desired outputs. (b) Unsupervised learning requires no teacher. (c) Graded or reinforcement learning. A global signal is required (true and false).

2. Learning with structure changes only: (a) Learning techniques which physically change the network topology. (b) Recruitment learning. Weight change only and allocate previously unused connections and units.

Apart from these the learning may be stochastic (Boltzmann and Cauchys Machine) or deterministic. Also, the learning can be similarity based or instruction based. For a backpropagation network the weight updation is done after minimising the mean squared error by using recursive least squares procedures. This is shown in Fig. 11. Learning is a key area of artificial neural network research.

The problem selection and its analysis for neural application is very much important. Problem analysis does include the information regarding conventional control (algorithms) techniques, availability of experts with lucid IF-THEN rules, and the nature of the available data (exact, univariant and deterministic etc).

The nature of the real world problems broadly fall into four types:

1. *Classification.* Process control, forecasting, signal processing etc.

2. *Pattern.* Image processing, symbol identification, data fusion etc.

3. *Optimisation.* Operation research problems.

4. *Real numbers.* Data forecasting (financial, power system load etc), robotics, process control, financial mapping etc.

Neural networks can be applied to all of the above cases. In classification, it is nothing but a network with output units active at a time. In patterned problems, the network to be used with all the output units activate simultaneously. In optimisation problems, the network will output a pattern of decisions.

It is now clear that neural network can tackle all such problems. But we know the real world problems are complex, nonlinear and uncertain in characteristics. Neural networks due to their massive interconnection, parallel architecture, inherent nonlinearity, and fault tolerance can well suit these complex problems, making these to be suitable for intelligent control.

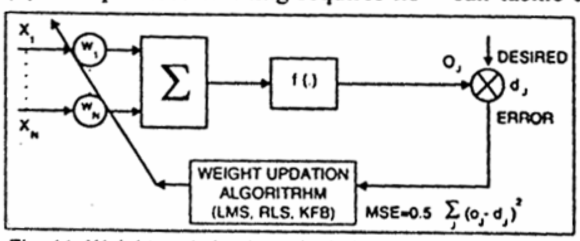

Fig. 11: Weight updation in a single-layer Neuron.

Applications

Intelligent control for adaptive process control is an obvious choice due to the difficulties of traditional control theory to deal with complex varying or uncertain environment. Not only in process control but also in many other applications, intelligent control has proved its efficiency. Now let us see some of the applications of neural networks.

Refinery control. Process control systems being usually complex and highly nonlinear are difficult to control and derive a dynamic model. A neural network refinery control scheme is described here.

Puget Sound Refinery of Texaco with a capacity of 120,000 barrels of oil per day has been applied a neural network model to control a debutaniser which separates and condenses hydrocarbons according to their molecular weights. The neural network used has seven inputs of control and disturbance variable, and two outputs of manipulated variables. For the training of the network 1440 data sets were taken. A feedback mechanism has been provided to eliminate unexpected errors. It has been reported that this neural network model remains in control about 80 per cent of the time and even more during unstable processing.

Temperature control. An inverse dynamic model of a laboratory water bath temperature control process is developed with a 3-layered neural network with eight hidden units and one output unit. The performance of this real-time neural controller is compared with that of PI controller. It has shown that the neural network performs better under load disturbances for variable dead time process.

Quality control. A chemical process plant of Cleveland, Ohio uses a neural network system for quality control. Usually, trained experts are required for controlling the quality of chemical products. In this plant the extracted product samples during changeovers and other routine process stages are analysed on an infrared spectroscope to varify proper chemical ratios, and the absence of contaminants. A neural network is trained with a training set of known contaminants, and their associative spectroscopic output. It has the advantage of verification of the product quality without programming knowledge of the technician or the spectroscopy expert.

Air traffic control. Nertrologic of San Diego has developed a neural network for air traffic control (ATC) using a simulation program called TRACON. This uses a local or associated neural network for each monitored aircraft. Each local network receives information such as conflicts in the next 't' minutes, and whether the next waypoint is a tower, regarding other aircraft (one network for each aircraft) as input, and conflicts are avoided by extrapolating current velocities and positions of aircraft on the screen, on to the future. The outputs of the network are "change speed", "turn right", and "increase altitude", etc. Netrologic has also developed a network based real-time decision aid called an ATC conflict field interaction network (FIN).

Loudspeaker diagnosis. Loudspeaker defect classification using a neural network is developed by CTS Electronics of Brownsville, Texas. A

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neural network with ten inputs of distortion at ten discrete frequency points, and four outputs of speaker defects, classifies speakers into four output classes. The network training time is 40 minutes. A test sweep and evaluation takes only one second.

Apart from these applications the neural network has found its place in many diverse fields like NASA's hubble telescope scheduling with Hopfield based network; bond rating prediction by G.R. Pugh and Co. of Cranford, New Jersy, which predicts the next year's corporate bond rating of 115 companies; sales support system by Veratex Corp., using one backpropagation network; orange juice quality control as per the manufacturers' labelling and purity guidelines, developed by Seifollah Nikdel of Florida Department of Citrus; financial market analysis by Karl Bergerson of Seattle's neural trading company and many more.

Intelligent control, in spite of its many advantages, suffers from the stability problems. Neural network in the form of intelligent control is better for solving complex, uncertain, dynamic and nonlinear problems due to its massive interconnection, inherent parallelism and nonlinearity. In process industries intelligent control gives better yield, quality and stable operation. In power sector it offers faster, smoother and more reliable operation. In mechanical system design it results in higher precision, faster control, reduced maintenance and reliability.

In the near future, the diverse information processing capabilities like pattern recognition, learning, adaptation etc will be able to give a better shape to the intelligent control systems for real world problems. ❑