Neurocomputing: picking the human brain essay

Life, Relationships

INTRODUCTIONThe concept of intelligence is complex, and hence many theories, definitions and taxonomies have emerged to explain its essence. The limited triumph has given rise to the idea that such a multidimensional concept cannot be explained by a single theory. As an outcome, a multidisciplinary approach has led to significant advancement in the theory of intelligence. Consequently, the necessity to build intelligent systems has resulted in the development of a range of techniques.

Over recent years, numerous computational intelligence paradigms have been established. As an alternative form of information processing, neurocomputing is fast becoming a recognized discipline, and several neural networks are already on the market (Kandel, 1979). Neural networks are good at some things that usual computers are bad at.

They do well, for example, at solving complex pattern-recognition problems implicit in understanding continuous speech, identifying handwritten characters, and determining that a target seen from various angles is in fact one and the same object. Neural networks parallel-process huge quantities of information. Yet for a long time the only way to implement them was by simulating them laboriously, inefficiently, and at huge expense on standard, serial computers. That circumstance is shifting. Neurocomputers – hardware on which neural networks can be implemented efficiently – have reached the prototype stage at numerous companies, and a few are already commercially available.

All are coprocessor boards that plug into conventional machines. Developers include IBM Corp., Science Applications International Corp.

(SAIC), Texas Instruments Corp., Hecht-Nielsen Neurocomputer Corp. (HNC), and TRW Inc. For the meantime, researchers at Boston University, the Helsinki University of Technology, Johns Hopkins University, the University of California at San Diego, the California Institute of Technology, and other universities have been investigating the theory behind neural networks and exploring their potential to solve problems that have stumped algorithmic computing for decades. GENERAL DISCUSSIONNeurocomputing methods are loosely based on a model of the brain as a network of simple interconnected processing elements corresponding to neurons (Dmitry O. Gorodnichy, W.

W. Armstrong). These methods derive their power from the collective processing of artificial neurons, the chief advantage being that such systems can learn and adapt to a changing environment. In knowledge-based neurocomputing, the emphasis is on the use and representation of knowledge about an application. Explicit modeling of the knowledge represented by such a system remains a major research topic. The reason is that humans find it complicated to interpret the numeric representation of a neural network. The anatomical structure of a typical neuron is shown in Figure 1. The diagram depicts the three key parts of a neuron: Figure 1.

Anatomical structure of a typical neuronThe cell body is consisting of the nucleus and all other biochemical machinery needed to sustain the life of cell. The diameter of the cell body is on the order of 10-20? m. The dendrites extend the cell body and provide the key physical surface on which the neuron receives signals from other neurons. In various types of neurons, the length of the dendrites can vary from tens of microns to a few millimeters (Eliashberg, 1988).

The axon provides the pathway throughout which the neuron sends signals to other neurons. The signals are encoded as trains of electrical impulses (spikes). Spikes are generated in the area of the axon adjacent to cell body called the axon hillock. The duration of a spike is on the order of 2-4msec. The length of several axons can exceed one meter. A usual axon branches several times (Grossberg, 1982).

Its final branches, terminal fibers, can reach tens of thousands of other neurons. A terminal fiber ends with a thickening called the terminal button. The point of contact between the axon of one neuron and the surface of another neuron is called synapse. In most synapses, the axon terminal releases a chemical transmitter that affects protein molecules (receptors) embedded in the postsynaptic membrane.

About fifty various neurotransmitters are identified at the present time. A single neuron can secrete numerous different neurotransmitters. The width of a typical synaptic gap (cleft) is on the order of 200nm. The neurotransmitter crosses this cleft with a small delay on the order of one millisecond. All synapses are divided into two categories: a) the excitatory synapses that increase the postsynaptic potential of the receiving neuron, and b) the inhibitory synapses that decrease this potential.

The typical resting membrane potential is on the order of -70mV. This potential swings somewhere between +30mV and -80mV during the generation of spike. Not all axons form synapses. Some serve as “ garden sprinklers” that release their neurotransmitters in broader areas. Such non-local chemical messages play important role in various phenomena of activation (Nicholls, Martin, Wallace, 1992).

A plain concept of a neuron-like computing element is shown in Figure 2. The (a) and (b) parts of this figure show two different graphical representations of this model. Figure 2. A simple concept of a neuron-like computing elementIn Figure 2, xk is the input (presynaptic) signal of the k-th synapse, and gk is the gain (weight) of this synapse. The net postsynaptic current, inet is equal to the scalar product of vectors g and x.

In this expression, the excitatory and inhibitory synapses have positive and negative gains, correspondingly. In the graphical notation shown in Figure 2b, the excitatory and inhibitory synapses are represented by small white and black circles, correspondingly. To show this agreement, Figure 2b demonstrates an inhibitory synapse located on the body of the neuron. The incoming line and the outgoing line can be thought of as the dendrites and the axon, correspondingly. The dynamics of the postsynaptic possible u is explained by the first-order differential equation (2). The output signal y, explained by Exp (3), is a linear threshold function of u. For the sake of simplicity the threshold is equal to zero.

Usual applications of neurocomputing technology are frequently grouped into one of three domains: Analysis, prediction and control (Hecht-Nielsen, 1987). Data analysis applications are considered to be used to discover relationships and recognize patterns within data. Data mining and pattern classification are usual analysis applications. In data mining, the enormous quantities of data accumulated illustrating the operations and storing this information in “ data warehouses.” Understanding the relationships in this data creates applications that can predict sales, foresee a competitor’s bid, recognize new markets, and identify fraud. While, pattern classification is patterns in data can be detected and classified based on a series of input measurements. Applications comprise optical character recognition, face recognition, trend analysis, sensor data classification, and signal detection.

Prediction or forecasting is the ability of the system to foresee future values and outcomes based on current input values. Applications include predictive maintenance and load forecasting. Based on data gathered over time on the health of a piece of machinery (including breakdowns), a predictor is used to schedule machine maintenance before the next breakdown occurs. Historical load data is used to create a model that can forecast future load values. Successful applications include electrical power load forecasting, and telecommunications switch load forecasting. The control of machines or processes frequently requires high-speed computations and function inversion (the capability of the model to provide the required input given a desired output). Applications consist of automotive control systems and computer-controlled prostheses. Computer controlled active suspension systems permit a vehicle to adaptively adjust the firmness of the suspension system and develop handling.

Computer assisted walking aids for spinal cord injured persons are used to control walking gait by detecting the user’s intended action.

CONCLUSIONNeurocomputing is an alternative approach to programmed computing, principally well suited to problems in areas such as pattern recognition, data analysis, sensor processing, prediction and control. Neurocomputing refers to systems that learn the relationships between data throughout a process of training. Neural networks are the main information processing structure used in neurocomputing.

Neurocomputing benefits comprise and are frequently measured in terms of: a reduction in the quantity of software needed to solve the problem; a reduction in the time it takes to solve the problem when compared to the programmed computing approach; and a convenient solution to the problem that may be too complex for programmed computing. The key assumption of knowledge-based neurocomputing is that knowledge is accessible from, or can be represented by, a neurocomputing system in a form that humans can understand. That is, the knowledge embedded in the neurocomputing system can also be represented in a symbolic or well-structured form, such as automata, rules, Boolean functions, or other recognizable ways. The focal point of knowledge-based computing is on methods to encode prior knowledge and to extract, process, and revise knowledge within a neurocomputing system.

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