Conventional digital computers are extremely good at executing sequences of instructions that have been precisely formulated for them, with the "stored program" representing the processing steps that need to be done. The human brain, on the other hand, performs well at such tasks as vision, speech, information retrieval, and complex spatial and temporal pattern recognition in the presence of noisy and distorted data—tasks that are very difficult for sequential digital computers to do at all. How does the brain accomplish this, given that its "processing elements" (neurons) are significantly slower than the processing elements of contemporary supercomputers? Neurons, which are electrochemical devices, can respond in milliseconds, whereas current, off-the-shelf electronic technology can switch states in nanoseconds.

Current estimates place the number of neurons in the human brain at $10^{11}$. They are organized in a complex, unknown interconnection structure, and individual neurons may be connected to several thousand other neurons. It is not yet understood how this massively parallel interconnected system of neurons (a "biological neural network") allows us to store, represent, retrieve, and manipulate data such as images, smells, sensations, and thoughts. We do not know how it...
represents a person’s face, for example, so
that merely seeing someone’s eyes allows
us to formulate a complete image in which
we recall other important personal informa-
tion—such as the way he or she walks. We do not know how we store
equations, how we manipulate ideas with-
out writing them down, or how we learn to
speak, see, and hear. Yet, we do all of these
things amazingly well.

Once vision and speech, for example,
are well-enough understand to be reduced
to algorithmic form, they can be realized
on conventional digital computers just as
well as on artificial neural systems. At that
point, it will be a cost/performance issue
as to which technology or combination of
technologies will be employed to realize
these capabilities.

Both the literature and the number of
professional society meetings focusing on
artificial neural systems are growing at an
amazing rate. A number of technical dis-
ciplines are involved in the wide variety of
independent industrial, government, and
university-based activities and studies.
Neurobiologists, neurophysiologists,
mathematicians, physicists, psychologists,
computer scientists, and engineers are
studying and formulating theories about
how computations actually occur in
nature.

Some researchers are undertaking these
studies so as to ultimately understand how
the brain works and thus closely adhere to
or attempt to understand the biology
involved. Others are evolving entirely new
computation paradigms based on the sim-
ple models that are part of the new the-
ories. Some of the new paradigms are best
termed “biologically influenced” because
they involve assumptions that are not bio-
logically accurate. These biologically
influenced computational paradigms have
been used to solve difficult optimization
problems and to implement associative
memories.1 Although the field of artifi-
cial neural systems has roots going back
over 25 years,1,2 there currently is no con-
sensus of what is important to study or
how to go about studying it. Some
researchers are combining conventional
AI’s symbolic and heuristic approach to
complex problem solving with the symb-
olocical approach, where neural models
apparently perform well.3

This special issue of Computer is enti-
tled “Artificial Neural Systems”—that is,
“artificial” as opposed to the “biological”
natural systems appearing in nature. The
study of artificial neural systems goes
under the guise of many names in the lit-
erature: neural networks, connectionist
models, parallel distributed processing
models, layered self adaptive systems, and
self-organizing systems. Terms like neu-
rocomputers, neuromorphic systems,
netware, and cyberware are being intro-
duced into our technical “jargon.” For a
good introduction to computing with arti-
ficial neural systems—one that reviews six
important neural models used for pattern
classification—see Lippmann.2

This issue is exclusively dedicated to
those of interesting and important
work in various areas of artificial neural
systems. Because workers in the field are
exploring many different areas, the articles
reflect the diversity and robustness of these
interests. Some of the authors closely
adhere to the biology involved, while
others are developing biologically
influenced models and systems. Results
are presented that are based on

1) using the most elementary model of
a neuron (one that sums its N “weighted”
inputs and outputs the result through a
nonlinearity),

2) interconnecting these “simple neu-ons” in a network topology involving
feedback, and

3) employing various rules by which
weights are adjusted (that is, the way in
which learning—self-adaptation, self-
organization—occurs).

Applications such as visual pattern recog-
nition, speech recognition, motion detec-
tion, adaptive pattern recognition, as well
as VLSI and simulation implementations
of artificial neural systems are presented.

I hope you enjoy reading these articles.
Clearly, this newly reincarnated field has
some interesting and promising results to
share, but it is not known how these results
will scale up to more real-world related
tasks. Numerous important research ques-
tions emerge from even this small sampling
of articles. For example: Are specific
models more appropriate for given classes
of computations than other models? How
does the sample set of learning situations
affect the resulting characteristics of the
neural system both during training and
during operation? How can supervised
and unsupervised learning be combined in
such systems? How do the various inter-
connection structures affect the computa-
tional and operational characteristics of
the system? What hardware is best for sup-
porting the particular neural-network
models? What algorithms can be formu-
lated using the massively parallel paradigm
of neural networks? And on and on...□

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