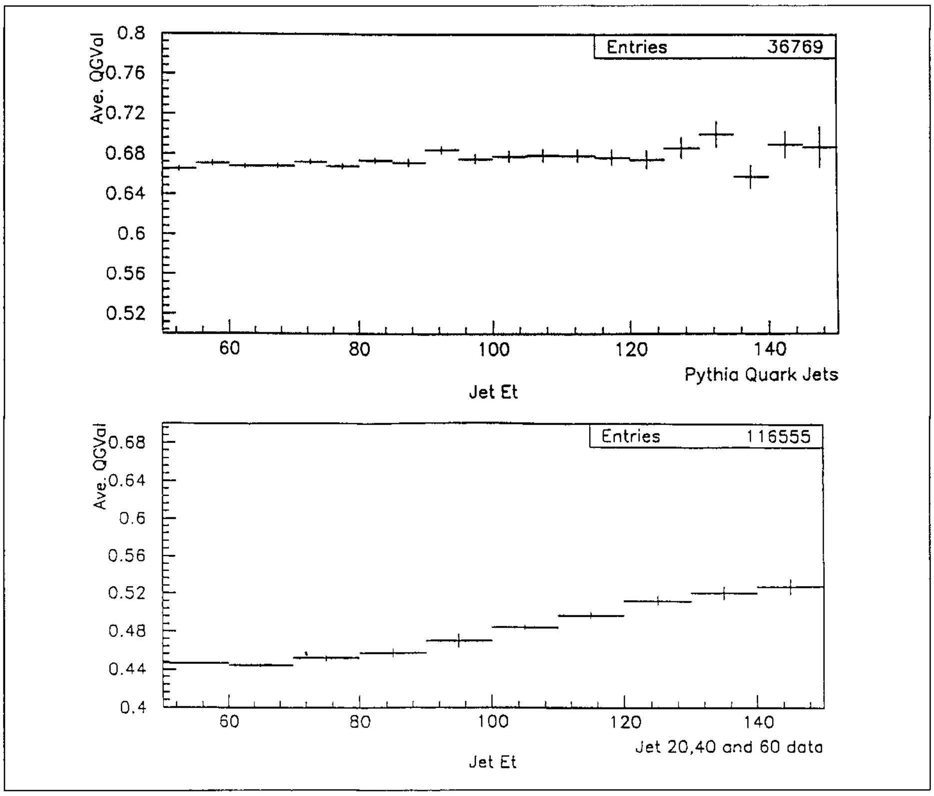
Physics monitor



Neural networks can tell the difference. Top – a simulation-trained neural network, tested on simulated (Pythia) quark and gluon jets, detects no variation with jet transverse energy. However when the network is tested on real jets (from the CDF experiment at Fermilab's tevatron proton-antiproton collider), the result slowly rises with transverse energy, consistent with the quark/gluon mixture becoming richer in quarks, as expected from the underlying theory.

Neural networks

The 1980s saw a tremendous renewal of interest in 'neural' information processing systems, or 'artificial neural networks', among computer scientists and computational biologists studying cognition. Always on the lookout for new techniques, high energy physicists were not long to follow suit, and the first papers on applying neural networks to pattern recognition in particle tracking appeared in 1987 and 1988.

Since then, the growth of interest in neural networks in high energy physics, fueled by the need for new information processing technologies for the next generation of high energy proton colliders, can only be described as explosive.

In January, at the Second International Workshop on Software Engineering, Artificial Intelligence and Expert Systems in High Energy and Nuclear Physics at La Londe-les Maures, Côte d'Azur, France (May, page 12) there were some 25 individual contributions on applications of neural networks in high energy physics in the Artificial Intelligence sessions. For comparison, at the first workshop in this series, in Lyon, France, in March, 1990, there were just two such presentations.

Last year, CERN's first Neural Net Workshop, commissioned by Walter Hoogland and organized by Jacques Altaber and J.-P. Porte, included 33 contributions on neural network applications in high energy physics.

Artificial neural networks are data processing architectures with many simple processors, or neurons, operating in parallel. Usually arranged in layered structures, these architectures are modeled on current understanding of pattern recognition in animal nervous systems. Neural networks are used in high energy physics as an algorithm for data analysis, and are also beginning to be used as hardware for triggering systems.

In data analysis applications, the neural network algorithm is valuable for classification since it provides a good approximation to an optimal classifier (the Bayes classifier) with a minimum of computational overhead. In addition, the neural network can be 'trained' to recognize certain classes simply by presenting it with correctly classified examples, without specifying a precise algorithm.

An example comes from the Delphi experiment at CERN's LEP electron-positron collider. Electrons and muons are easily identified, so the relative decay rate of LEP's Z particles into pairs of electrons and pairs of muons is well known. However measuring the relative decay rate of the Z into the five known quark species, (up, down, strange, charm, beauty) is considerably more difficult. The quark species must be inferred from the event topology and from the properties of the resultant particle jets.

Neural networks use all the available event information to construct feature variables which reliably identify the quark. The network, trained in simulations, is able to capture correlations in the input variables which would be difficult to find using a more traditional analysis. With the neural network technique, the Z branching ratios into the five known quark species have now been determined with errors of the order of only a few percent.

A similar analysis of Aleph data at LEP compared neural network and conventional discriminant analysis for extracting b-quark events in Z de-

At Fermilab, Bruce Denby (right) and Clark Lindsey fit a special chip to the neural network board attached to the readout motherboard of their drift chamber. In this pioneer neural network hardware experiment, muon track angles and intercepts are calculated on-line from the chamber's analog sense wire signals. The agreement between network and offline track fitting is excellent (below).

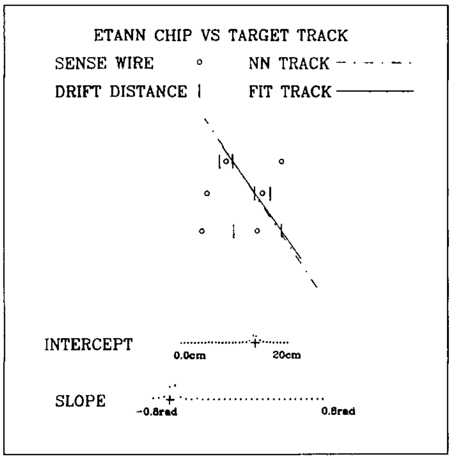
cays, with encouraging results. People in L3 have looked at neural network possibilities for interpreting the output from the BGO crystals of their electromagnetic calorimeter.

Another exciting result using a neural network in data analysis comes from the CDF experiment at Fermilab's Tevatron collider. A number of simulation studies have used neural networks to distinguish between jets resulting from quarks and jets resulting from gluons, but the Fermilab result hints at a reliable separation of these two classes of jets in real proton-antiproton collider data.

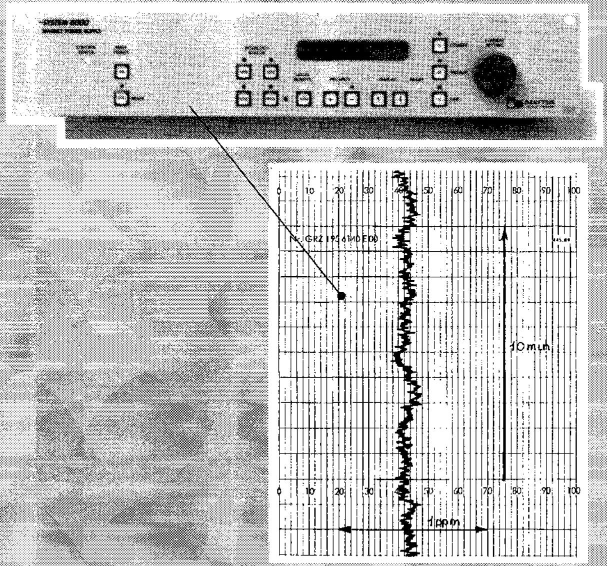
This will be very important in searches for the sixth ('top') quark. Top quark-antiquark states will most often decay into quark jets, while background processes will predominantly contain gluon jets. In the Fermilab analysis, a neural network was simulation-trained to tell quark jets from gluon jets using jet shape variables. The trained network was then applied to samples of jets from real proton-antiproton collisions. With neural networks, the probability of recognizing a quark jet among simulated gluon and quark jets does not vary sharply with the transverse energy of the jet. However using networks with real CDF jets, the quark jet probability increases steadily with jet transverse energy. This is consistent with the increasing fraction of quark jets at higher transverse energies expected from quantum chromodynamics. The measurements are continuing.

Because of the parallel nature of neural computing, neural networks can be implemented as very fast electronic systems. With processing times less than a microsecond, it should be possible to implement sophisticated pattern recognition algorithms within the trigger hardware of a high energy physics experiment.

The first such application comes from a recent Fermilab test beam experiment, where a VLSI neural network chip was interfaced to the data acquisition system of a prototype drift chamber. Drift time information from the sense wires, encoded as voltages, was passed to the neural network, which calculated the slope and intercept of the track traversing the chamber and sent this information back to the mother readout board to be read out with the rest of the event, without any dead time.



Neural network hardware is also finding its way into other trigger systems. The CDF experiment has three neural network triggers in place for its 1992 run: an isolated endplug electron trigger, an isolated central photon trigger, and a semileptonic B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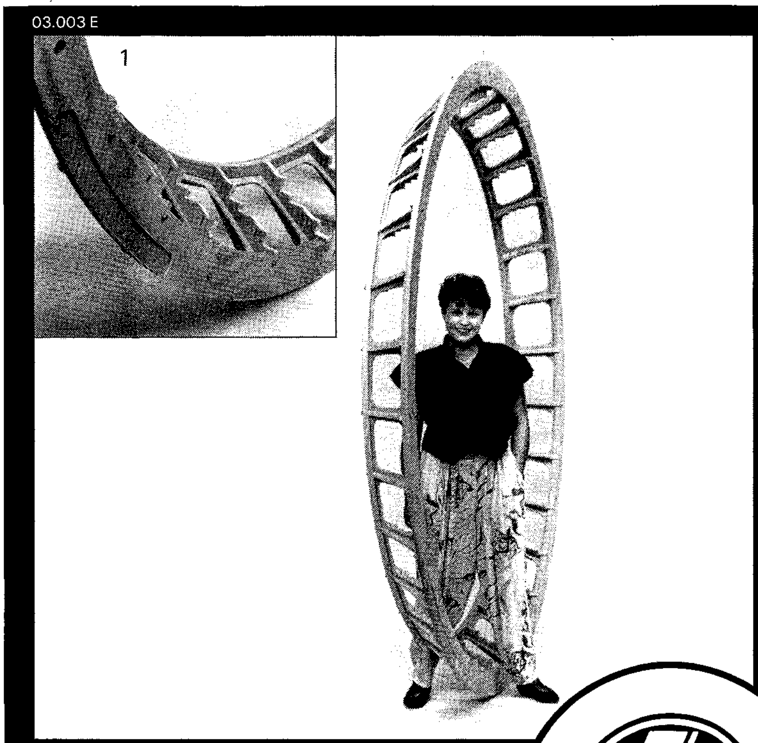
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