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SOLENOIDAL DETECTOR NOTES

CONCEPTUAL DESIGN OF A NEURAL NETWORK PIPELINE PROCESSOR FOR THE FIBER TRACKER'S L1 TRIGGER

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INTRODUCTION

The use of trained feed-forward neural networks has the promise of providing a novel approach to performing extremely fast pattern recognition which could be incorporated into a first-level trigger. Extensive Monte Carlo simulations specifically written for high energy particle physics, in addition to neural network simulator programs, are being used at UTD and at the SSC Laboratory to train and test the accuracy, efficiency, and speed of these networks. The final goal of this research is to determine the optimum architecture, training process and most cost efficient method of hardware implementation.

SDC TRIGGER REQUIREMENTS

The critical process of separating the proverbial 'needle in a haystack' is planned to be accomplished by performing different levels of event triggering. The most significant of these levels is the one that is directly related to this research, first-level triggering or L1. It is here that the largest reduction (or discarding) of events is planned. Currently, the L1 trigger rejection factor is 10^{-3} to 10^{4}, and it is expected for the trigger to return a decision every 16 nsec with a 2-4 μsec latency. This latency time is provided by large FIFO (First In First Out) memory buffers that will temporarily hold an event's data while the trigger makes its decision. The next level of triggering is the second-level triggering or L2. At this level, there will be a rejection factor of only 10^{-1} to 10^{-2} and 10 msec of decision time. This is a reduction in events that is 100 times smaller than L1, and it has about 1000 times more time to make its decision. These conditions allow for the L2 trigger to use a more precise algorithm and apply larger amounts of scrutiny on the events that are passed to it. Beyond L2 is the third-level trigger farm or L3 Farm which is actually a parallel array of computers all running the same triggering algorithm. This trigger will have approximately the same reduction rates as L2 but will apply even further scrutiny to the less than 1000 events/sec passed to it and try to reduce the number of events that are actually written to tape to about 10 to 100 events per second.[Sm91]

Now focusing attention to the L1 trigger in the central tracking volume, the basic requirements that are stipulated by the SSC can be examined. First and foremost, the L1 trigger has to 'flag' events when

and only when a programmable number (or more) of charged particles of transverse momentum, $p_\perp \geq 10$ GeV/c, pass through the tracking chamber. Secondly, it must be able to tell the position of a track with at least the same resolution as the calorimetry system and return an accurate estimate of the energy (or $p_\perp$) of the particle. Lastly, it must be very fast in order to keep up with the decision rate as mentioned above. In any triggering algorithm, the efficiency is usually degraded by false and missed triggers. Combinations of low $p_\perp$ tracks that coincidentally mimic the track of a high $p_\perp$ particle are the usual culprit and a good example of a false trigger.

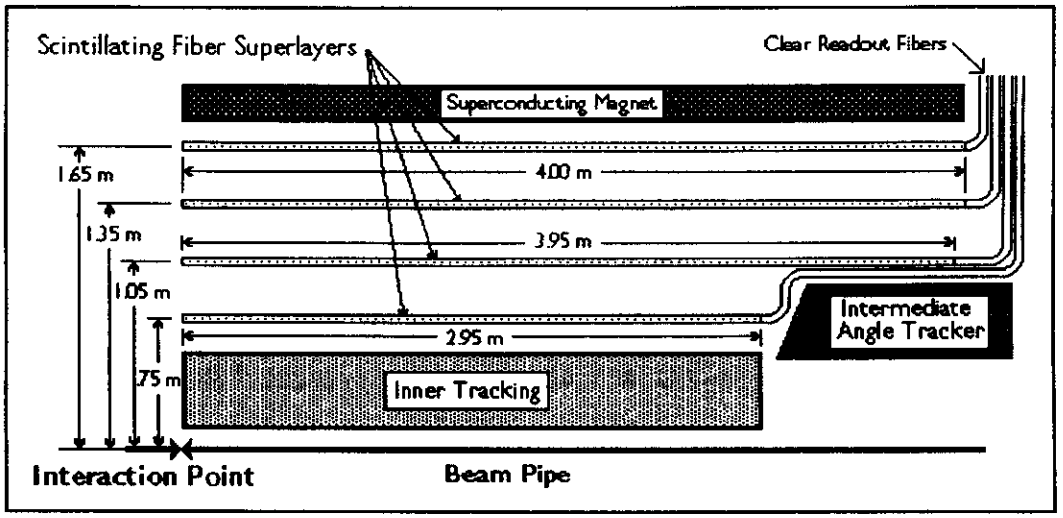

Figure 1. Schematic quadrant view of the scintillating fiber detector. It should be noted that the tracker configuration used in actual simulations is continuously being updated to match the most current design adopted hy the Fiber Tracking Group (FTG).

NEURAL NETWORKS

Neural networks (neural nets) are a massively parallel and intricately connected collection of relatively simple processors. Based on the same basic design upon which the human brain operates, they are usually started in a random state and trained into responding correctly for problems which no one good solution algorithm is present. For the purposes of triggering in the SDC detector one particular type of network, the feed-forward neural net, is preferred due to it's fast parallel processing capability. The processors (or neurons) contained in layers above the input layer begin by summing all of the products of the input values and the synaptic weights which the input values travel on to reach the neuron. Then a threshold value, unique to that neuron, is then subtracted from this sum. The remainder then becomes the argument for a Heaviside step function. If the remainder is larger than zero (0), then that neuron will pass on the value of one (1) to all neurons above it and pass on zero (0) otherwise.[Figure 2] Once the general architecture is determined for the application, a set of preferably non-redundant input patterns, or vectors, that cover the entire range and scope of the input phase space that is to be learned is compiled. These input examples must also be accompanied by the desired output vector or value. The training process is primarily comprised of repetitive presentations of input patterns and a comparative analysis of the networks output to the desired output. For each incorrect response, the synaptic weights and thresholds are slightly adjusted to better facilitate the correct output for that input pattern on the next

presentation. This process continues until convergence, error = 0, or some maximum number of attempts has been reached. A non-convergence situation is usually the result of one or both of the following problems: 1.) The capacity of the network is too small. In other words, there are not enough neurons and synapses to properly 'map' all of the input vectors to the desired output vectors. 2.) The training set has two or more conflicting patterns. An example of this would be if one pattern were to inadvertently put into the training set twice with different output vectors. It is quite easy to see how this second case would be a non-converging network. Once training is completed, the network can operate in an extremely fast recall mode as would be needed for an L1 trigger.

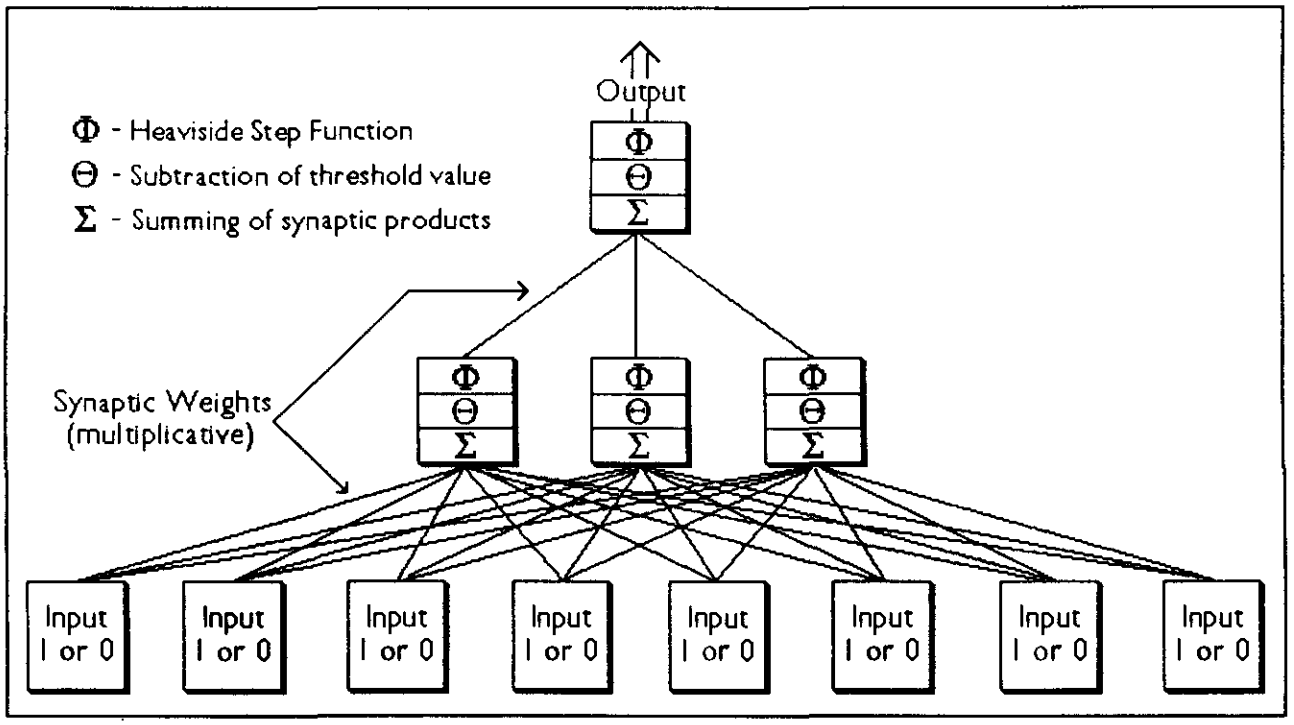

Figure 2. Generic feed-forward neural network with 8 inputs, 3 hidden neurons and 1 output neuron.

GOALS AND APPROACHES

The main goals of this research work are to: 1.) perform an unbiased investigation into finding the best pattern recognition neural network for detecting stiff tracks in a cylindrical scintillating fiber tracking chamber and be able to make quantitative classifications, such as transverse momentum of those found, and 2.) Find the most accurate and cost-effective method for hardware implementation of this neural network.

The planned method for attaining these goals is to use a repetitive 'train and test' process of the neural networks until the optimum performance is obtained. These networks will be trained with data that will be generated by SDCSIM (a.k.a. the SHELL). This program was created (and is constantly being modified) by simulation experts within the SDC to most realistically simulate the performance of the detector as a whole. The neural network simulator being used is JETNET v2.0.[Lu91] The majority of the intensive computations will be performed on the SSC's Physics Detector Simulation Facilities (PDSF).

GENERAL DESCRIPTION

In order to meet the planned reduction factor of 10^{-3}, the first-level trigger for the scintillating fiber tracker has to quickly identify the small fraction events that contain highly energetic decay products. These decay products pass through the 2 Tesla magnetic field with very little deviation from straight radial lines when viewed end on. This prominent feature intuitively makes the division of each half of the barrel into a wedge-type geometry, the best candidate for parallelization. As an initial configuration, contiguous wedges ($2\Pi/320$ angular displacement in ϕ) will have no overlap, but at a later date an optimization study will be performed in order to determine the overlap, if any. A copy of the digital, binary signals from every Z-axis scintillating fiber of the inner most superlayers in a given wedge is sent through a two stage triggering process [Figure 3]. [Sd92]

In the first stage, a 4:1 data compression, referred to as clustering, performs an 8 bit boolean function on contiguous fibers and returns a TRUE (or +1) output, if the hit combination could have been caused by a particle with a $p_{\perp} \geq 10$ GeV/c and a FALSE (or 0) otherwise. The preprocessor outputs now become the inputs to a much larger second stage neural network. It will basically be a pyramid-style of

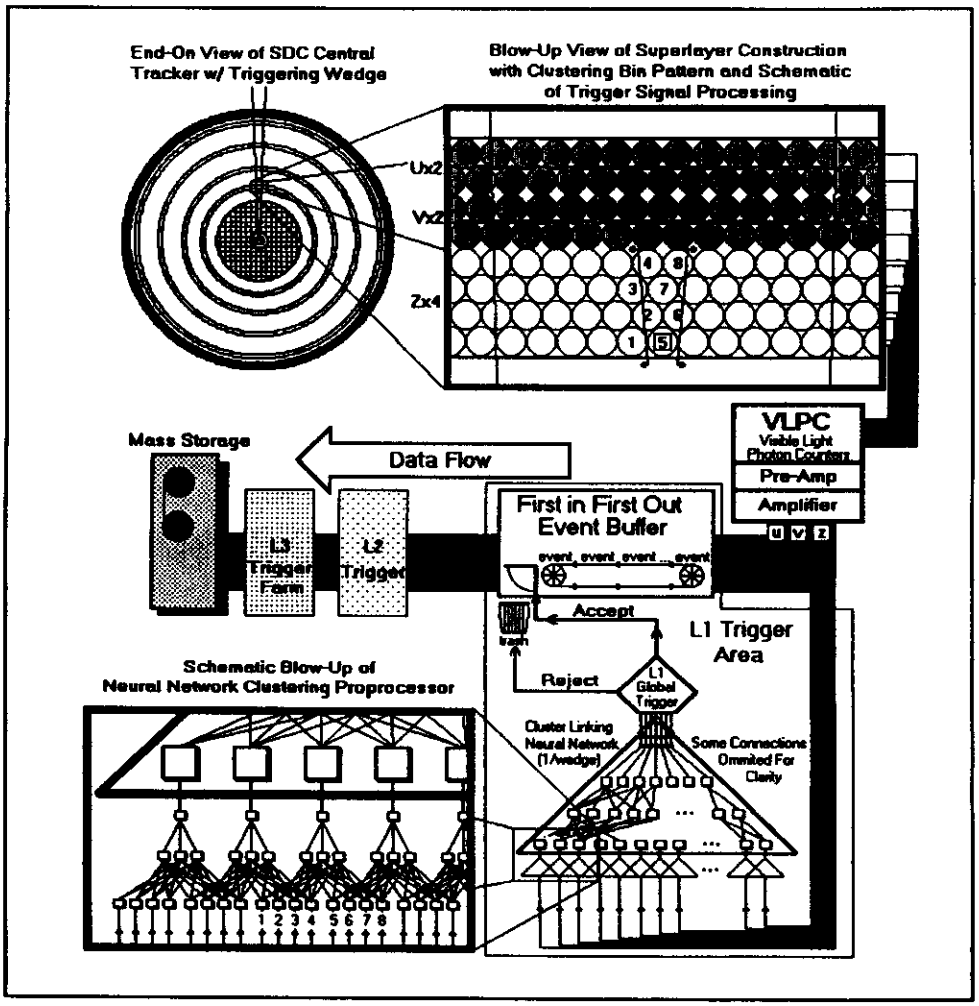

Figure 3. Schematic diagram of the proposed neural network triggering system. Current simulations have each half of the barrel detector divided into 320 triggering wedges in ϕ.

architecture with 4 bits of $p_\perp$ output at the top and a yet undetermined number of hidden layers and neurons per hidden layer. All of the non-zero transverse momenta and corresponding wedge locations will then be sent to a programmable track/shower max trigger processor that will use this information to determine if this event should be passed onto the global (all component) L1 trigger. At this point it is important that it be noted that the scope of this research does not include the design of the above mentioned programmable 'total tracking volume' trigger processor nor the global L1 trigger.[Sm91]

TRAINING, TESTING AND OPTIMIZATION

Being one of the most important aspects of this research project, integration into the framework of the SHELL allows for the most realistic, raw data to be generated for training and will also serve as a standardized platform from which the algorithm can be benchmarked for comparisons in accuracy and efficiency to all other triggering algorithms. The SHELL can basically be described as a compilable and executable collection of large programs. PYTHIA, ISAJET and HERWIG, which are event generators; and GEANT, a detector simulator, make up the majority of the SHELL with the remainder being subroutines for SDC-specific initialization and code management.

Testing of the full triggering algorithm will be done in two phases. The first and most recently completed phase consists of sending single particles of varying $p_\perp$ through wedges in order to measure the efficiency of the clustering network as a function of $p_\perp$ [Figure 4]. The second and larger phase

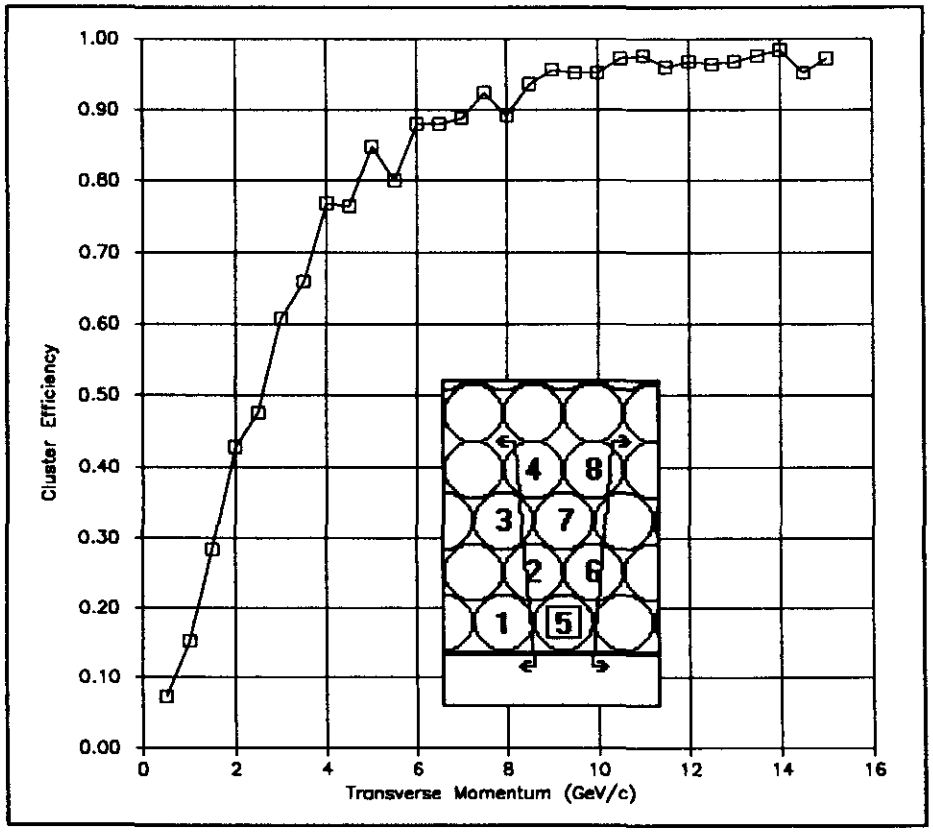

Figure 4 Clustering efficiency vs. transverse momentum for quadruplet superlayer configuration using 8-bit cluster pattern (inset). Each data point based on approximately 750 cluster candidates generated by SDCSIM.

consists of using full detailed events to see how well a trained neural net can distinguish between wedges containing high $p_\perp$ tracks and those that do not, in order to provide a benchmark quantity which will take both efficiency and false trigger rates into account and give an overall performance rating to the trigger's performance.

In order to get a crude approximation of the performance of the second (linking) stage, a very course simulation was constructed which utilized 1 cm, rather than 1 mm, fibers. The result was a wedge that had only 16 possible clusters in four superlayers. Single particles were then shot through the wedge and the hits with their corresponding transverse momentum were trained on a 16 input - 1 output neural network. After training on single track events, randomly generated events were triggered yielding ~95% accuracy. When a second, lower $p_\perp$ 'noise' particle was added (for which the network had not yet been trained to recognize), the accuracy level dropped to ~77% [Figure 5]. These very course tests showed a definite capacity for neural nets to perform pattern recognition in this type of detector geometry.

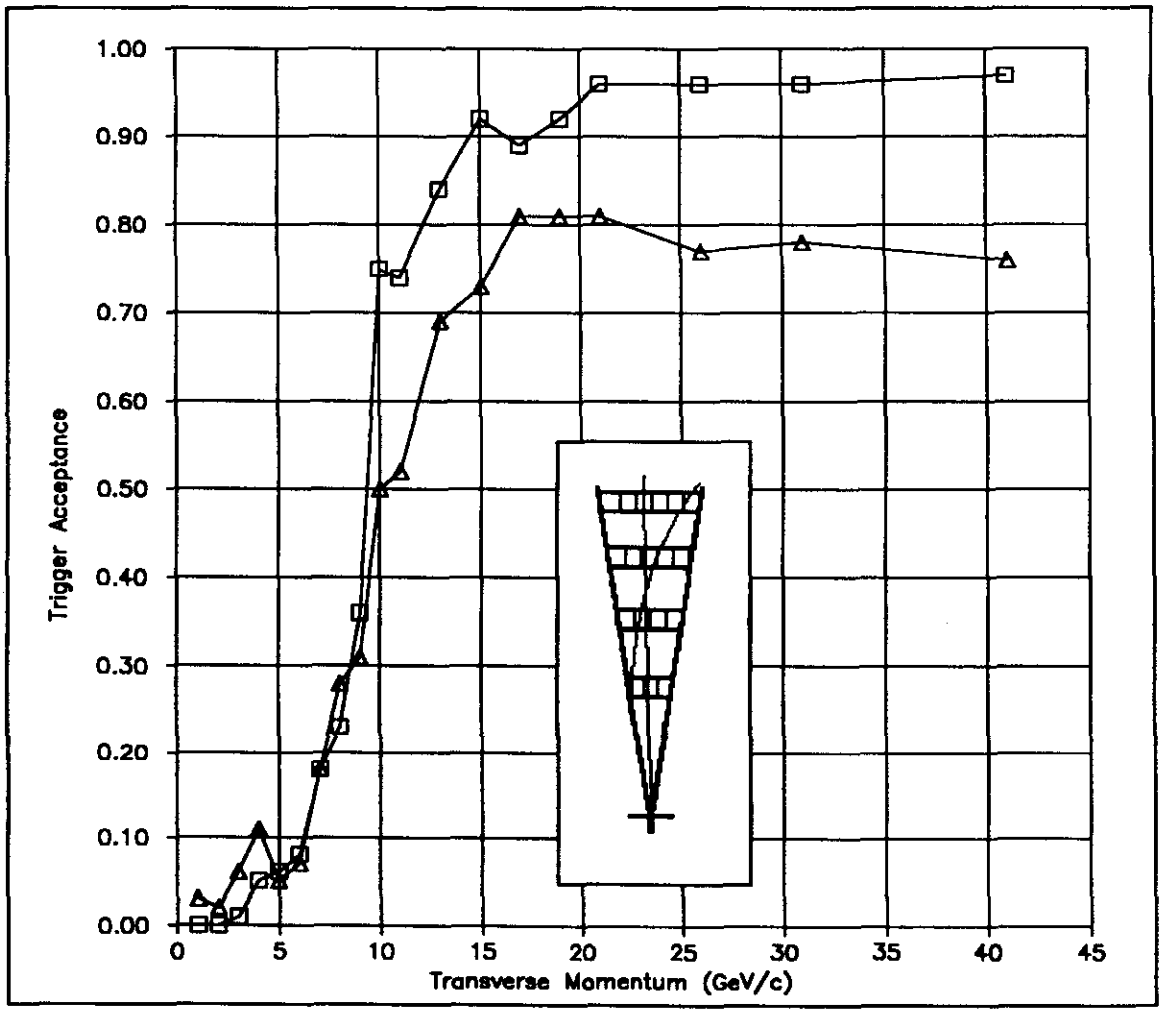

Figure 5. Trigger acceptance vs. transverse momentum. Squares represent single particle events and triangles represent two particle events with the first at the designated transverse momenta and the second at some randomly chosen transverse momenta lower than the first. Each data point is based on 500 events passed through a triggering wedge with 1 cm fibers (16 fibers total, see inset).

At the present status of this research, there are three optimization studies that need to be performed. The first, which is currently under way, is to determine the optimum architecture of the second stage (linking) network needed to provide triggering with acceptable momentum resolution. The second optimization study deals with determining the overlap, if any, needed to have the best probability of catching any given high $p_\perp$ track in a wedge. The third optimization, which will take place after training and testing are complete, involves the minimization of the network's size by removing non-essential neurons and synapses in order to facilitate easier hardware implementation.

Two basic detector configurations will be used as a final test-bed for this research work. The first will consist of using the most recently adopted configuration with superlayers consisting of dual-doublets separated by a 1.6 cm Rohacel spacer, as currently adopted by the FTG.[Sd92] The second configuration will differ from the first only in that the Z-axis fibers of the superlayers will be comprised of a single quadruplet (as depicted in Figure 3).

CONCLUSION -- ADVANTAGES OF NEURAL NETWORKS

By far, the most predominant advantage to using neural networks is their very fast parallel processing speed over any type of serial processor. Another advantage of neural networks operating in an SDC environment is their high degree of error resistivity. Unlike serial computers that may completely fail if one bit or a single instruction is incorrect, it usually takes a sizable fraction of the network to fail before a degradation in performance is noticeable [Nn90]. Lastly, it is hopeful that results from this proposed research will be able to show that neural networks are also an economical advantage that may not necessarily come only in the form of low cost neural network hardware implementation but more possibly in the form of peripheral savings such as smaller FIFO buffer space.

Hopefully this work will be the first step of a best case scenario in which research would lead to further testing, prototyping, production and SDC trigger implementation by the year 2000.

REFERENCES

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