AN ARTIFICIAL NEURAL NETWORK COMPUTATIONAL SCHEME
FOR PATTERN MATCHING PROBLEMS IN HIGH-ENERGY PHYSICS

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ABSTRACT

Large multiplicity events, generated by recent high-energy physics experiments, require high granularity two-dimensional detectors to provide unambiguous information on tracking and vertex detection. These devices produce spot-composed representations of events, which involve the use of sequential time-consuming algorithms for data analysis. A computational scheme based on linear threshold units to solve pattern matching problems is proposed. The scheme is designed as a two-layer neural network with forward connections. The performances of this approach are evaluated by the analysis of a set of images produced by an optical Ring Imaging Cherenkov (RICH) detector at CERN.

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1. INTRODUCTION

In high-energy physics, the particle identification covers an important role in the analysis of experimental data. For this purpose, measurements are taken for each event and a suitable classification criterion is evaluated.

The presence of high-track multiplicity in the phase-space region, where particle identification is needed, makes this task even more complicated. The use of optical imaging detectors provides an advanced solution of the problem, at least in experiments where the event rate is not extremely high [1], but even in this case some events might contain particles rejected or misclassified during the recognition phase due to the statistical nature of experimental data.

The output produced by optical imaging detectors consists of grey-level images which record the light yield stored in each pixel. These data structures, with geometrical information inside, can be handled efficiently with parallel algorithms to speed up pattern recognition tasks.

Several pattern recognition algorithms have been proposed up to now to solve automatically many decision-making problems [2]. Depending on the problem to be solved, the design strategy of recognition systems is based on one of the following criteria:

- template matching,
- detection of similarity, and
- clustering.

Indeed, for each of them, implementative methodologies such as:

- heuristic,
- mathematic, and
- syntactic,

can be used [3].

In this paper, an artificial neural network scheme for pattern matching problems, encountered in analyzing images produced by imaging devices, is proposed. The software simulation of the net has been implemented on a SISD architecture machine. An application on RICH images is also presented.

2. THE NEURAL NETWORK MODEL

The neural network model proposed here is based on the well-known adaptive linear threshold units or formal neurons. It consists of an input and an output layer with feed-forward interconnections between them. The first layer supports the incoming
images while the last is split in several planes to provide the shift invariance of the position of the stimulus pattern [4]. By defining

$$I \text{ and } I(x,y)$$  \hspace{1cm} (1)

as the input layer of the network and the (nxn) binarized input image respectively,

$$O = \{p_1, p_2, \ldots, p_m\}$$  \hspace{1cm} (2)

with m finite as the set of m planes composing the output layer of the network where each plane consists of (hxh) neurons,

$$s_k(v)$$,  \hspace{1cm} (3)

as the v-th formal neuron belonging to the k-th plane where \( k \in \{1, 2, \ldots, m\} \) and \( v = (i,j), i,j \in \{1, 2, \ldots, h\} \),

$$A_{k,v}(u)$$,  \hspace{1cm} (4)

as the synaptic strength of the \( s_k(v) \) neuron connections where \( u = (i,j) \) ranges into the receptive field dimension, the answer of a neuron \( s \), located into the plane k-th with coordinates \( v = (i,j) \), is computed as follow:

$$s_k(v) = \sum u I(v_0 + u) A_{k,v}(u),$$  \hspace{1cm} (5)

where \( v_0 \) is the receptive field centre coordinate on I of the neuron located in v. For sake of simplicity, the net emphasizing of a single neuron per plane is shown in fig. 1.

![Fig. 1 The neural network model](image-url)
Moreover, it must be pointed out that neurons in the plane $P_k$ have the same synaptic spatial distribution $A_k$ and are connected with presynaptic neurons belonging to the receptive field in such a way that the relative position among them reflects on the receptive field centres [4] (fig. 2).

![Diagram of synaptic pattern distribution for two neurons](image)

**Fig. 2** Sinaptic pattern distribution for two neurons

The network adaptation is performed during the learning phase, when the trainer introduces the noise-free pattern prototype thus specializing an available plane to recognize it. In particular, for each $u$, the weight $A_{k,vc}(u)$ is set equal to $1/N$ if $I(v_0 + u) = 1$ or equal to 0 otherwise, $vc$ is the central neuron of the $k$-th plane and $N$ is the number of non-zero elements in the pattern. The process is applied to all the remaining neurons in the same plane using the shifted versions of the prototype. In this way every output plane will be trained to recognize $m$ different patterns. The learning phase provides a response in the (0,1) range, giving the degree of correlation between the stored shapes and the incoming pattern.

During the recognition phase, the output of the network is computed using the winner-takes-all strategy that sets its neurons to zero, except the ones for which the inner product (5) yields the largest value.

3. APPLICATION TO RICH DATA

The neural network model proposed has been tested with images produced by the optical RICH detector prototype built at CERN for the NA35 Experiment [5]. The detector cross section is shown in fig. 3.

Data were taken at the CERN–PS with positive hadrons in the range $1.5 \pm 3.0$ GeV/c. The beam hit the centre of the chamber and the optical system covered the whole detector surface. An incoming charged particle first traverses the multistep avalanche counter, the fused silica window and then the liquid freon radiator (FC-72). The emitted Cherenkov photons are focused back into the detector by an array of spherical mirrors with high reflectivity in the UV region. The photons are then converted in the first gap of the counter producing photoelectrons that are largely increased in the next two
amplification gaps. The light, resulting from the avalanche process, is peaked at 480 nm by an appropriate gas mixture and is read out by a $208 \times 144$ pixels CCD camera through an image intensifier.

Fig. 3 Side view of the RICH prototype

Typical raw events generated by the detector are shown in fig. 4. Images show a circular shape, whose radius is the quantity to be measured to obtain the physical information on the particle crossing the detector. The random background of narrow isolated scattered peaks, generated by the imaging system, also appears; this further complicates the off-line pattern recognition tasks.

Fig. 4 Raw event and superimposition effect
4. RESULTS

A software simulation of the net has been implemented in C-language on a SISD machine. The design parameters are listed below:

- input layer dimension $171 \times 171$,  
- number of planes 7,  
- plane dimensions $45 \times 45$,  
- receptive field dimensions $111 \times 111$,  
- synaptic connections matrix for each neuron in a plane $111 \times 111$,  
- detectable circle radius by the k-th plane $33 + k \times 3$, $k = 1, \ldots, 7$.

Figure 5 shows typical responses of the net trained with a Montecarlo generated sample of circular patterns to match the real events recorded by the optical RICH detector.

![Typical responses of the net](image)

Radius of circle 45,  
Thickness of circle 3,  
Matching degree 0.301,  
Centre circle (x,y) (78.83).  

Radius of circle 39,  
Thickness of circle 3,  
Matching degree 0.233,  
Centre circle (x,y) (76.84).

**Fig. 5** Typical responses of the net

The behaviour of the network shown in fig. 6 over a set of input images is in good agreement with the results obtained through standard procedures (fig. 8b of ref.[5]).
5. CONCLUSION

In this paper, a parallel computational architecture for pattern matching problems has been proposed. The classification scheme is unaffected by shifts in position of the input pattern and can tolerate the noise-buttered images. Finally, it should be pointed out that the neural network topology is suitable for massively-paralleled machines, though our simulation has been performed on a computer with the traditional Von Neumann architecture.

REFERENCES


