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PROCEEDINGS

HBT analysis in ALICE with ITS stand-alone and combined neural tracking (preliminary results)

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Abstract A neural network based algorithm to perform track recognition in the ALICE Inner Tracking System (ITS) for high transverse momentum particles (p_t > 1 GeV/c) is presented. The model is based on the Denby-Peterson scheme, with some original improvements which are necessary to cope with the large track density expected at ALICE. Results are shown for central Pb-Pb events at 5.5 A TeV in the center of mass system and the comparison with the Kalman filter results is included. Data coming from this tracking procedure are used for 1-dimensional HBT correlations and results are presented.

Key words intensity interferometry (HBT) • neural networks • pattern recognition • track reconstruction • ALICE experiment

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Introduction

ALICE [7] is one of the four planned experiments at the CERN Large Hadron Collider (LHC). It will study high energy heavy ion collisions (up to Pb-Pb at 5.5 ATeV in the c.m.s.) with the aim of observing the predicted phase transition from normal hadronic matter to a plasma of deconfined quarks and gluons (QGP).

The track density resulting from such collisions is expected to reach up to 8×10^4 primary particles in the whole phase space. As a consequence, the tracking procedure in ALICE is an unprecedented challenge. This task is usually accomplished using the track information from both the Time Projection Chamber (TPC) [9] and the Inner Tracking System (ITS) [8], by means of a tracking algorithm based on the Kalman filter [2, 5, 6]. We will refer to this algorithm as the standard TPC+ITS tracking.

In this paper, we present an artificial neural network algorithm [1] for high transverse momentum tracking in the ITS stand-alone, i.e. when the information from the TPC is not available. This could be useful for two purposes:
– tracking events collected with only the fast modules of the ALICE detector (ITS, Muon-Arm, Transition Radiation Detector, etc.), in high rate acquisition runs;
– recovering some particles which decay in the TPC barrel or fall into the TPC dead zones and are not found by standard tracking procedure. In this case, our procedure works in a combined mode on the track points not used by the standard tracking.

This work is on the same track of other approaches which aimed in the past at setting up a neural tracking procedure for the ALICE ITS in the stand-alone mode [4, 13].

The model

The network

The neural network schema used here is an improvement of the Hopfield model [10], known as Mean Field Theory (MFT) approximation [16]. It consists of a single and fully connected layer of neurons with a real valued activation function a whose sigmoid shape depends on the temperature parameter T and synaptic weights w_{ij}:

$$a_i = \frac{1}{1 + \exp\left(-\frac{\sum_j w_{ij} a_j}{T} \right)}. \tag{1}$$

As in the Hopfield model with binary activations, a positive weight gives a contribution that increases the activation while a negative weight has the opposite effect.

Problem mapping

The ALICE ITS consists of six sensitive layers of silicon pixel detectors, silicon drift detectors and double-side silicon strip detectors [8], hence an experimental track is essentially a six-points polygonal. According to the Denby-Peterson model [15, 17], we associate a neuron to an oriented segment connecting two points, and we represent it with two non permutable indexes ($n_{ij} \neq n_{ji}$).

In such a representation, a neuron represents the most elementary step along the particle's path through the ITS, while its orientation takes into account the correct time direction according to which all points are produced.

We must create many possible segments starting from each point and ending in each one. Then, the neural network will turn off the wrong segments, returning only the correct ones. Finally, we will create our track candidate by simply connecting the active units into chains going from layer 1 to layer 6.

Synaptic weights

Under the most reasonable hypothesis of track continuity, non-zero weights will be allowed only for couples of neurons sharing a point, with two possible configurations.

Two units like n_{ij} and n_{jk}, define a sequence *i-j-k*. In our final track, we really want to have a chain of neurons connected in this way, so we must associate a positive weight to this kind of relation. Anyway, given that the high-p_t tracks are almost straight, we define a quality parameter which favors the well aligned pairs of segments, so that the resulting weight is:

$$w_{ijk} = A \cdot (1 - \sin\theta_{ijk})^n \tag{2}$$

where A and n are parameters of the model and θ_{ijk} is the angle between the oriented track segments corresponding to the neurons n_{ij} and n_{jk}.

On the contrary, two units like n_{ij} and n_{ik} or like n_{ij} and n_{kj} are in competition because bifurcations are not allowed. This relation is implemented in the form of a negative constant weight $-B$ which is also a parameter of the network.

In each updating cycle a neuron will receive a gain contribution from all sequenced neurons and a cost contribution from all competing ones. If the first is sensibly larger than the second, the unit will very likely be turned on, and this happens essentially for well aligned sequences of neurons. The kinked units are, instead, very likely to be turned off.

Selection criteria

The number of ITS space points in a typical central Pb-Pb event is of the order of 10^5. If we created a neuron for each possible pair, we would obtain some billions of neurons. This number is too large for many reasons:
– too big to be held in a typical PC memory;
– the neural network is very likely to get confused and give a wrong answer;
– the computing time would be too large.

In order to reduce the number of neurons, we choose to connect only points lying on adjacent ITS layers. Furthermore, given that the physical shape of a high momentum track is a helix with a very small curvature, we also apply some selection criteria on the following quantities:
– the difference in the polar angle θ of the track segments;
– the curvature of the circle in the transverse plane, passing through the primary vertex (found with the method shown in Ref. [3]) and the two candidate points;
– the expression $|z_i/l_i - z_j/l_j|$, where l is the arc of the circle defined above, going from the vertex to the space points having coordinates z_{ij} along the axis of the two colliding beams. This quantity is zero if the points exactly fit the same geometrical helix so, due to experimental errors, we can only impose that it should be smaller than a quantity ε which is another parameter of the model.

Reconstruction

Once the tracks have been recognized, space points belonging to them have to be fitted to a helix in order to determine the track parameters and their resolutions. The used fit procedure is based on the following helix parameterization:

$$\varphi = \varphi_0 + \arcsin\frac{Cr + (1 + CD)D/r}{1 + 2CD} \tag{3}$$

$$z = D_z + \frac{\tan\lambda}{C}\arcsin\sqrt{\frac{r^2 - D^2}{1 + 2CD}} \tag{4}$$

where C is one half of the track curvature, D and D_z are the impact parameters along the transverse and longitudinal directions, φ_0 is the azimuthal angle of initial momentum direction, and λ is the track dip angle ($\tan\lambda = p_z/p_t$). The fit is performed by means of a Kalman filter procedure with a seed given by a rough estimation of the helix passing through the two innermost points and the vertex.

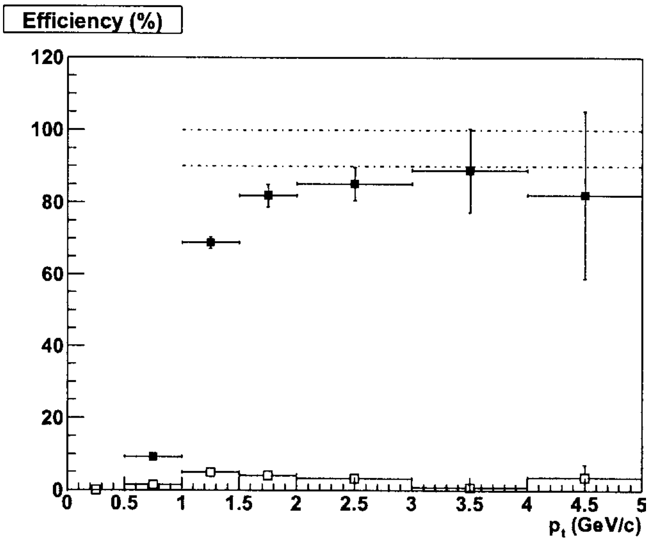

Fig. 1. Track recognition efficiency (closed points) and fake track probability (open points) in the ITS stand-alone.

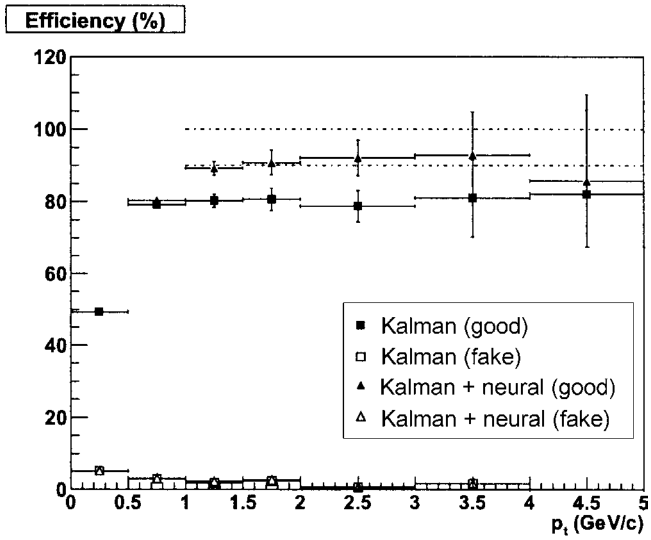

Fig. 2. Track recognition efficiency (closed points) and fake track probability (open points) of the standard and combined tracking. The meaning of all histograms are well explicated by the labels. In the lower part of the plot, there is the fake track probability. Due to a very negligible contamination of the combined tracking step, the two histograms look superimposed.

Results

In order to evaluate the performances of the algorithm described so far, some tests have been made with simulated central Pb-Pb collisions at LHC energy (5.5 A TeV in the c.m.s.) by means of a parameterization of the HIJING generator [14]. About 130 events have been generated with the multiplicity of 4000 particles per unit of rapidity at mid-rapidity, and a magnetic field of 0.4 Tesla. For this purpose, some C++ classes simulating the neural network have been implemented in AliRoot [11], the object oriented ALICE simulation and reconstruction framework. Figure 1 shows the track recognition efficiency (closed points) and the fake track probability (open points) as a function of the transverse momentum. A track is considered good if it leaves at least five correctly recontructed points in the six sensitive ITS layers. Otherwise, it is tagged as fake. For all good tracks which have been found by the neural network, track parameter resolutions have also been evaluated for p_t, ϕ_0, λ, D and D_z with the method cited above. Standard deviations of the track parameter resolutions are reported in Table 1 together with the values obtained with the standard Kalman TPC+ITS procedure. It is worth stressing here that the neural tracks only contain 6 ITS points, while the ones found with the standard method can contain up to 160 TPC points. This explains why track parameter resolutions obtained with the neural tracking are worse than those obtained with the Kalman filter.

Table 1. Track parameter resolutions for the neural and the standard tracking.

Parameter	Neural	Kalman
p_t (%)	7.45 ± 0.08	1.57 ± 0.02
λ (mrad)	1.88 ± 0.02	1.60 ± 0.08
ϕ (mrad)	1.90 ± 0.03	1.40 ± 0.08
D_t (μm)	77.6 ± 0.9	50 ± 0.01
D_z (μm)	164.8 ± 1.5	150 ± 0.01

We also tried to perform the neural tracking in a combined mode, as explained above. We performed a standard TPC+ITS tracking and, after removing the ITS points used by the Kalman filter, we performed the neural tracking. The results are shown in Fig. 2. The circles are relative to the global efficiency after the standard Kalman TPC+ITS procedure, while the boxes are relative to the global efficiency after the neural procedure. One can see how the neural network increases by almost 10% the tracking efficiency for transverse momenta larger than 1 GeV/c.

Hanbury-Brown Twiss (HBT) interferometry analysis

Given that the statistics obtained with these events is still too few in order to perform a 3-dimensional HBT analysis, we used the 1-dimensional HBT analysis as a function of Q_{inv}. Thanks to the collaboration with the Warsaw University of Technology, an interface has been implemented in order to translate the track information coming from the neural tracks into the internal format of the AliRoot HBT analyzer [12].

The HBT correlation have been generated for like pions by means of the method of weights, according to its implementation in the HBTAN package [12] and the source settings are the ones commonly used for other studies presented in the ALICE Collaboration for HBT studies: $R = 8$ fm and $\lambda = 0.5$. Results are shown in Fig. 3. In order to evaluate preliminary results with a clean signal, we switched off the Coulomb interaction effects and included Quantum Statistical correlations only. For comparison, we also show in Fig. 4 a correlation function (CF) calculated in exactly the same way, but with all the correlations switched off in the generator. The falling down of the CF for small values of Q_{inv} is clearly visible. Given that the particles are bosons and that the Coulomb effect has not

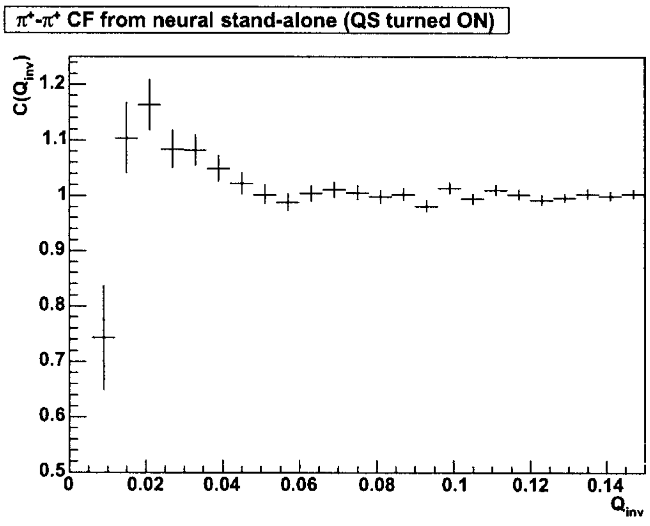

Fig. 3. Mono-dimensional correlation function as a function of Q_{inv} for 130 events generated with the multiplicity of 4000 particles/unit of rapidity at mid-rapidity and a magnetic field of 0.4 T.

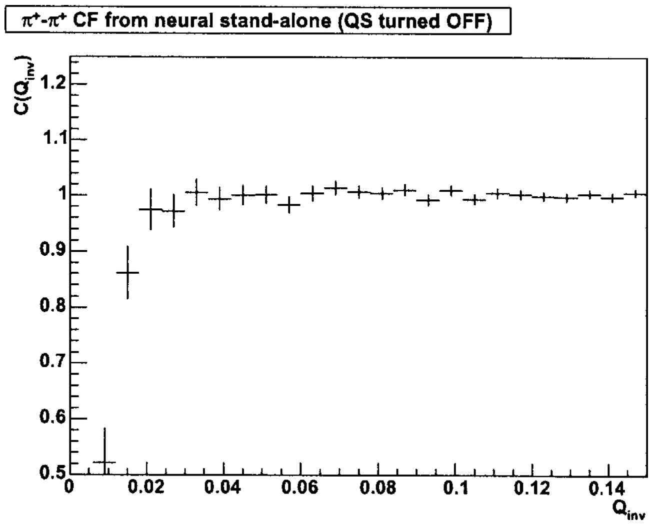

Fig. 4. Mono-dimensional correlation function obtained for the same settings of the previous Figure, when all correlation effects are switched off in the generator.

been taken into account, then we can conclude that this behavior of the CF is just due to the double-track resolution of the Neural Tracking. Anyway, looking at the figures, we can notice that the enhancement is well evidenced, even if the CF falls down at very small values of Q_{inv}. In order to give a quantitative evaluation of this results, we compared the obtained correlation function with a flat distribution equal to 1 in the region where the fall-down of the CF is no more evident, by means of a χ^2 test. The result of the test is the following:

$$\chi^2 = 42.8, \qquad N_{dof} = 23 \tag{5}$$

which means, according to the critical values for the compatibility, that the experimental CF and a flat distribution are incompatible with a probability of 99%. Then, we can state from this result that the HBT correlation signal is detectable with the tracks coming out from the Neural Tracking in the ITS stand-alone.

Conclusions

In this paper we have presented a modified Hopfield neural network to perform a track finding and reconstruction in the ALICE Inner Tracking System stand-alone for high transverse momentum tracks (p_t > 1 GeV/c). The results obtained are encouraging for a further use of this method during real event reconstruction.

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