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Elastic Tracking versus Neural Network Tracking for Very High Multiplicity Problems

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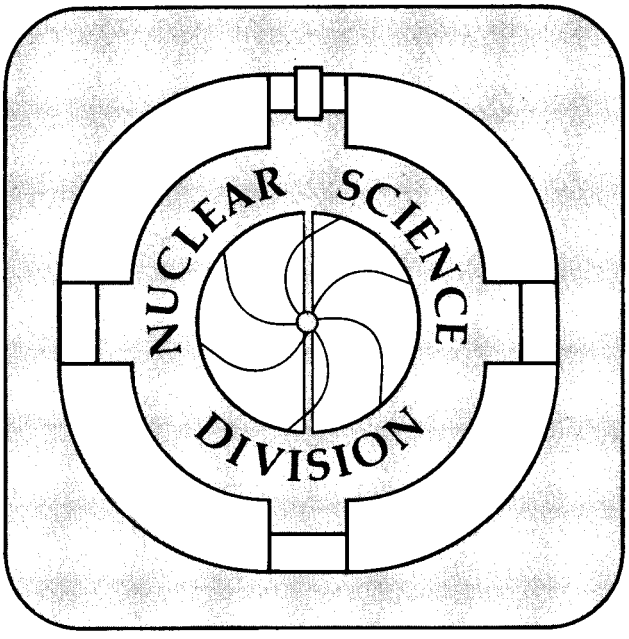

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Elastic Tracking versus Neural Network Tracking for Very High Multiplicity Problems*

Contribution to the Austrian Artificial Intelligence Conference 1991, Vienna

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Abstract:
A new Elastic Tracking (ET) algorithm is proposed for finding tracks in very high multiplicity and noisy environments. It is based on a dynamical reinterpretation and generalization of the Radon transform and is related to elastic net algorithms for geometrical optimization. ET performs an adaptive nonlinear fit to noisy data with a variable number of tracks. Its numerics is more efficient than that of the traditional Radon or Hough transform method because it avoids binning of phase space and the costly search for valid minima. Spurious local minima are avoided in ET by introducing a time-dependent effective potential. The method is shown to be very robust to noise and measurement error and extends tracking capabilities to much higher track densities than possible via local road finding or even the novel Denby-Peterson (DP) neural network tracking algorithms.

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1 Introduction

Detecting curves within a complex pattern of points is a classic problem in pattern recognition and computer vision with many important practical applications[1]. In the context of high energy and nuclear physics, a common problem is the detection of the ionization paths of many charged particles in a device such as a bubble, streamer, or time projection chamber and the determination of particle momenta by fitting physical trajectories consistent with known electric and magnetic fields (see e.g. [2]). Of course, many local and global methods have been developed to solve this problem[1, 3, 4]. Thusfar, most experiments had to cope only with rather low multiplicities and track densities, and conventional tracking methods have proven adequate. However, there is a need to develop more powerful methods to cope with the increasingly complex pattern recognition tasks that future high energy and nuclear experiments may face. For example, future heavy ion experiments [5] at RHIC/BNL and LHC/CERN could be confronted with trying to track up to 10^4 charged particles per event. Our aim was to explore theoretical limitations of present tracking methods and to propose a new elastic tracking (ET) method that extends present tracking capabilities to much higher track densities. By track density, ρ_{track}, we mean the average ratio of the distance between measured points along a track to the distance between points belonging to different tracks or random noise points.

This work was also motivated by the pioneering work of Denby [6] and Peterson [7] on applications of Hopfield type neural networks [8, 9] to tracking and other pattern recognition tasks in high energy physics (see also [10]). Since the performance of such neural network tracking methods has not yet been compared to that of more conventional algorithms, one aim of our work was to carry out such a comparison. In particular, we used as a benchmark the conventional local Road Finder (RF) algorithm [4].

A detailed description of the algorithms and techniques we used and the results can be found in Ref. [12].

2 Elastic Tracking

Elastic Tracking is based on a reinterpretation and dynamical generalization of the Radon transform. The Radon Transform just counts the number of

data points inside a tube around a trajectory. Scanning the feature space and calculating the Radon Transforms for all possible trajectory parameters $\mathbf{p}$ will give a function depending on $\mathbf{p}$ with maxima at points where the parameters fit to a real track. This procedure is very expensive if high resolution is desired or the feature space is high dimensional (> 2).

To avoid the problem of scanning the entire feature space, we proposed a dynamic approach to the problem of looking for the maxima of the Radon transform. We employ template trajectories (e.g. helices or straight lines) and assign a positive charge distribution along the track. That track is then allowed to interact with the negative (ionization) charge distribution measured by the experimental device. The problem is then reduced to minimizing the energy of this template trajectory. Given a distribution of data points $\rho(\mathbf{x})$ this energy is evaluated as

$$E(\mathbf{p}_T, t) = -\int d\mathbf{x} d\mathbf{x}' \rho(\mathbf{x}) V(\mathbf{x} - \mathbf{x}', t) \rho_T(\mathbf{x}') \ , \tag{1}$$

The minimum of this function is found by solving the (gradient descent) equations of motion for the template parameters, which in our case is the three momentum $\mathbf{p}_T$ of the particle producing the ionization density:

$$d\mathbf{p}_T/dt = -\nabla_{\mathbf{p}_T} E(\mathbf{p}_T, t) \ , \tag{2}$$

There is of course considerable freedom in the choice of the effective potential. We adopt for convenience a simple Lorentzian form,

$$V(x, t) = w^2(t)/(x^2 + w^2(t)) \ , \tag{3}$$

with a time dependent range

$$w(t) = b + (a - b)\exp(-t/c) \ . \tag{4}$$

A slow iteration time dependence of the range is introduced to get a global view on a scale a at an early stage of the iteration process and to focus later on more closely to the track being converged to. This also avoids getting caught in local minima. The natural scale for the asymptotic range is $b \sim \Delta x$, where Δx is the rms measurement error of the data points.

In this way ET performs a nonlinear adaptive fit. The nonlinearity in (3) reduces greatly the sensitivity to outlier points from other tracks or noise when the interaction length $w(t)$ approaches its final small value b.

Once convergence is achieved for one track, another one could be looked for by starting with a new random initial template and waiting until a new valid minimum is found. However, convergence for new tracks can be speeded up by introducing multiple elastic track dynamics. Since two trajectories should not converge to the same track, an effective repulsive interaction between trajectories should be introduced. The repulsive interaction can be taken into account by evolving the present template in the screened field due to the positive charge distribution of all already converged tracks as well as the negative distribution generated by the data points. In effect a converged track neutralizes the ionization density around that track making it easier for later tracks to converge to new solutions.

We emphasize that ET can be used with the unprocessed real charge distributions measured by TPC's and other particle detectors without expensive and error producing preprocessing steps. It also eliminates the need for post-processing usually needed to fit the track parameters since the output of ET is directly the particle momentum (and possibly the vertex origin). This is a major advantage against probably all other methods which need real discrete data points to construct tracks and fitting algorithms to get the track parameters.

3 Other Methods

3.1 Road Finder

To compare the performance of ET with that of more conventional approaches we implemented two other methods of trackfinding. One is the conventional and widely used so called Road Finding algorithm (RF), which we like to call the "Follow Your Nose" method. The principle is very simple and also very efficient if track density is low.

We start by picking three nearly collinear points in a low density region of the detector. Projecting this line in direction of the vertex, a chain of points is to be built up as long as a point is found inside a certain cone along the projected line and distance from the last point in the chain. If more than one point is found inside the cone both are ignored. Each point has to be labeled if it is was touched once, since it can belong only to one track. Labeling and skipping however can introduce gaps large enough that it doesn't make sense

to continue searching. Therefore the result of this procedure will be a set of tracklets to be combined to tracks afterwards. Fitting track parameters has to be done in addition at the very end.

3.2 Denby - Peterson Net

Another approach was proposed recently by Denby [6] and Peterson [7]. They constructed a Hopfield type net with a neuron as a link between a pair of data points, that should relax to a state where only neurons relating to valid links should be on. Therefore a weight function has to be constructed that penalizes heavily kinks and long links. The energy function is given by

$$E = \frac{1}{2} \sum_{ijk} s_{ij} s_{jk} W_{ijk} \quad , \tag{5}$$

with the weight function

$$W_{ijk} = (A - (A + B)\cos^{2n}(\theta_{ijk}/2))/(r_{ij} + r_{jk}) \quad , \tag{6}$$

where we took $A = 4, B = 0.5$, and $n = 16$. Here θ_{ijk} is the angle between the links $\mathbf{r}_{ij}$ and $\mathbf{r}_{jk}$. The dynamics of the net evolve according to the mean field equations

$$s_{ij} = \frac{1}{2}(1 + \tanh(-\frac{1}{T}\frac{\partial E}{\partial s_{ij}})) \quad , \tag{7}$$

which are solved by iteration.

4 Results

Numerical simulations have shown that ET performs substantially better in case of real hard problems e.g. very high track densities. Figure 1 shows what a hard problem is. Using all information about the long range correlations in the data ET can resolve all tracks with correct multiplicity even in an environment with 100% noise. In Figure 2 the three methods are shown in comparison. The Road Finder fails first, than the Denby-Peterson Net and ET performs perfect in all cases.

Since this high track densities can be created in 2D with less data points (N) than in 3D we have chosen a 2 dimensional geometry for computational

efficiency. In 3D TPC's of the future however the data will be as dense as it is shown in Figure 1 and very high speed computers will be necessary to handle the data.

It has to be noted that the Road Finder is always the fastest algorithm, since it scales $\sim N^2$ with a small prefactor. ET scales also with $\sim N^2$ but with a much higher prefactor and the problem of determining convergence of the algorithm. The DP Net scales at least with $\sim N^3$ and takes longest in almost all cases.

Considering these results ET appears to be an especially promising data analysis method for highly correlated data with lots of noise. Parallel hardware implementations however could it make even applicable for real time problems.

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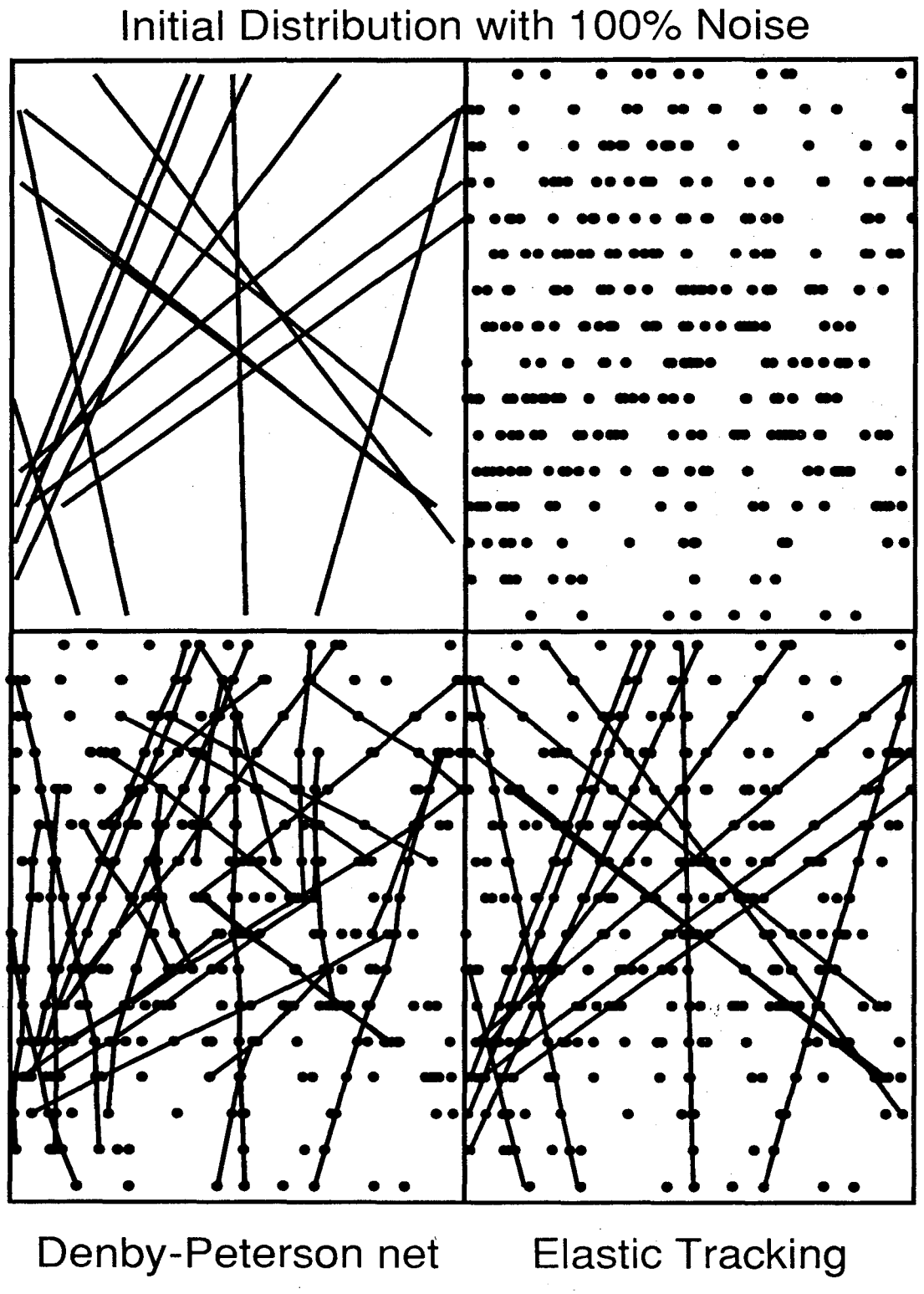

Figure 1: A real hard problem: 20 tracks with 100 percent noise.

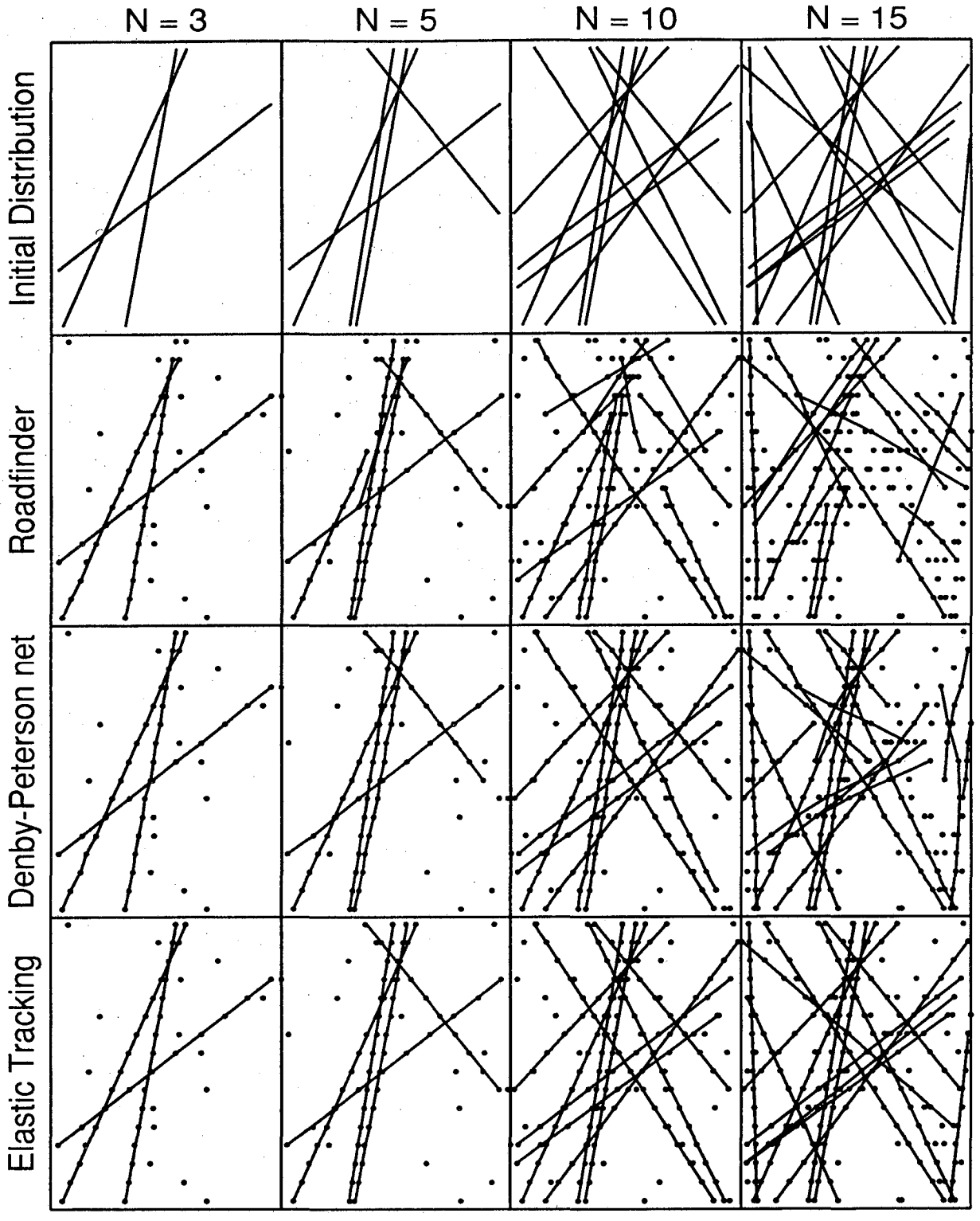

Figure 2: Road Finder, Denby Peterson Net and ET in 2 dimensions
for multiplicities of 3,5,10 and 15.

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