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Nuclear Instruments and Methods in Physics Research A 566 (2006) 157–165

NUCLEAR INSTRUMENTS & METHODS IN PHYSICS RESEARCH Section A

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Reconstruction of charged tracks in the presence of large amounts of background and noise

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Available online 2 June 2006

Abstract

We consider the problem of track reconstruction with very large amounts of background and noise. This paper is the sequel to a previous publication [R. Frühwirth, A. Strandlie, Nucl. Instr. and Meth. A, to appear], which deals with track finding in various noise scenarios. We extend the study by considering the full track reconstruction chain, i.e., by submitting the track candidates from the track finding procedure to a track fit for obtaining final estimates of the track parameters. It is shown that a standard least-squares estimator such as the Kalman filter does not reach optimal precision after the track fit and that the estimates can be improved by using the Deterministic Annealing Filter (DAF) for the final hit assignment and parameter estimation.

PACS: 07.05.Kf; 29.85.+c

Keywords: Track finding; Track fitting; Combinatorial Kalman filter; Gaussian-sum filter; Deterministic annealing filter

1. Introduction

Track reconstruction is traditionally divided into two separate tasks: track finding and track fitting. The track finding procedure starts out with a set of measurements of hit positions in a track detector and aims to divide this into a number of subsets, each subset containing measurements believed to originate from the same particle. Such a subset is called a *track candidate*. There is also an additional subset with measurements believed not to come from any of the interesting particles. The track fit starts out with the track candidates as provided by the track finder and aims to optimally estimate a set of parameters describing the state of the particle somewhere in the detector, for instance close to the interaction vertex. The track fit is also used to evaluate the quality of the track candidates and to discard those which do not pass a given quality criterion, often in terms of a cut on the value of a χ^2-statistics.

With the introduction of the Kalman filter as a track fitting algorithm [2,3], the boundary between track finding and track fitting became more fuzzy. Due to the recursive nature of the Kalman filter, it was soon realized that it could also be used for track finding [4]. The currently most popular approach is the so-called combinatorial Kalman filter (CKF) [5], which builds up a combinatorial tree of track candidates, starting from a seed. In the end, the best of the track candidates is kept and submitted to the Kalman smoother (KSM) for the final track fit.

A more recent development—the Deterministic Annealing Filter (DAF [6])—assigns measurements to the track concurrently with the estimation of the track parameters. Starting out from a preliminary estimate of the track parameters as given by the track finder, it iteratively adapts the parameters such that the track is attracted to the correct hits. It down-weighs the influence of noise and background by assigning small weights to such hits in the track fit.

In this paper we address the problem of track finding and track fitting in environments with very large amounts of background and noise. It is shown that for such scenarios a classical least-squares fit is not the optimal track fitting method, even if a very elaborate and cumbersome track finding procedure has been applied

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doi:10.1016/j.nima.2006.05.026

beforehand. Better estimates can be obtained by applying an adaptive track fitting algorithm such as the DAF after the track finding. Scenarios with various noise and contamination levels and with various upper limits on the number of components kept during track finding are studied.

The paper is organized as follows. In Section 2, the track finding and track fitting methods used in this study are briefly described. Section 3 presents results from various simulation studies. A discussion of the results and some conclusions can be found in Section 4.

2. The track reconstruction strategies

2.1. Track finding

Several adaptive generalizations of the CKF have been investigated with respect to their track finding capabilities in a previous study [1]. Here the two most successful algorithms are studied in more detail: the CKF itself and the Gaussian-sum filter (GSF, [6,7]). Whereas the CKF is building up a tree of independent track candidates, the GSF introduces the notion of competition between the different track candidates originating from the same seed. This can be understood from the expression of the posterior weights q_k^{ij} of the candidates or components [6]

$$q_k^{ij} \propto \pi_k^j \varphi(\boldsymbol{m}_k^i; \boldsymbol{H}_k \boldsymbol{x}_{k|k-1}^j, \boldsymbol{V}_k + \boldsymbol{H}_k \boldsymbol{C}_{k|k-1}^j \boldsymbol{H}_k^{\mathrm{T}})$$

where π_k^j is the prior weight of component j, φ is a Gaussian probability density function, $\boldsymbol{m}_k^i$ is measurement i with covariance matrix $\boldsymbol{V}_k$, $\boldsymbol{x}_{k|k-1}^j$ is the predicted state vector of component j with covariance matrix $\boldsymbol{C}_{k|k-1}^j$ and $\boldsymbol{H}_k$ is the observation matrix. The index k denotes that the quantities are defined at detector layer k. The constant of proportionality is determined by the requirement that the sum of all q_k^{ij} is equal to 1, implying that the most compatible combinations of predicted components j and measurements i tend to down-weigh the less compatible combinations. When a posterior weight drops below a value of 10^{-3}, the corresponding component is dropped. It was shown in Ref. [1] that this feature of track candidate competition made the GSF slightly faster than the CKF.

Both the CKF and the GSF allow for missing hits. This is accomplished by creating in each layer a candidate with no hit from this layer, in addition to the candidates with the compatible hits from this layer. The number of missing hits is, however, limited, and candidates with too many missing hits are dropped. It is also helpful to put a separate, upper limit on the number of consecutive missing hits. Finally, a candidate that differs from another candidate only by a missing hit in a previous layer is dropped. In addition, a (loose) χ^2-cut is applied to all candidates at each layer.

2.2. Selection of the best candidate

Both the CKF and the GSF may retain several candidates after incorporation of the last observation in the track candidate. In most cases, these candidates are very similar, differing only at a few positions. Before the track fit the "best" candidate has to be selected. The decision criterion should take into account both the quality of the fit, expressed in terms of a χ^2-statistics, and the number of hits in the track candidate, expressed in terms of the number of degrees of freedom n_{dof} of the fit. The well-known Akaike information criterion [8] cannot be applied directly as it is designed for model selection with a fixed number of observations and a variable number of parameters, whereas in our case there is a fixed number of parameters and a variable number of observations. The analogous criterion in this case would be $\chi^2 - 2n_{\mathrm{dof}}$. This, however, has the drawback that it prefers candidates with small chi-squares and fewer degrees of freedom over ones with larger, but perfectly acceptable, chi-squares and more degrees of freedom, at the expense of the resolution and at the risk of a higher fake rate. We have therefore used a modified criterion which damps the influence of the chi-square and thus gives more weight to the number of degrees of freedom

$$t = \ln(\chi^2) - 2n_{\mathrm{dof}}.$$

The selected track candidate is the one that minimizes the criterion t.

2.3. Track fitting

Two different methods of track fitting have been investigated. The first one is a standard KSM running on the best candidate—in terms of the smallest value of the selection criterion t—after track finding. However, in environments with large amounts of background and noise it is plausible that track finding algorithms are not able to completely resolve all ambiguities. We have therefore developed an alternative track fitting strategy based on the DAF [6]. Measurements are collected in a band around the best candidate from the track finding, and the DAF is run until convergence on this set of measurements. In the results shown below, four iterations were performed. Such a strategy defers the final assignment of measurements from the track finding to the track fit, as the DAF makes such an assignment in parallel with estimating the track parameters.

In the ATLAS-like setup of Experiment 2 (see Section 3.2) the DAF has also been deployed as a combined track finder/fitter in the transition radiation tracker, without invoking the CKF or the GSF first. This is possible because of the high quality of the track segment in the silicon tracker that is used as the seed. In such a stand-alone mode of the DAF the track parameters from the seed are propagated directly to the end of the detector, picking up measurements compatible with the prediction in the