Vertex reconstruction framework and its implementation for CMS

T. Boccali
CERN, Geneva, Switzerland
R. Frühwirth, W. Waltenberger*
Institut für Hochenergiephysik der ÖAW, Vienna, Austria
K. Prokofiev, T. Speer
Physik-Institut der Universität Zürich, Switzerland
P. Vanlaer†
Interuniversity Institute for High Energies, ULB, Belgium

The class framework developed for vertex reconstruction in CMS is described. We emphasize how we proceed to develop a flexible, efficient and reliable piece of reconstruction software. We describe the decomposition of the algorithms into logical parts, the mathematical toolkit, and the way vertex reconstruction integrates into the CMS reconstruction project ORCA. We discuss the tools that we have developed for algorithm evaluation and optimization and for code release.

1. INTRODUCTION

As many reconstruction problems, vertex reconstruction can be decomposed into the following steps:

- Pattern recognition, or vertex finding. This step consists in finding clusters of compatible tracks among a set of tracks given on input. The search can either be inclusive, like in the search of a secondary vertex in a b-jet, or be guided by the a-priori knowledge of the decay channel.
- Fitting. This step consists in estimating the vertex position most compatible with the set of tracks given on input, and constraining the momentum vector of the tracks using the vertex position.

In high-luminosity experiments, vertex reconstruction algorithms must be able to deal with large track multiplicities, frequent ambiguities in the separation of primary and secondary tracks, and track misreconstructions leading to biases in the estimated track parameters. As an illustration of the difficulty to separate primary and secondary tracks, the resolution on the transverse impact parameter of the CMS tracker ranges from $\sim 100~\mu\mathrm{m}$ for tracks with $p_T=1~\mathrm{GeV}/c$ to $\sim 10~\mu\mathrm{m}$ for tracks with $p_T=100~\mathrm{GeV}/c$ [1, 2], while the transverse impact parameter of secondary tracks in 50 GeV b-jets is on average much smaller than 1 mm.

Although the algorithmic part of the problem is the most difficult to solve, an additional constraint comes

from the CPU time available online in LHC experiments. Simulation studies have shown the interest of primary vertex finding for online event filtering [3, 4]. In addition, b-jet tagging by detecting a secondary vertex inside the jet cone seems to perform almost as well as impact parameter tagging [5], and to complement this method to some extent.

For this to be applicable, the CPU time that vertex finding takes should be small, O(50 ms) on the processors expected in 2007. As vertex finding is often based on repeated compatibility checks between tracks and fitted vertices, this translates into very strong CPU constraints on vertex fitting algorithms as well.

2. MOTIVATION FOR A FRAMEWORK

When developing vertex reconstruction code, physicists face the following issues:

- The algorithmic problem is complex. The optimal algorithm cannot be guessed from the start, and there will probably be no single optimal algorithm but several, each optimized for a specific task.
- The mathematics involved is complex, but often localized in a few places. Development would be made easier by providing a toolkit of mathematical classes.
- Performance evaluation and comparison between algorithms is not trivial. Vertex reconstruction uses reconstructed tracks as input, and features of the vertexing algorithms must be disentangled from those of the tracking algorithms. Criteria to compare Monte Carlo simulated and reconstructed vertices are ill-defined and need to be standardized.
- Finally, the problem is quite generic and decoupled from the detector geometry once tracks are

^{*}Supported by the Fonds zur Förderung der wissenschaftlichen Forschung, Project 15177.

[†]Corresponding author. Supported by the Belgian Federal Office for Scientific, Technical and Cultural affairs through the Interuniversity Attraction Pole P5/27.

given. This makes a good case for providing a framework reuseable in other HENP experiments.

We have thus decided to develop a flexible framework in order to ease the development and evaluation of algorithms. This is realized within the CMS object-oriented reconstruction project ORCA [6]. Section 3 describes the vertex fitting framework. Section 4 deals with the vertex finding framework, with a focus on evaluation and optimization tools. Section 5 explains the use of a simplified configurable event generator for faster code development and release tests.

3. VERTEX FITTING FRAMEWORK

The fitted parameters are the solution of a minimization problem involving the residuals between the vertex parameters \vec{x} and a transformation f of the track parameters $\vec{p_i}$:

$$Min_{\vec{x}} F[\vec{x} - f(\vec{p_i})]; \quad i \in \text{input tracks.}$$

Fitting algorithms may differ by the choice of the track parametrization, and by the choice of the function F to minimize. Each algorithm is a different implementation of the abstract VertexFitter class.

A usual choice for F is the sum of the reduced residuals squared, this is the well-known Least Sum of Squares, or Least Squares, technique. In this case the minimum of F can be expressed explicitly as a function of the $\vec{p_i}$'s, which is CPU-effective. This requires however to linearize the transformation f in the vicinity of the true vertex position.

3.1. Linearization

The linearization is performed on demand and cached for performance. This is done by instances of a concrete class, the LinearizedTrack. Currently we use 2 linearizations, corresponding to different track approximations:

- A straight line approximation, and a constant track error matrix hypothesis.
- A helix approximation, and a linear error propagation using the first derivatives of f with respect to the track parameters as Jacobians.

Formally the second approximation is much more precise, but in the p_T range of interest at the LHC, both have negligible contributions to the precision of the fitted vertex.

The LinearizedTrack is also responsible for providing the parametrization required by the algorithm. All useful parametrizations are supported. We currently use (x, y, z) at the point of closest approach to

the vertex, together with the straight line approximation, and $(q/p_T, \theta, \phi_p, d_0, z_p)$ the 5 track parameters at the perigee, with the helix approximation.

Linearization around the true vertex position requires a first guess of this position. This is provided by LinearizationPointFinder algorithms. These compute the average of the crossing points of N track pairs (N=5 by default). In order to use tracks of best precision, the 2*N tracks of highest p_T are selected. Two implementations are available, one using the arithmetic average of the crossing points, and one using a Least Median of Squares (LMS) robust averaging technique [7, 8].

These algorithms rely on fast computation of the points of closest approach of 2 tracks. The system of 2 transcendent equations is solved for the running coordinates along the tracks using a highly optimized Newton iterative method. The maximum CPU time required for finding the linearization point is 0.1 ms on 1 GHz processors.

3.2. Iterative vertex fitting

Iterations arise naturally when:

- The linearization point is too far from the fitted vertex.
- The function F has no explicit minimum. This is the case in robust fitting techniques. Robust estimators can be reformulated as iterative, reweighted Least Squares estimators [7, 8].
- Several vertices are fitted together, accounting for ambiguities in an optimal way [9]. In such a Multi-Vertex Fit, one LinearizedTrack can contribute to several vertices with different weights.

This lead us to the introduction of another concrete component, the VertexTrack. It relates a LinearizedTrack to a vertex, and stores the weight with which the track contributes to the fit. To avoid having to care for the ownership of these objects, LinearizedTrack and VertexTrack are handled through reference-counting pointers.

3.3. Sequential vertex update

Apart from cases where some hits are shared, tracks are uncorrelated. This allows sequential update of the fitted parameters, by adding one track at a time. This procedure is faster than a global fit [10]. The VertexUpdator is the component responsible for updating the fitted parameters with the information of 1 track.

To compute the χ^2 increment, the VertexUpdator uses the VertexTrackCompatibilityEstimator.

This increment can also be used at vertex finding to test the compatibility between a track and a vertex. The VertexUpdator and the VertexTrackCompatibilityEstimator are abstract and there are 2 implementations, 1 for each parametrization.

The CPU time for track linearization and vertex update is < 0.25 ms per track on 1 GHz processors.

3.4. Constraining the track momentum vectors

The momentum vectors of the tracks can also be improved using the vertex as a constraint. This is done by considering the $3N_{tracks}$ momentum components as additional parameters in the vertex fit. However the calculation of the constrained momenta and their correlations is CPU-consuming, and often only the fitted vertex position is needed.

We could separate this step in a VertexSmoother component. It is run after fitting the vertex coordinates, using intermediate results cached into the VertexTrack objects. The user configures the VertexFitter so as to use this component or not.

4. VERTEX FINDING FRAMEWORK

The variety of vertex finding algorithms that we currently explore is large [8], and the decomposition of algorithms into components still evolves while new common features appear. We will thus not describe them, but rather focus on the evaluation and optimization tools.

4.1. Evaluation

4.1.1. Performance estimation

We wish to compare the performance of the algorithms in finding the primary and secondary vertices, in producing ghost vertices from random track associations, and in assigning the tracks to their vertex efficiently and with a good purity. The first 3 figures concern the vertex finding proper, and are evaluated by implementations of the VertexRecoPerformanceEstimator class. The last 2 figures concern the assignment of tracks to vertices. They are computed by implementations of the VertexTrackAssignmentPerformanceEstimator. These estimators are updated each event.

4.1.2. Vertex selection and association

The user needs to tell to these estimators which simulated vertices are important to reconstruct. A standard Filter is provided, which keeps only the simulated vertices for which at least 2 tracks were successfully reconstructed. This allows to study the algorithmic efficiency of vertex finding.

The user also tells how to associate a simulated vertex to a reconstructed one. This is defined by a VertexAssociator. Association can be done by distance or by tracks, counting the tracks common to the simulated and the reconstructed vertex. In standard tests the association is done by tracks. A simulated vertex is considered found if there is a reconstructed vertex with > 50% of its tracks originating from it. The association of the reconstructed and simulated tracks is performed by a TrackAssociator provided by the ORCA track analysis framework.

4.2. Optimization

Vertex finding algorithms have a few parameters that need to be tuned in order to get optimal performance for a given data set. Often, every physicist has to write his own code which scans the parameter range and finds the optimum parameter values.

We propose a simple and elegant automatic tuning framework. The components of this framework are an abstract TunableVertexReconstructor, which interacts with a FineTuner object, and a special run controller which stops analysing events when the desired precision on the tuned parameters is reached. The TunableVertexReconstructor provides the FineTuner with the initial range of parameter values to be scanned. The FineTuner is an interface to an optimization engine. It maximises a Score, which is a function of the performance estimators configurable by the user:

$$Score = (EffPV)^a . (EffSV)^b . (1 - FakeRate)^c ...$$

The user only has to re-implement the TunableVertexReconstructor for the concrete algorithm and parameters that are to be tuned. Currently the FineTuner implementation available is a 1D maximizer, allowing to tune 1 parameter at a time

5. TESTS WITH CONTROLLED INPUT

Parts of vertex reconstruction algorithms rely on models describing prior information. This information is for example the event topology (size of beam spot, number of vertices,...) or the track parameter distributions (Gaussian resolution and pulls, tails...). Data often depart from these models, which affects the performance of the algorithms.

To disentangle this from more intrinsic features of the algorithms, we have developed a simple Monte Carlo generator. It allows to simulate data in perfect agreement with the prior assumptions, or distorted in a controlled way. The number and position of the vertices, the number and momentum of the decay prongs, the track parameter resolutions and tails are defined by the user.

This simulation takes O(10) ms per event, more than a thousand times faster than full event reconstruction. The time needed to perform most of the code debugging is reduced by the same factor. Another important advantage is that most of the release tests of the vertex reconstruction code can be run independently of the status of the reconstruction chain upstream. The simple Monte Carlo generator is currently being interfaced with the CMS fast Monte Carlo simulation (FAMOS) [11] to account for track reconstruction effects in a more realistic way.

6. CONCLUSION

We have developed an efficient and flexible class framework for the development of vertex fitting algorithms. It allows the coding of usual least-squares algorithms as well as robust ones. We provide a friendly environment for the evaluation and optimization of vertex finding algorithms. As shown at this conference [8], the performance of the vertex fitters and finders tested for the CMS experiment are already close to matching the requirements for use online at the LHC.

References

[1] CMS Collaboration, The Tracker Project - Technical Design Report, CERN/LHCC 98-6, 1998.

- [2] A. Khanov et al., Tracking in CMS: software framework and tracker performance, Nucl. Instr. and Meth. A 478 (2002) 460.
- [3] CMS Collaboration, The TriDAS project Technical Design Report, Volume 2: Data acquisition and High Level Trigger, CERN/LHCC 02-26, 2002.
- [4] D. Kotlinski, A. Nikitenko and R. Kinnunen, Study of a Level-3 Tau Trigger with the Pixel Detector, CMS Note 2001/017.
- [5] G. Segneri, F. Palla, Lifetime based b-tagging with CMS, CMS Note 2002/046.
- [6] http://cmsdoc.cern.ch/orca/
- [7] R. Frühwirth et al., New developments in vertex reconstruction for CMS, Nucl. Instr. and Meth. A 502 (2003) 699.
- [8] see W. Waltenberger, *Vertex reconstruction algo*rithms in CMS, these proceedings.
- [9] R. Frühwirth, A. Strandlie, *Adaptive multi-track fitting*, Computer Physics Communications 140 (2001) 18.
- [10] R. Frühwirth et al., Vertex reconstruction and track bundling at the LEP collider using robust algorithms, Computer Physics Communications 96 (1996) 189.
- [11] S. Wynhoff, Dynamically Configurable System for Fast Simulation and Reconstruction for CMS, these proceedings. http://cmsdoc.cern.ch/famos/