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Flavour tagging studies for the TESLA linear collider

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Abstract. The ability to distinguish the flavour of jets formed in an event is a very important parameter to evaluate, when designing a high performance vertex detector to use in a future e^+e^- linear collider. In this work we concentrate on a CCD (Charged Coupled Device) pixel vertex detector. We first evaluate the basic tracking perfomance. We then estimate the flavour tagging performance of the present detector layout, using a neural network approach. We conclude by studying the energy dependence of the perfomance.

INTRODUCTION

The tagging of jets containing heavy flavours is crucial for the studies planned for the future high energy Linear Collider (LC). One of the main goals will be to study in detail the Higgs boson and its branching ratios to different quarks. LEP and SLD have shown that high b tagging performances can be achieved, and that they are an essential element in precision measurements and new particle searches. At the next LC, with a more ambitious programme in the Higgs sector and the possibility of complex supersymmetry processes, charm tagging also becomes important. This poses more stringent requirements on the vertex detector, because of the kinematics of charm decays. The studies described here show that the current design for the CCD detector should certainly fulfill the requirements of the LC physics program, and provide very high quality physics results in this new energy regime.

DETECTOR AND SIMULATION TOOLS

The studies described in this paper are carried out with the generation package JETSET7.4 and with the detector simulation and track reconstruction package for

TESLA, BRAHMS 2.01 [1]. The tracking detectors used are:

- a CCD vertex detector, 5 layers, starting at 1.5 cm from the beam line, and with a point resolution of 3.5 μm. This is described in [2].
- a Time Projection chamber, extending radially from 32 to 170 cm, with a half length in z of 273 cm, and providing 118 points with a resoluton in $r-\phi$ of 160 μm and in z of 1 mm.
- a Silicon Intermediate Tracker, two cylinders of radii 16 and 30 cm, and half length in z up to 66 cm.
- a Forward Tracker (pixel/strips) at positions in z from 20 to 130 cm, and extending radially between 15 and 30 cm.

The software used for jet reconstruction, vertex finding and fitting, and neural network tagging is fully described in [3]. This work represents an update of that study, to take into account recent changes in the design of the TESLA detector and in the simulation/analysis software.

Ideal pattern recognition is used in this paper, to study in a clearer way the performance of the tagging algorithm.

IMPACT PARAMETER RESOLUTION

The first, simple measurement of the performance of a vertex detector (combined with the information from the outer tracking system), is the resolution of the distance of closest approach of a track to a point (e.g. the nominal interaction point). Fig. 1 shows the results obtained from full track fits for the resolution in $r-\phi$ plane, which goes like:

$$\sigma_{r-\phi} = \sqrt{a_\phi^2 + (b_\phi/p\ sin^{3/2}\theta)^2}$$

where a_ϕ depends on the point resolution of the detector, and b_ϕ represents the resolution degradation due to multiple scattering. The value for a_ϕ is 4.19 μm, and for b_ϕ is 4.00 μm. This performance is much improved with respect to [3], and to the SLD CCD detector where the same constants took values of 14 μm and 33 μm respectively. This is due to the reduced CCD detector layer thickness, and to the fact that the inner layers of the vertex detector are placed closer to the interaction region.

HEAVY FLAVOUR TAGGING

The tagging algorithm

The neural network tagging algorithm used in this study is fully described in [3]. It uses information from three different algorithms: an impact parameter joint

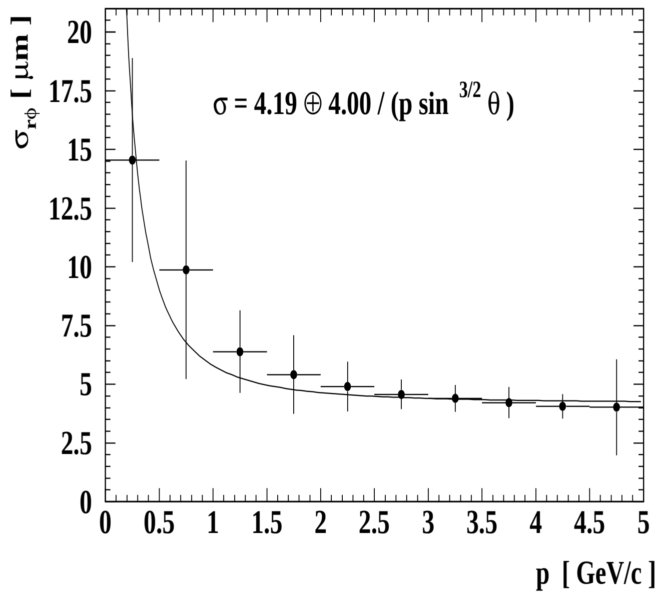

FIGURE 1. Distribution of impact parameter resolution versus momentum, for single pions generated at 90° with respect to the beam axis. The function best fitting the impact parameter dependence on momentum and polar angle is included on the plot. The magnetic field is 4 Tesla.

probability tagging algorithm from ALEPH [5], a topological vertex finder called ZVTOP, written for the SLD experiment [7], and a one-prong charm tag using the largest and second largest track impact parameter significances in $r-\phi$ and $r-z$ in jets where ZVTOP could only find one vertex (the primary vertex).

The neural network has three outputs (bnet,cnet and bcnet) which are used respectively to discriminate b jets against uds and c jets, c jets against uds and b jets, and b jets against c jets (assuming no uds background). Three classes of jets are used for the neural network training: jets where zero or one vertex (primary vertex) were found, jets where two vertices (primary and one secondary) were found, and jets where three or more vertices (primary and at least two secondaries) were found.

In fig. 2 and fig. 3 is shown the value of the bnet and cnet output for uds, c and b flavour jets, for one of the event classes studied.

Performance

For this study, 30000 events of type $e^+e^- \rightarrow Z^0/\gamma \rightarrow q\overline{q}$ were generated with PYTHIA at an energy in c.m. of 91.2 GeV, and then sent through BRAHMS. This was done to compare the performance with that obtained in the same physics processes by previous experiments at other facilites, and because 45 GeV jets are

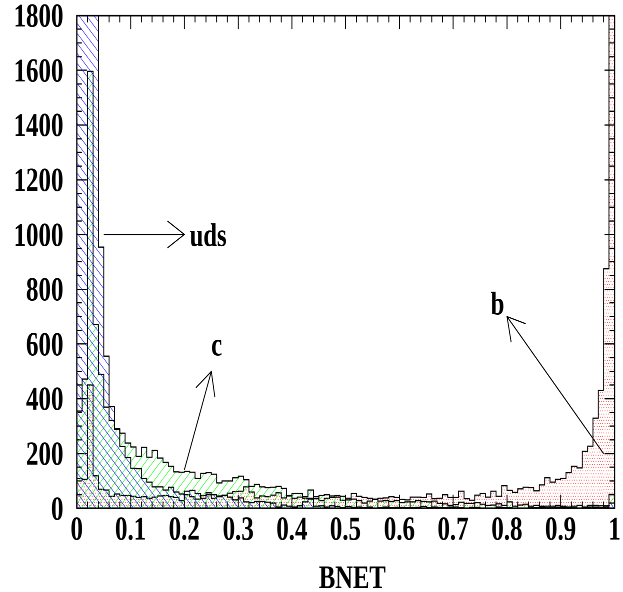

FIGURE 2. Distribution of b tagging neural network output for uds, c, and b jets in $q\overline{q}$ events at 91.2 GeV in the c.m.s.

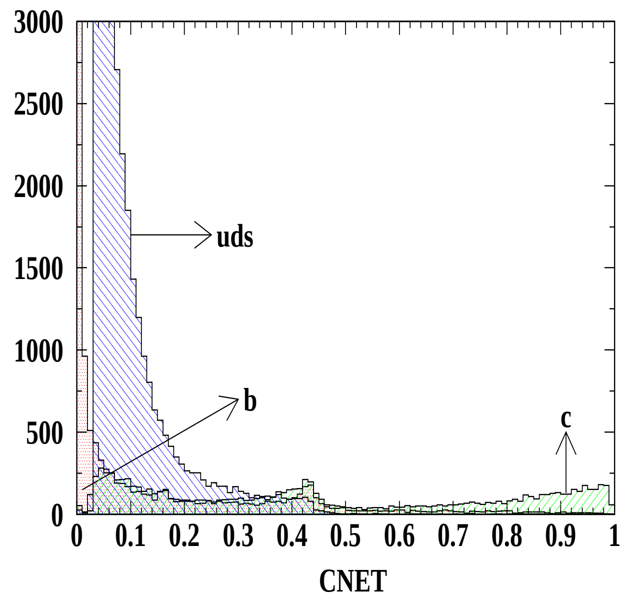

FIGURE 3. Distribution of c tagging neural network output for uds, c, and b jets in $q\overline{q}$ events at 91.2 GeV in the c.m.s.

representative of many physics processes at the high energy collider.

The performance shown in the following figures has to be understood as "per jet", and for each hemisphere in the event, the most energetic jet is used. A minimal number of 6 tracks is required for the event to be accepted. Candidate jets are found using the cone jet finding algorithm of L.A. del Pozo [6], with cut on half angle of 0.65 rad, and minimal energy 5 GeV.

Figure 4 shows the simulated detector performance for heavy flavour tagging in these events. Plots b and c show the performance of a neural net analysis for beauty and charm tagging respectively. These studies are just beginning, and there are several ideas for further improvements. For comparison, the best b and c tagging results currently achieved are shown, from the SLD experiment [4]. The gain in b tagging efficiency at TESLA is modest, whereas there is an improvement by a large factor (2 to 3) in charm tagging efficiency with high purity; this will provide a powerful new tool for physics. The third plot (labelled *c(b bkgr)*) shows the spectacular performance for charm tagging in an environment with mainly b background, relevant for example to the measurement of Higgs branching ratios.

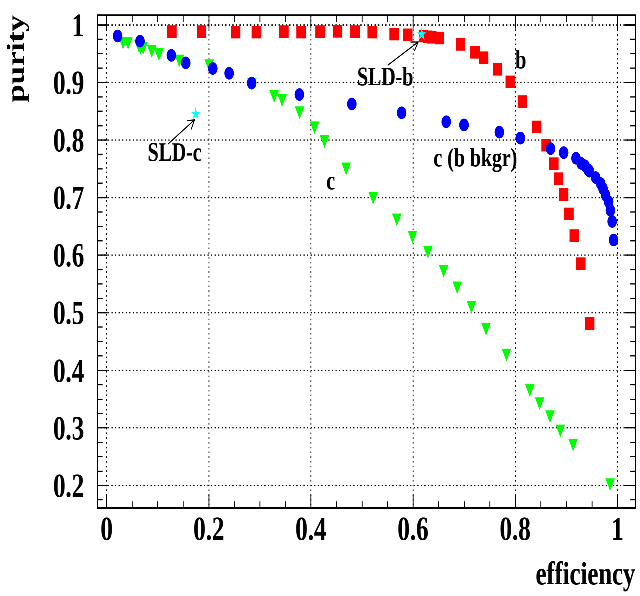

FIGURE 4. Purity versus efficiency for jets of beauty and charm flavour, generated in $q\overline{q}$ events at 91.2 GeV in the c.m.s.

Fig. 5 shows the dependence of the purity of b and c flavour events on cosinus of the jet polar angle, for a cut in the b and c neural network output at 0.48 and 0.43 respectively (corresponding to an efficiency of 80% and 50% respectively). The reduction in performance at the ends of the angular coverage (which is important for physics) is modest.

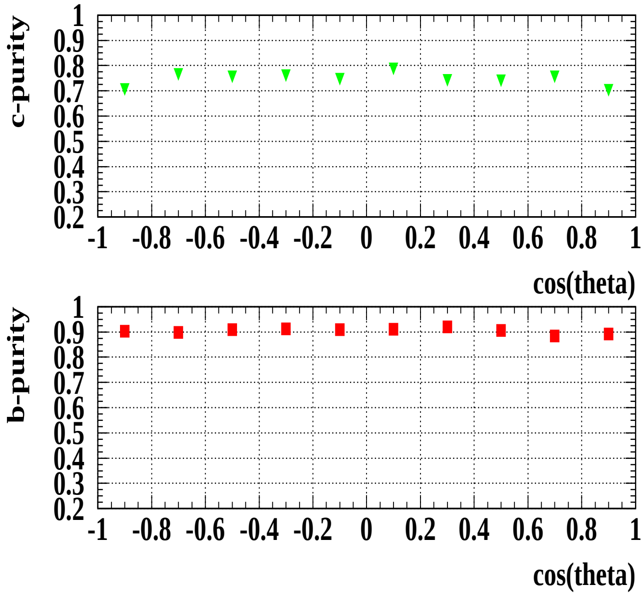

FIGURE 5. Purity versus cosinus of the jet angle for beauty (top) and charm (bottom) flavour jets, generated in $q\overline{q}$ events at 91.2 GeV in the c.m.s.

Dependence of performance with energy

It is important to study the dependence of the performance of the tagging algorithm on jet energy, since the TeV-scale collider will include events with a wide range of jet energies.

Figures 6 and 7 show the variation in quality of the flavour tagging with jet energy, in monojet events. This study has been carried out generating monojets with PYTHIA, and is based on the neural net training used for the studies of $e^+e^- \rightarrow q\overline{q}$ events. The neural network is at the moment being modified, to allow a more general retraining procedure.

The figures show the efficiency for tagging each 'unwanted' flavour as function of the efficiency for tagging the wanted flavour. As seen in the figures, the power for rejecting unwanted flavours (for a given efficiency for the wanted flavour) is extremely stable. It can be expected that by retraining the neural net directly on monojets, this rejection power will improve with energy.

The performance shown in these figures should not be expected to be exactly the same for 'real' physics processes at the linear collider. The monojet events here simulated are "unphysical", and used purely to test the performance of the tagging algorithm itself with energy. Without including additional real physics effects due to different energies, one can clearly test better the stability of the tagging procedure.

For physics studies, the analysis should be carried out for the specific signal and background processes, such as $e^+e^- \rightarrow q\overline{q}$, since the detailed fragmentation of the jets is important. The neural net should also be retrained for each scenario.

Looking briefly at $e^+e^- \rightarrow q\overline{q}$ events for energy in c.m.s. of 45, 91.2 and 200 GeV, one sees that the performance is indeed slightly different with respect to the monojets runs, as expected since the composition and kinematics of the events is different. For unwanted efficiencies $\geq 10^{-2}$, the performance improves with $\sqrt{s}$. For very high rejection efficiencies the trend is reversed. It is suspected that this may be due to non optimal treatment of gluon splitting to $b\overline{b}$ and $c\overline{c}$ in the high energy events, but these studies are now only beginning.

CONCLUSION

These studies have demonstrated that a vertex detector compatible with the conditions at the future TeV-scale linear collider (TESLA as an example) will provide a powerful tool for physics. Currently, the performance of tagging for jets in $e^+e^- \rightarrow q\overline{q}$ events far exceeds that of the LEP/SLD vertex detectors, particularly in the area of charm tagging. This performance is preserved as the jet energy is increased. With further study, it is expected that the performance for high energy jets will in fact be enhanced.

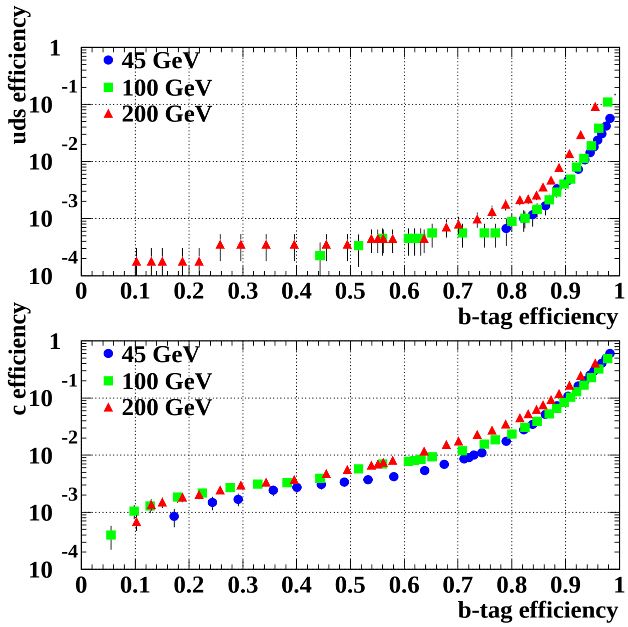

FIGURE 6. Tagging performance for b jets of different energies. Efficiencies for 'unwanted' uds jets and charm jets are shown as function of the b-tag efficiency.

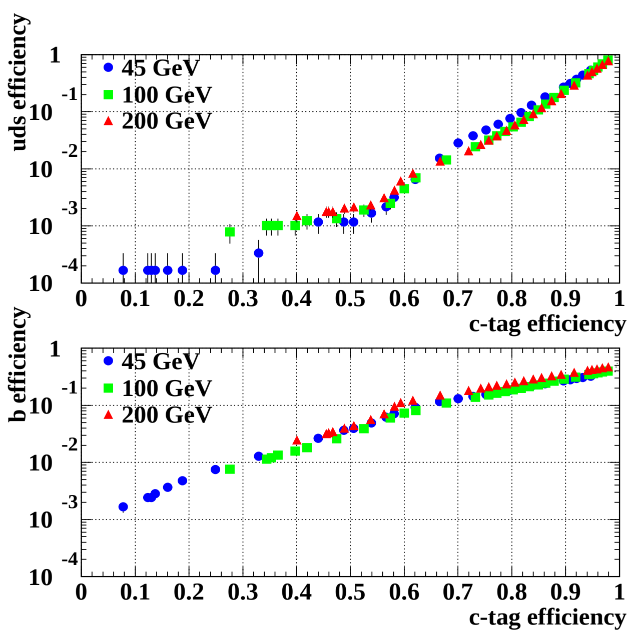

FIGURE 7. Tagging performance for charm jets of different energies. Efficiencies for 'unwanted' uds jets and b jets are shown as function of the c-tag efficiency.

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