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IDENTIFICATION OF EVENTS WITH A SECONDARY VERTEX IN THE EXPERIMENT EXCHARM

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A simple algorithm for identifying events with secondary vertices (signal events) is suggested. The differences R_x, R_y between the largest and the smallest impact parameters D_i of the tracks belonging to each of the events analysed are used in establishing the identification criteria for signal and background events. An effective method for identifying the tracks associated with a particular secondary vertex in an event is developed. The method is based on the differences between the asymmetries exhibited by the sets D_i for individual signal events and background events. The algorithm has been tested using simulated data.

The investigation has been performed at the Laboratory of Computing Techniques and Automation, JINR.

Идентификация событий со вторичной вершиной в эксперименте ЭКСЧАРМ

А.Ю.Бонюшкина и др.

Предлагается простой алгоритм идентификации событий со вторичной вершиной (сигнальных событий). Для классификации сигнальных и фоновых событий используются переменные R_x и R_y, представляющие собой разность между наибольшим и наименьшим значениями промахов треков D_i в *XOZ*- и *YOZ*-проекциях для каждого анализируемого события. Для выделения треков, отвечающих вторичной вершине, разработан эффективный метод, основанный на асимметрии выборок $\{D_i\}$. Указанные алгоритмы апробированы на модельных данных.

Работа выполнена в Лаборатории вычислительной техники и автоматизации ОИЯИ.

Introduction

The experimental set-up EXCHARM is intended for investigation of the production and decay mechanisms of charmed particles and for searching for exotic multiquark states at the U-70 accelerator in the 50 GeV neutron beam*. As such processes have small cross sections, it is necessary to develop fast and efficient algorithms for their identification taking into account the specific features of the concrete physical set-up (see, for instance,

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*The construction of the neutron channel at the U-70 and the EXCHARM set-up are described in papers [1,2,3].

Refs. [5,6,7]), and to construct a specialized trigger, permitting classification of detected events in the real time of the experiment [8].

A characteristic feature of the processes indicated is the presence of primary and secondary (due to the decay of a neutral meson) vertices separated in space. The authors of paper [5] make use of the information on track coordinates in passing to the variables D — the impact parameter* — and the angle φ between the direction of a track and the beam and suggest calculating the moment functions on the basis of the entire sets D_i and φ_i for an individual event and, then, inputting them to a three-layered perceptron for the discrimination of background events.

This approach with various modifications has shown its efficiency in a number of experiments [5,7,9]. But our efforts to implement it in the EXCHARM experiment have yielded no positive result (see sec.2). In the present work, a new algorithm for identifying events with secondary vertices is considered. Moreover, a method is suggested which permits singling out the charged particle tracks departing from the secondary vertex.

1. Experiment

The basis of the EXCHARM spectrometer [1,2,3] is a spectrometric magnet, used for analysing the momenta of secondary charged particles. The centre of the gap between the poles of the magnet is taken for the origin of «right-handed» Cartesian coordinate system (XYZ), with the OZ-axis directed along the beam, and the OY-axis coinciding with the main component of the magnetic field. Proportional chambers are used as coordinate detectors to register the linear segments of charged particle trajectories before and after the analysing magnet.

Figure 1 presents (in the XOZ-projection) the layout of the target, of the analysing magnet and of those coordinate detectors, which are placed between the target and the magnet.

In developing the algorithms for classifications of signal and background events, data obtained with the help of a simulation program SSIMUL were used [4]. The program SSIMUL was developed on the basis of the GEANT package [10], and it permits simulating various physical processes taking place within the EXCHARM set-up during the real experiment. With the help of this program, interactions between the primary neutrons and the target nucleons were simulated, the particles produced were traced through the detectors and the known magnetic field taking into account Coulomb scattering, energy losses, etc. Secondary unstable particles were made to decay in accordance with their lifetimes and decay probabilities via different channels; the decay particles were also traced through the spectrometer.

The SSIMUL code was used for generating two types of reactions, and the relevant information was recorded in two respective files. The first file contained the data for a set of 2300 events involving Λ_c^+ production (signal events) with secondary vertices: only 5-

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*The impact parameter of a track in the plane passing through the center of the target and perpendicular to the beam.

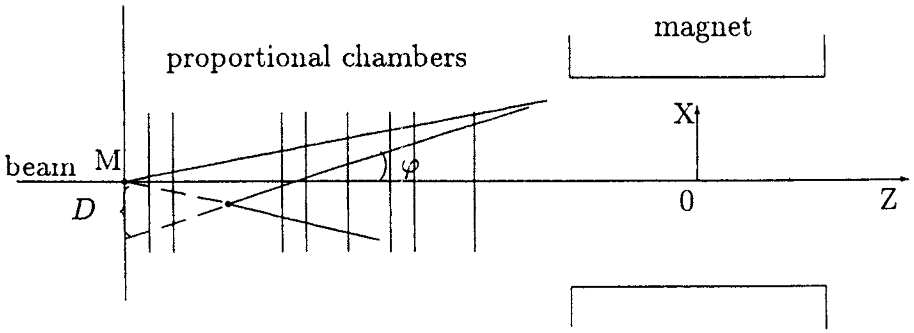

Fig.1. Layout of target *M*, analysing magnet and coordinate detectors (XOZ-projection). Decay scheme of secondary short-lived particle

track events were taken into account. The second file contained 2300 background events corresponding to reactions without the production of short-lived particles: the number of secondary particles was required to exceed 3.

2. Algorithm for Event Classification

The algorithm considered here, as well as the one described above [5], is based on the coordinate information for the trajectories of secondary particles detected by the set of proportional chambers placed in front of analysing magnet.

Using the parameters of linear tracks, we shall determine the variables D — the impact parameter of a track in the plane passing through the centre of the target and perpendicular to the beam — and the track angle φ (see Fig.1). In accordance with Ref. [5], we shall calculate the moment functions on the basis of the entire set of variables D and φ for each individual event, as follows:

$$\eta_{02} = \frac{1}{N} \sum_{i=1}^{N} (D_i - \overline{D})^2,$$

$$\eta_{11} = \frac{1}{N} \sum_{i=1}^{N} (\varphi_i - \overline{\varphi})(D_i - \overline{D}).$$

Here N is the number of tracks in the event, $\overline{D}$ and $\overline{\varphi}$ are the mean values of D_i and φ_i [5].

These variables have behaved very well, for instance, in the investigation of processes involving the production and decay of *B*-mesons [5,9] and Λ^0-s [7]. But in our case the distributions of the variables η_{02} and η_{11} for the background and signal events are

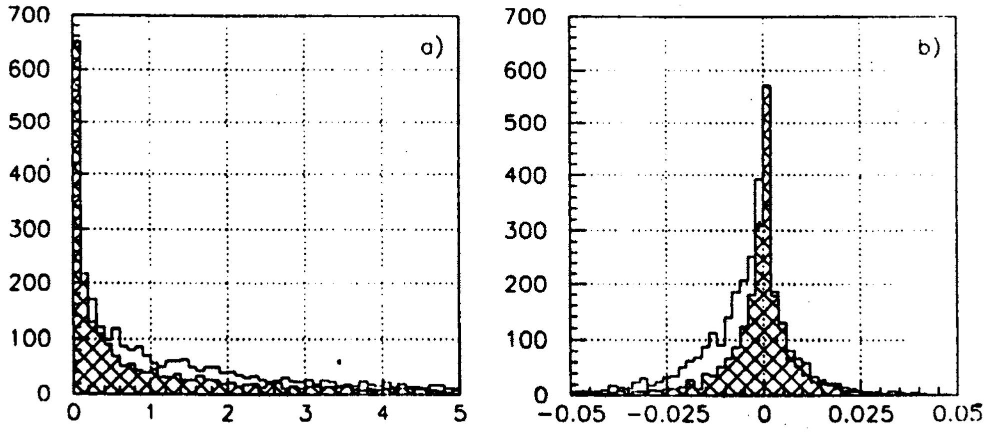

Fig.2. Distribution of random variables η_{02} (a) and η_{11} (b) for background (shaded histogram) and signal (empty histogram) events

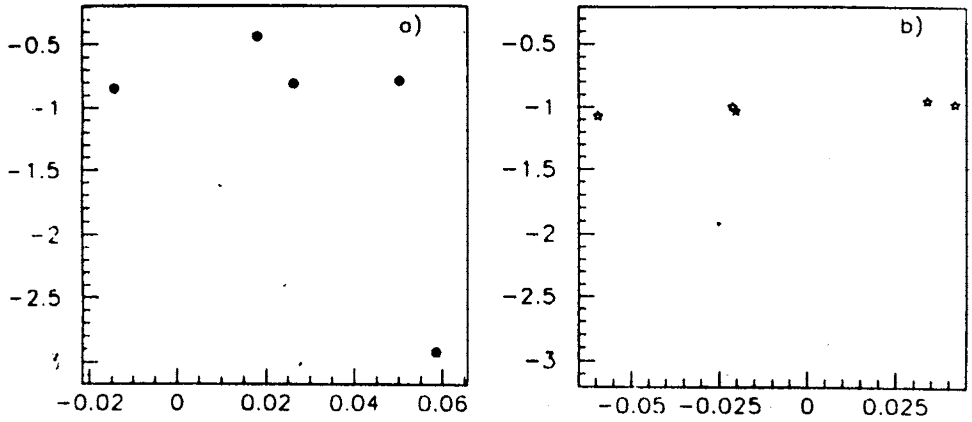

Fig.3. Two-dimensional distributions (φ, D) for typical signal (a) and background (b) events in XOZ-projection

practically indistinguishable (see Fig.2) owing to the large transverse size of the target (its radius equals 3 cm) and to the neutron beam not being focused. Therefore, we have tried to find another approach to the solution of the problem considered.

Comparison of the background and signal events in $\varphi - D$ space reveals the impact parameters D for all the tracks of a background event to be grouped within a quite narrow corridor, while certain individual tracks of the signal event have impact parameters differing significantly from the other D values of the set $\{D_i\}$. Figure 3 presents examples of the distributions in $\varphi - D$ space for typical signal (a) and background (b) events.

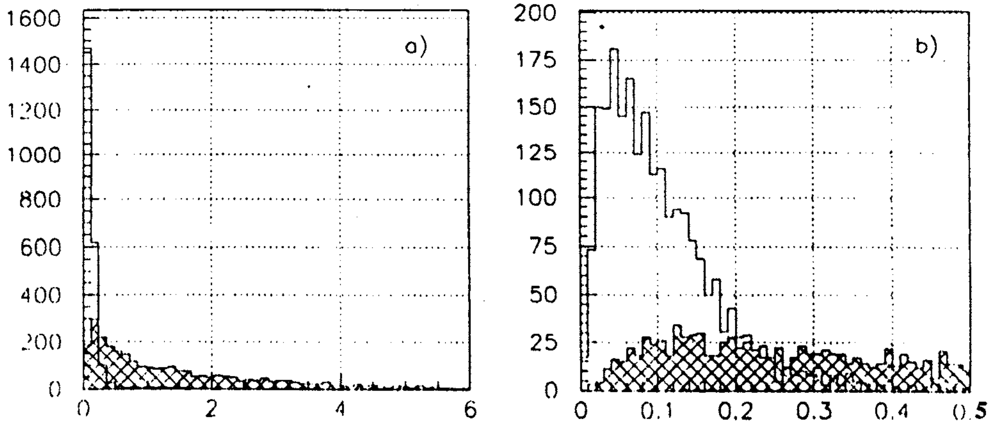

Fig.4. Distributions of random variables R_x (a) for background (empty histogram) and signal (shaded histogram) events; (b) — same distributions in the region of small R_x

Thus, to identify events with a secondary vertex we may take advantage of the difference between the maximum, $D^{\max}$, and minimum, $D^{\min}$, values in the set $\{D_i\}$, $i = 1, ..., N$. For the *XOZ*- and *YOZ*-projections these values are:

$$R_x = D_x^{\max} - D_x^{\min},$$

$$R_y = D_y^{\max} - D_y^{\min}.$$

The complete distributions of the variables R_x for the background events (empty histogram) and for the events involving Λ_c^+-production (shaded histogram) are presented in Fig.4,a. The respective distributions can be seen from the figure to differ significantly*. The same distributions in the region of small R_x values are shown in Fig.4b.

2.1. Classification of Events by a Neural Network. To classify the events in the space of the variables R_x and R_y a multilayer neural network with a feed-forward architecture from the JETNET3 package [11] was used. A three-layered perceptron comprising two input neurons, ten units in the hidden layer and one output neuron was adopted as a working model. The random variables R_x and R_y transformed to the interval $[-1, 1]$ were supplied to the input neurons. At the training stage the *back-propagation* algorithm [12] was used for minimization of the error functional.

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*Distributions of the random variables R_y have the same character

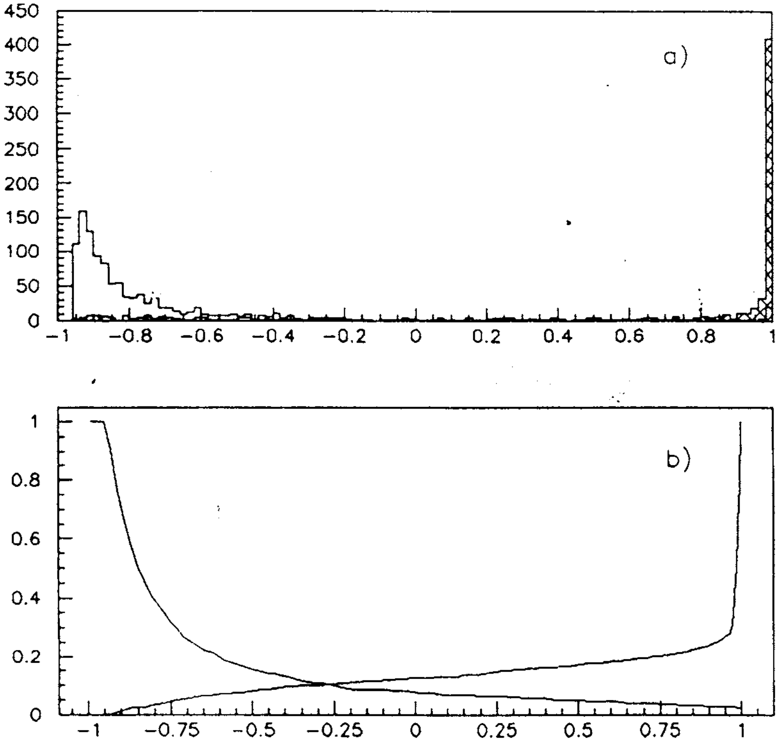

Fig.5. Result of neural network test with mixture of signal and background events (a); dependences of cumulative probability $F(y_g) = P_r(y < y_g)$ for events with Λ_c^+ and probability $1 - F(y_g)$ for background events against chosen threshold (b)

All the events, comprising 2300 background events and 2300 events with Λ_c^+, were mixed and divided into two sets with the same number of events. The first set was used for training the neural network and the second for estimating the network performance.

During testing of the network an event was classified by the value of the output signal y: if it does not exceed the chosen limit value y_g, the event is considered to be a background event, otherwise it is a signal event. Figure 5a shows the results of the network test; the dependence of the distribution function $F(y_g) = P_r(y < y_g)$ for events with Λ_c^+ and the dependence $1 - F(y_g)$ for background events against the chosen threshold are presented in Fig.5b.

For a threshold $y_g = 0$, the fraction of correctly identified events from the mixture was 90%; in this case, the error of the 1st kind (the fraction of background events classified as signal events) amounted to 7%, and the error of the 2nd kind (the fraction of events with Λ_c^+ classified as background events) was 12%.

3. Identification of Tracks Associated with a Secondary Vertex

As it was mentioned above, certain individual tracks in the signal events have impact parameters, differing significantly from the other D values of the set $\{D_i\}$. The distributions of the impact parameters D_x (a) and D_y(b) for a typical signal event are presented in Fig.6. An analysis of tracks with «falling out» D has revealed such tracks to be associated with the decay of a neutral particle ($K^0, \Lambda^0, \overline{\Lambda}^0$).

Hence, to single out such tracks we can make use of the asymmetry of the set $\{D_i, i = 1, ..., N\}$ corresponding to the current event:

$$G_1 = \frac{m_3}{\sqrt{m_2^3}}, \tag{1}$$

where m_2 and m_3 are sampling central moments of the distribution considered:

$$m_r = \overline{(x-\overline{x})^r} = \frac{1}{N}\sum_{k=1}^{N}(x_k-\overline{x})^r, \quad r = 2, 3. \tag{2}$$

and N is the number of tracks in the event.

In accordance with expressions (1) and (2), the asymmetries of the sets $\{D_i^x\}$ and $\{D_i^y\}$ (corresponding to the individual event) for projections XOZ (G_1^x) and YOZ (G_1^y) were

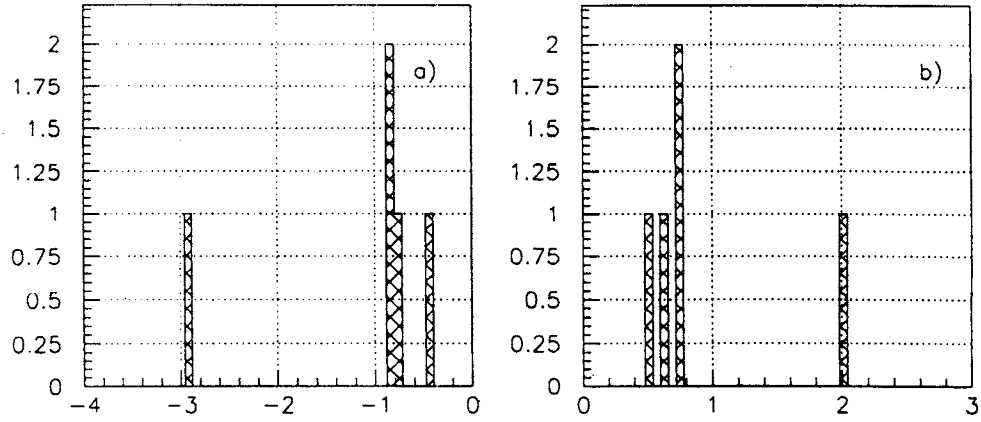

Fig.6. Distribution of random values D_x (a) and D_y (b) for typical event with secondary vertex

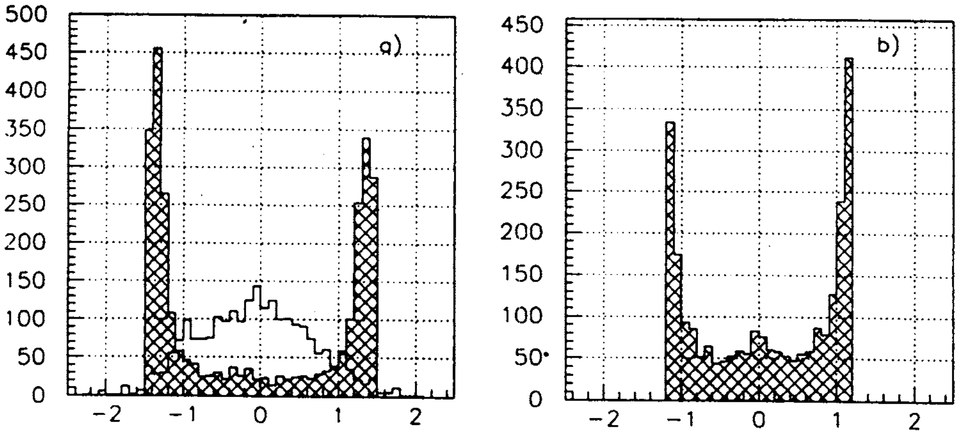

Fig.7. Distributions of random values G_1^x (a) for background (empty histogram) and for events with secondary vertex (shaded histogram); distribution of values G_1^x (b) for events with secondary vertex after exclusion of track with the largest G_1^x absolute value from sample under consideration

calculated. In Fig.7a, the distributions of asymmetries for the signal (shaded histogram) and background (empty histogram) events in the *XOZ*-projection are presented. It can be seen that events with secondary vertices are characterized by a well pronounced asymmetry*.

The clearly seen difference between these distributions permits us to propose the following procedure for identifying tracks associated with a secondary vertex.

An asymmetry $G_1^x > 0$ indicates the distribution has a long «tail» on the right, and in this case the track with the largest impact parameter most probably belongs to the secondary vertex. If the asymmetry $G_1^x < 0$, the track associated with the secondary vertex is determined by the smallest impact parameter. Therefore, using the G_1^x value one can point to the *XOZ*-projection of the first track belonging to the secondary vertex.

Applying a similar procedure for analysing the asymmetry G_1^y, we can single out the *YOZ*-projection of the track sought. If the *XOZ*- and *YOZ*-projections selected belong to different tracks, the problem is solved, and we have two tracks composing the secondary vertex. In the opposite case, the D value corresponding to the selected track is excluded from the set $\{D_i\}$, and further analysis is performed on the basis of the cut set $\{D'_i\}$.

The distribution of random variables G_1^x constructed on the basis of the set $\{D'_i\}$ is presented in Fig.7b. It can be seen from the figure that after exclusion of the first track the character of the indicated distribution did not change, on the whole. In searching for the

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*The distributions of random variables G_1^y have the same character second track associated with the vertex, preference is given to the projection, for which the absolute value of asymmetry is larger.

In the analysis of 2653 events with Λ_c^+ the first track of the secondary vertex was correctly identified in 2514 cases; and the second track, in 2336 cases. So, tracks were identified correctly for 88% of the events.

Conclusion

A simple algorithm for identifying events with a secondary vertex is developed. For classification of events the variables R_x and R_y are used. R_x and R_y are the differences between the largest and the smallest impact parameters $\{D_i\}$ of tracks in the *XOZ*- and *YOZ*- projections. Application of a neural network for identification of signal events in the space of the indicated variables permits significant suppression of background events. An effective method, based on the asymmetries of sets $\{D_i\}$ differing for signal and background events, is proposed for singling out tracks associated with the secondary vertex.

The considered algorithms have been tested for simulated data. Comparison of the new algorithms with algorithms applied at present by the EXCHARM collaboration and their tests with real experimental data is of certain interest.

References

1. Aleev A.N. et al. — JINR Preprint P13-94-312, Dubna, 1994.
2. Aleev A.N. et al. — JINR Preprint P13-94-124, Dubna, 1994.
3. Aleev A.N. et al. —JINR Preprint P13-94-520, Dubna, 1994.
4. Aralbaeva G.A. et al. — JINR Communications, P1-93-85, Dubna, 1993.
5. Gupta L. et al. — «Neural Network Trigger Algorithms for Heavy Quark Event Selection in a Fixed Target High Energy Physics Experiment». FERMILAB-Pub-91/17, FNAL, Batavia, 1991.
6. Ososkov G.A., Rusakovich N.A., Chernov N.I. — JINR Preprint P10-90-367, Dubna, 1990.
7. Ivanov V.V., Pontecorvo D.B. — JINR Preprint P10-93-271, Dubna, 1993; In: Proc. of Inter. Conf. «Programming and Mathematical Methods for Solving Physical Problems». Edited by Yu.Yu.Lobanov and E.P.Zhidkov, World Scientific, 1994, p.283—286.
8. Denby B. — In: Proc. of the Second International Workshop «Software Engineering, Artificial Intelligence and Expert Systems in High Energy Physics». January 13—18, 1992 L'Agelaude France-Telecom La Londe-les-Maures (France). New Computing Techniques in Physics Research II, edited by D.Perret-Gallix, World Scientific, 1992, p.287.

9. Ivanov V.V., Poroshin N.O., I.V.Puzynin, B.Purevdorj — JINR Preprint P10-94-300, Dubna, 1994.
10. Brun R. et al. — GEANT Long Write-Up, CERN Program Library, W5013 (1989).
11. Peterson C., Rognvaldsson Th. — «JETNET-3.0 — A Versatile Artificial Neural Network Package», LU TP 93-29, CERN-TH.7135/94.
12. Rumelhart D.E. et al. «Learning Internal Representations — In: D.E.Rumelhart and J.L.McClelland (eds.) «Parallel Distributed Processing: Explorations in the Microstructure of Cognition», vol.1, MIT Press, Cambridge, MA, 1986.

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